Expert Systems

Article

DOI: 10.1111/j.1468-0394.2010.00566.x

Hybrid recommendations for mobile commerce based on mobile phone features

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Abstract: *Mobile data communications have evolved as the number of third generation (3G) subscribers has increased. The evolution has triggered an increase in the use of mobile devices, such as mobile phones, to conduct mobile commerce and mobile shopping on the mobile web. There are fewer products to browse on the mobile web; hence, one-to-one marketing with product recommendations is important. Typical collaborative filtering (CF) recommendation systems make recommendations to potential customers based on the purchase behaviour of customers with similar preferences. However, this method may suffer from the so-called* sparsity problem, *which means there may not be sufficient similar users because the user-item rating matrix is sparse. In mobile shopping environments, the features of users' mobile phones provide different functionalities for using mobile services; thus, the features may be used to identify users with similar purchase behaviour. In this paper, we propose a mobile phone feature (MPF)-based hybrid method to resolve the sparsity issue of the typical CF method in mobile environments. We use the features of mobile phones to identify users' characteristics and then cluster users into groups with similar interests. The hybrid method combines the MPF-based method and a preference-based method that uses association rule mining to extract recommendation rules from user groups and make recommendations. Our experiment results show that the proposed hybrid method performs better than other recommendation methods.*

Keywords: mobile web, one-to-one marketing, product recommendation, collaborative filtering, mobile phone features, association rules

1. Introduction

In the last decade, mobile communications have evolved from 2G/2.5G to 3G/3.5G. As a result, the data transfer rate has been progressively upgraded from 64 Kbps (2.5G/GPRS) to 384 Kbps (3G/WCDMA), and 3.5 Mbps (3.5G/HSDPA), which is comparable to the wired Internet. The evolution has triggered an increase in the use of mobile devices, such as mobile phones, to conduct mobile commerce (m-commerce) on the mobile web (Chae & Kim, 2003; Venkatesh *et al.*, 2003; Ngai & Gunasekaran, 2007). M-commerce covers a large number of services, one of which is mobile shopping. Retailers have also increased their investment in mobile shopping channels to deliver dedicated products, content and promotions to customers.

Recommender systems have emerged in m-commerce or e-commerce applications to support product recommendation, which provide individual product recommendation for each customer. Recommender systems assist business in implementing one-to-one marketing strategies, relying on customer purchase history to determine preferences and identify products that a customer may purchase. Recommender systems increase the probability of cross-selling, establish customer loyalty and fulfill customer needs by discovering products in which they may be interested in purchasing (Schafer *et al.*, 2001). Recommender systems are widely used to recommend various items, such as consumer products, movies and music, to customers based on their interests (Hill *et al.*, 1995; Shardanand & Maes, 1995). Generally, recommender systems can be classified as collaborative or content-based filtering techniques. Collaborative filtering (CF), which has been used successfully in various applications, utilizes preference ratings given by customers with similar interests to make recommendations to a target customer (Resnick *et al.*, 1994; Linden *et al.*, 2003; Lee, 2004; Cho *et al.*, 2005; Liu & Shih, 2005). In contrast, content-based filtering derives recommendations by matching customer profiles with content features (Mooney & Roy, 2000; Martinez *et al.*, 2007).

A number of product recommendation systems have been developed for m-commerce on the mobile web (Kim *et al.*, 2004; Choi *et al.*, 2007; Lee & Park, 2007). For example, VISCOR is a mobile recommender that combines collaborative and content-based filtering to provide better wallpaper recommendations (Kim *et al.*, 2004). MCORE considers users' context data to recommend mobile services (Choi *et al.*, 2007). In addition, mobility information about user locations obtained from global positioning systems (GPS) is usually used in m-commerce. A number of mobile recommendation systems use customers' mobility patterns to make recommendations (Brunato & Battiti, 2003; Yang *et al.*, 2008). Mobile phone features (MPF) such as Bluetooth and card slots have been used as product attributes to recommend mobile phone products. iTVMobi recommends mobile phone products based on the users' preferences for MPF (Virvou & Savvopoulos, 2007). Existing works use MPF as product attributes to recommend mobile phone products, instead of using the features of mobile phones as the users' characteristics (profiles) to recommend products.

The typical CF method relies on finding users with similar interests to make recommendations. However, it may suffer from the so-called *sparsity problem* because users only rate a few items. As a result, the user-item rating matrix is very sparse, so the recommendation quality is poor due to the difficulty of finding users with similar interests. In mobile shopping environments, active users may only browse/purchase a few items on the mobile web; thus, it is difficult to find users with similar interests based on the product preferences derived from users' browsing/purchasing histories.

In this study, we propose a MPF-based hybrid method to resolve the sparsity issue of the typical CF method used in mobile environments. The MPF-based method uses the features of users' mobile phones as user profiles to cluster users into groups with similar characteristics and then makes recommendations. The MPF indicate users' motivations for using mobile services; thus, they can be used to identify users with similar product preferences. For example, the profiles of businessmen or sales representatives who own mobile phones with intelligence and GPS features may indicate a strong interest in high-tech 3C (Computer, Communication and Consumer) products. Thus, we consider MPF as user characteristics to help find users with similar interests. However, some users who own mobile phones with the similar features may not have the similar product preferences. Hence, we still need to refer users' product preferences for making recommendations. Thus, we propose a hybrid method which combines the MPF-based method and the preference-based method to improve recommendation quality by considering both MPF and product preferences. Similar to the MPF-based method, the preference-based method makes recommendations based on user groups that are clustered according to the users' product preferences. Experiments were conducted to compare the performance of the proposed hybrid method with that of MPF-based, preference-based and typical CF methods. The results show that the hybrid method outperforms the other methods.

The remainder of this paper is organized as follows. In Section 2, we illustrate the background of related methods. In Section 3, we describe the proposed MPF-based, preference-based and hybrid recommendation methods. In Section 4, we present the evaluation metrics and the experiment results. Then in Section 5, we summarize our findings and draw some conclusions.

2. Background

Our proposed method is based on MPF, and uses association rule-based and most frequent item-based recommendation methods. In this section, we briefly introduce the concepts and methods that are used in our research. This section also illustrates the typical CF method that is compared with our approach in experiment evaluation.

2.1. MPF

Mobile phones have evolved from the traditional voice communication model to advanced digital convergence platforms with various features, such as Bluetooth technology, cameras, card slots, flash lights, as well as java, MP3, radio, touch screen, video and Wi-Fi functions (Ojanpera, 2006). These features enable users to access related mobile services, for example, download MP3 files, upload photos to blogs, video streaming and on-line shopping (Ko *et al.*, 2007). Ling *et al.* (2006) investigated the impact of MPF on user satisfaction and analysed the feature preferences of diverse ethnic groups as well as preferences based on gender. Virvou and Savvopoulos (2007) developed an intelligent application called iTVMobi, which recommends mobile phone products on an interactive television. The system uses *K*-means clustering to group users based on their preferences for the attributes of mobile phones. The system then applies an association rule-based approach to recommend mobile phones based on the users' preferences.

Existing works use MPF as product attributes to recommend mobile phone products, instead of using the features of mobile phones as user characteristics (profiles) to recommend products. The features of different types of mobile phones can be obtained from the respective websites. In this study, we log users' mobile phone types when they browse products on a mobile shopping website. Then, we derive the phone features preferred by each user and use them to compile MPF-based user profiles.

2.2. Users clustering

Clustering techniques, which are usually used to segment users (Punj & Stewart, 1983; Chen *et al.*, 1996), seek to maximize the variance among groups while minimizing the variance within groups. Many clustering algorithms have been developed, such as *K*-means, hierarchical and fuzzy *c*-means algorithms (Omran *et al.*, 2007). *K*-means clustering (MacQueen, 1967) is a similarity grouping method widely used to partition a dataset into *k* groups. The *K*-means algorithm assigns instances to clusters based on the minimum distance principle, which assigns an instance to a cluster such that the distance to the centre of the cluster is the minimum over all *k* clusters.

2.3. Association rule-based recommendation method

Association rule mining tries to find the associations between two sets of products in a transaction database. Agrawal *et al.* (1993) formalized the problem of finding association rules that satisfy the minimum support and the minimum confidence requirements. For example, assume that a set of purchase transactions includes a set of product items I. An association rule is an implication of the form: $X \Rightarrow Y$, where $X \subset I$, $Y \subset I$ and $X \bigcap Y = \Phi$. X is the antecedent (body) and Y is the consequent (head) of the rule. Two measures, support and confidence, are used to indicate the quality of an association rule. The support of a rule is the percentage of transactions that contain both X and Y, whereas the confidence of a rule is the fraction of transactions that contain X and also contain Y.

Sarwar *et al.* (2000) described the association rule-based recommendation method as follows. For each customer, a customer transaction is created to record all the products he/she purchased previously. An association rule mining algorithm is then applied to find all the recommendation rules that satisfy the given minimum support and minimum confidence. The top-N products to be recommended to a customer u, are then determined as follows: Let X_u be the set of products previously purchased by u. The method first finds all the recommendation rules $X \Rightarrow Y$ in the rule set. If $X \subseteq X_u$ then all products in $Y - X_u$ are deemed candidate products for recommendation to the customer u. The candidate products are then sorted and ranked according to the associated confidence of the recommendation rules, and the top-N candidate products are selected as the top-N recommended products.

2.4. *Most frequent item-based recommendation method*

The most frequent item-based recommendation method (Sarwar *et al.*, 2000) counts the purchase frequency of each product by scanning the products purchased/browsed by the users in a cluster. Next, all the products are sorted by the purchase frequency in descending order. Finally, the method recommends the top-N products that have not been purchased/browsed by the target customer.

2.5. *Typical CF method*

CF (Resnick *et al.*, 1994; Shardanand & Maes, 1995) utilizes the nearest-neighbour principle to recommend products to a target audience. The neighbours are identified by computing the similarity of customers' purchase behaviour or tastes. The similarity is measured by Pearson's correlation coefficient, which is defined as follows:

$$corr_P(C_i, C_j) = \frac{\sum_{s \in I}(r_{C_{i,s}} - \bar{r}_{C_i})(r_{C_{j,s}} - \bar{r}_{C_j})}{\sqrt{\sum_{s \in I}(r_{C_{i,s}} - \bar{r}_{C_i})^2 \sum_{s \in I}(r_{C_{j,s}} - \bar{r}_{C_j})^2}} \quad (1)$$

where $\bar{r}_{C_i}$ and $\bar{r}_{C_j}$ denote the average number of products purchased by customers C_i and C_j, respectively; variable I denotes the mix of the set of products; and $r_{C_{i,s}}$ and $r_{C_{j,s}}$ indicate, respectively, that customers C_i and C_j purchased product item s.

The typical CF method utilizes k-nearest neighbours (k-NN) to recommend N products to a target user (Sarwar *et al.*, 2000). The k-NN are identified by computing the similarity of customers' purchase behaviour or tastes. The similarity is measured by Pearson's coefficient, as shown in equation (1). After the neighbourhood has been formed, the N recommended products are determined by the k-NN as follows. The frequency count of products is calculated by scanning the data about the products purchased/browsed by the k-NN. The products are then sorted based on the frequency count, and the N most frequent products that have not been purchased by the target customers are selected as the top-N recommendations.

3. Proposed MPF-based hybrid recommendation method

In this section, we describe the proposed hybrid recommendation method, which combines an MPF-based method and a preference-based method, as shown in Figure 1. First, the MPF-based method extracts the features of users' mobile phones from the respective phone websites, as shown on the left-hand side of the figure. The features of users' mobile phones are taken as user profiles to identify users with similar characteristics. The system then applies the K-means clustering method to cluster users into groups based on the similarity of users' MPF. Next, the association rules and frequently browsed products are extracted from each cluster. The system then recommends products based on the association rules and frequently browsed products. However, there may be very few products recommended according to the association rules because of the limited number of products that can be browsed on the mobile web. If the association rule-based recommendations are not sufficient, the most frequent item-based recommendations are used to recommend

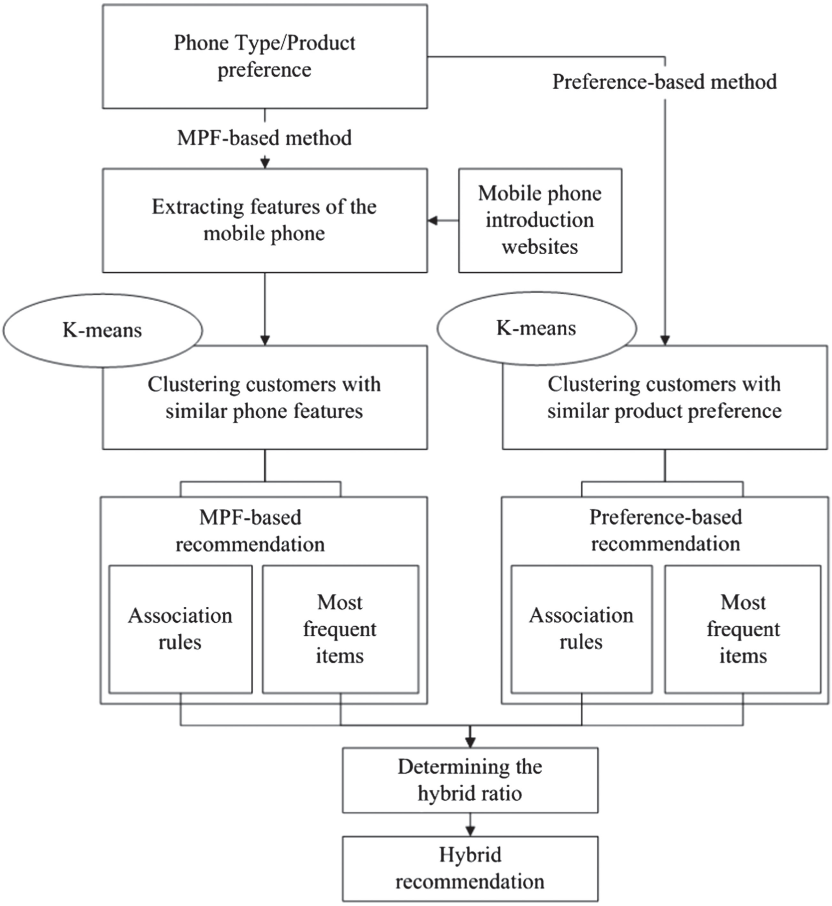

Figure 1: *An overview of the proposed hybrid recommendation scheme.*

products to users. Similar to the MPF-based method, the preference-based method, shown on the right-hand side of Figure 1, clusters users by the *K*-means clustering method based on Pearson's correlation coefficient of users' product preferences. It then recommends products based on the association rules and the most frequent items. Finally, the hybrid recommendation scheme combines the MPF-based recommendations and preference-based recommendations with the hybrid ratio determined by the preliminary analytical data to recommend products. We discuss the recommendation phase of the MPF-based, preference-based and hybrid recommendation schemes in Sections 3.2 and 3.3, respectively.

3.1. Data pre-processing and clustering

We obtained the features of each mobile phone from one of the mobile phone websites. There are more than 100 features on a mobile phone. It is hard to analyse all of them. Therefore, we selected the features based on the following three criteria. (1) Advertisements of a mobile phone retailer: The advertisements of a mobile phone retailer often list the important features for users' preferences and comparison; (2) Features with too many missing values are not suitable for analysis and thus are not selected; and (3) Features with values that can discriminate the differences of mobile phones. Table 1 lists the selected features, including Bluetooth

Table 1: *Mobile phone features*

No	*Feature*	*Data type*	*Value*
0	Bluetooth	Boolean	(0, 1)
1	Camera quality	Discrete	(Low, Medium, High)
2	Card slot	Boolean	(0, 1)
3	Flash light	Boolean	(0, 1)
4	Java	Boolean	(0, 1)
5	MP3	Boolean	(0, 1)
6	Radio	Boolean	(0, 1)
7	Video	Boolean	(0, 1)

technology, cameras, card slots, flash lights, as well as java, MP3, radio and video functions.

The price feature is complicated for analysis, since the prices of mobile phones may vary under different subscription fees provided by various service providers. Thus, we do not select the price feature. The price feature has been somewhat implicitly considered and depends on the selected eight features, because mobile phones with more features are often more expensive. The display feature is not listed in the advertisements of the mobile phone retailer and is a combination of three discrete data type features including screen size, colour and material. These values of the display features are missing and are difficult to collect. Thus, we do not select the display feature.

We calculate the similarity of users based on the selected features. The camera quality feature, which is a discrete data type, and the other seven features are Boolean data types. The camera resolution pixels (3.2, 2.0 and 1.3 mega-pixel resolution) need to be normalized to the semantic values of high, medium and low, as shown in equation (2) (Lin *et al.*, 2003). Therefore, we use three Boolean operators to represent high, medium and low quality camera resolution (1, 0, 0) represents high quality (0, 1, 0) represents medium quality, and (0, 0, 1) represents low quality.

$$Z_{\text{camera}} = \frac{X_{\text{camera}} - M(X_{\text{camera}})}{\sigma_{X\text{camera}}} \qquad (2)$$

where X_{camera} is the camera quality; and $M(X_{\text{camera}})$ and $\sigma_{X\text{camera}}$ are, respectively, the mean value and the standard deviation of the camera quality.

Next, we identify all the users' mobile phones and expand the phones' features to form a user-mobile phone feature matrix, as shown in Table 2. In the matrix, the values of the camera resolution mega-pixels are transformed into semantic values based on equation (2), with $Z_{\text{camera}} < -0.8$, $-0.8 \leqq Z_{\text{camera}} \leqq 0.8$ and $Z_{\text{camera}} > 0.8$, representing low-level, medium-level and high-level quality cameras, respectively. We then use the matrix to cluster the users into groups. The MPF-based method clusters users by the *K*-means clustering method with Pearson's correlation coefficient based on the users' preferred MPF.

User product preference clustering is more intuitive than user MPF clustering, as it clusters users directly based on the user-product preference matrix. The preference-based method clusters users by the *K*-means clustering method with Pearson's correlation coefficient based on users' product preferences.

3.2. The MPF-based and preference-based recommendation phase

After clustering users into groups based on similar MPF or product preferences, the association rules and the most frequent items in each group (cluster) are generated for the next step of the recommendation phase. The steps of the MPF-based and preference-based recommendation phase are shown in Figure 2 and described as follows. Let X_u represent the set of products browsed previously by a user u. For each association rule $X^k \rightarrow Y^k$, if $X^k \subseteq X_u$ then all products in $Y^k - X_u$, denoted by Y_u^k, are regarded as candidate products for recommendation to the user u. Let Y_u^{AR} be the set of all candidate products generated from all association rules that satisfy $X^k \subseteq X_u$. The products in Y_u^{AR} are ranked according to $c(Y_u^k)$, that is, the associated confidence of the association rule (AR) $X^k \rightarrow Y^k$.

We compare the number of candidate products $|Y_u^{\text{AR}}|$and the top-N recommendations. If the former is greater than the latter, the system

Table 2: *User-mobile phone feature matrix*

			Camera								
User ID	*Phone type*	*Bluetooth*	*H*	*M*	*L*	*Card slot*	*Flash light*	*Java*	*MP3*	*Radio*	*Video*
1	MOTO V191	0	0	0	1	0	0	1	1	0	1
2	Nokia N70	1	1	0	0	1	1	1	1	1	1
3	SAMSUNG SGH-Z238	1	0	1	0	1	0	1	1	0	1
4	Sony Ericsson K800i	1	1	0	0	1	1	1	1	1	1

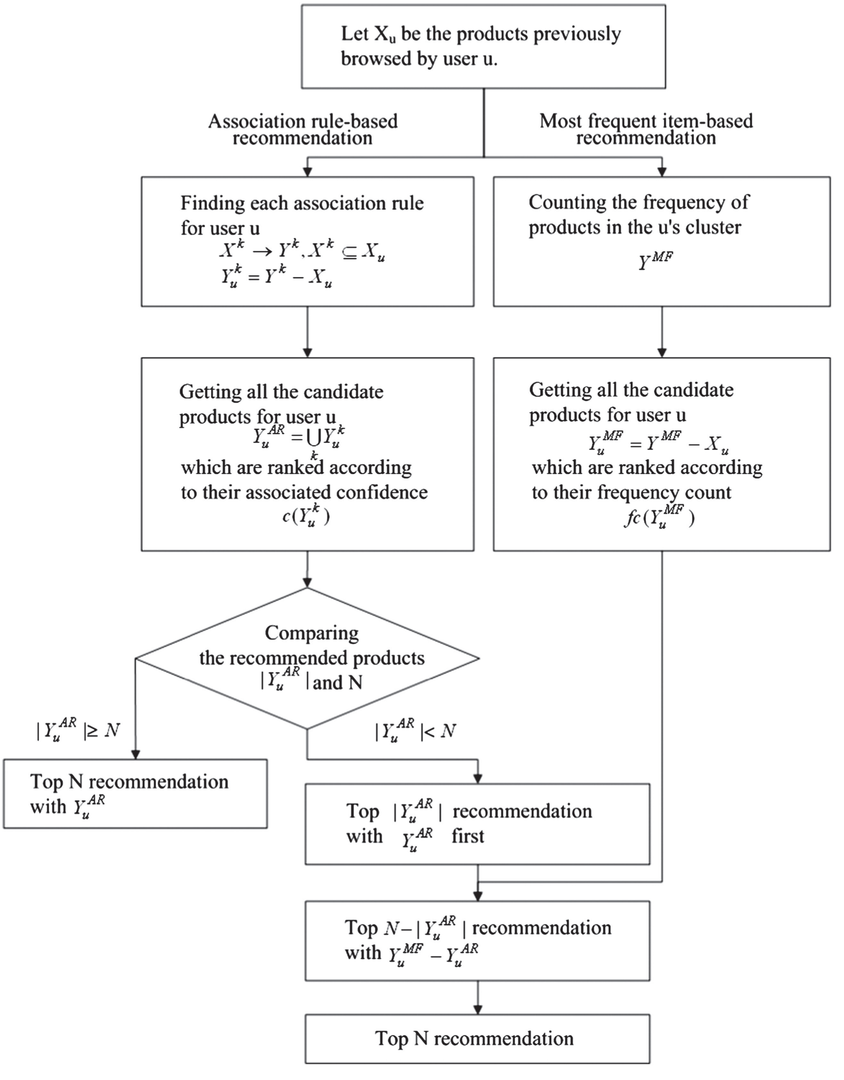

Figure 2: *The MPF-based and preference-based recommendation phase.*

recommends the top-N products among the products in Y_u^{AR}. On the other hand, if the number of candidate products $|Y_u^{\mathrm{AR}}|$ is less than the number of top N recommendations ($|Y_u^{\mathrm{AR}}| < N$), the remaining $N - |Y_u^{\mathrm{AR}}|$ products for recommendation are selected from Y_u^{MF}. The selected products are the most frequent items ranked according to the frequency count of products browsed by the users in the target user's cluster. Then, products in Y_u^{MF} that have not been browsed by the user u and have not been included in Y_u^{AR} are added to the recommended product list so that the number of top-N recommendations is sufficient.

3.3. The hybrid recommendation phase

The hybrid recommendation phase combines the MPF-based method and the preference-based method, as shown in Figure 3. Similar to the MPF-based method, the hybrid method first recommends products based on the association rules (AR); and then recommends products based on the most frequent item (MF) count. Let $X^{Mi} \rightarrow Y^{Mi}$ and $X^{Pj} \rightarrow Y^{Pj}$ be the association rules extracted from an MPF-based cluster (M) and a preference-based cluster (P), respectively; and let their associated confidence scores be c^{Mi} and c^{Pj}, respectively. In addition, let X_u represent the set of products previously browsed by the target user u; and let Y_u^{AR} be the set of all candidate products generated from all association rules that satisfy $X^{Mi} \subseteq X_u$ or $X^{Pj} \subseteq X_u$. The products in Y_u^{AR} are ranked according to the weighted sum of their confidence scores.

$$c^{\mathrm{H}} = w_{\mathrm{M}} \times c^{\mathrm{Mi}} + w_{\mathrm{P}} \times c^{\mathrm{Pj}} \tag{3}$$

where w_{M} and w_{P} are the weights assigned to the MPF-based approach and the preference-based approach, respectively.

Similar to the MPF-based method and the preference-based method, if the number of candidate products $|Y_u^{\mathrm{AR}}|$is less than the number of top N recommendations ($|Y_u^{\mathrm{AR}}| < N$), the remaining $N - |Y_u^{\mathrm{AR}}|$ products for recommendation are selected from Y_u^{MF}. The selected products are the most frequent items, which are ranked according to the frequency count of products browsed by the users in the target user's MPF cluster and preference cluster. The most frequent items are ranked as follows. Let $Y^{\mathrm{MF-M}}$ and $Y^{\mathrm{MF-P}}$ denote the set of most frequent items derived from the target user's MPF-cluster and preference cluster, respectively; and let fc^{M} and fc^{P} represent the frequency count of an item in $\mathrm{Y}^{\mathrm{MF-M}}$ and $\mathrm{Y}^{\mathrm{MF-P}}$, respectively. Products in Y_u^{MF} that have not been browsed by the target user u and have not been included in Y_u^{AR} are recommended based on the ranking order of the weighted sum of their frequency counts.

$$fc^{\mathrm{H}} = w_{\mathrm{M}} \times fc^{\mathrm{M}} + w_{\mathrm{P}} \times fc^{\mathrm{P}} \tag{4}$$

where w_{M} and w_{P} are the weights assigned to the MPF-based approach and the preference-based approach, respectively.

The relative effects of the MPF-based approach and preference-based approach on the recommendation quality may be different for different top-N recommendations; therefore, we set different values of w_{M} and w_{P}. We discuss the effects in detail in the next section.

4. Experiment evaluation

4.1. Experiment setup and data sets

Data for the mobile web log was collected between October 2006 and January 2007. The dataset, which contained information about 1692 users, 1416 products and 184 mobile phones, was divided as follows: 80% for training and 20% for testing. The training set was also used as the data set in the preliminary analytical experiment. Specifically, 55% of the data set was used to derive recommendation rules; and 25% was used as a preliminary analytical data set to determine the number of clusters, the feature combinations, and the hybrid weights assigned to the MPF-based and preference-based methods based on the quality of the recommendations. There were 1353 users and 165 mobile phones in the training data set, and 339 users and 93 mobile phones in the test data set. The

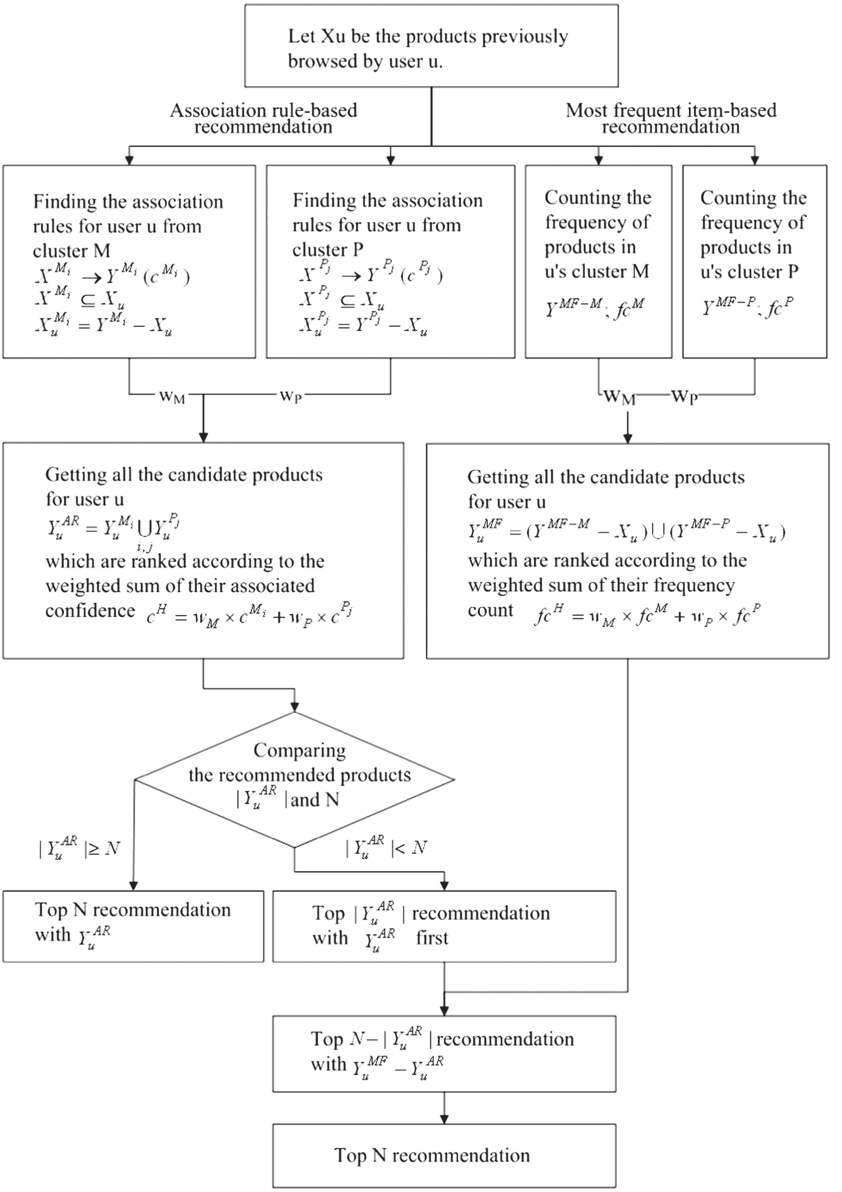

Figure 3: *The hybrid recommendation phase.*

minimum support was set at 0.004, and the minimum confidence level was set at 0.6.

4.2. Evaluation metrics

Two metrics, precision and recall, are commonly used to measure the quality of a recommendation. They are also used in the field of information retrieval (Van Rijsbergen, 1979; Salton & McGill, 1986). Product items can be classified into products that customers are interested in browsing, and those that they are not interested in browsing. The recommendation method then recommends products to the customers accordingly. The recall metric indicates the effectiveness of a method for locating interesting products, while the precision metric represents customers' level of interest in the recommended product items.

Recall is the fraction of interesting product items that can be located.

$$\text{Recall} = \frac{\text{number of correctly recommended items}}{\text{number of interesting items}} \tag{5}$$

Precision is the fraction of the recommended products that customers find interesting.

$$\text{Precision} = \frac{\text{number of correctly recommended items}}{\text{number of recommended items}} \tag{6}$$

The items that were considered interesting to customers were the products the customers browsed in the test set. Correctly recommended items were those that matched interesting items. Because increasing the number of recommended items tends to reduce the precision and increase the recall, the F1 metric is used to balance the tradeoff between precision and recall (Van Rijsbergen, 1979). The F1 metric, which assigns equal weights to precision and recall, is given by

$$\text{F1} = \frac{2 \times \text{recall} \times \text{precision}}{\text{recall} + \text{precision}} \tag{7}$$

Each metric was computed for each user, and the average value was computed for each cluster. The overall average (i.e. of all users) was calculated to measure the quality of the recommendations.

4.3. Experiment results

4.3.1. MPF and cluster number selection Although we selected eight MPF in Section 3.1, the recommendation quality may not be the best if we combine all the features. Therefore, we try all possible combinations of the eight features to determine the best combination and the number of clusters. We cluster users by the *K*-means clustering method with Pearson's correlation coefficient based on the selected features. Using the MPF-based method described in Section 3.2, we try various MPF combinations and various numbers of clusters between two and eight. The best recommendation quality of the preliminary analytical data is derived by combining five features, namely the Bluetooth, card slot, flash light, java and video functions, and the number of clusters is three. Hence, we use these five features with three clusters as the parameters for MPF-based recommendation.

4.3.2. Mobile phone and product preference cluster identification Based on the results derived in the previous section, we divide the training users into three clusters according to the five selected phone features, as shown in Table 3. The Bluetooth function enables users to connect to the other Bluetooth devices, including earphones and notebooks. The card slot function expands a mobile phone's data storage capacity for music, photos and movie files. The flash light function improves the quality of photographs taken in certain environments. Mobile phones with the java function can run java applications, including games; while phones with a video function are becoming increasingly popular for playing MP4 and movies in 3GP format.

Based on Table 3, we can calculate the feature frequency of each cluster by considering the frequency count and the representative MPF of each cluster that are above the frequency threshold of 50%. The frequency count of a feature is defined as the number of users' phones that have the feature divided by the number of users. According to the feature frequency of each cluster, the users are classified into three types of MPF. Users in cluster 0 prefer camera phones with advanced features, such as Bluetooth, card slot and flash light functions; users in cluster 1 prefer simple phones with basic java features and video functions; and users in cluster 2 prefer feature phones with Bluetooth and card slot functions for device connectivity and data storage.

The preference-based method clusters users according to their product preferences, that is, products browsed by users. We cluster users into four groups based on the best recommendation

Table 3: *Mobile phone cluster classification*

Cluster ID	Users	Bluetooth	Frequency (%)	Card slot	Frequency (%)	Flash light	Frequency (%)	Java	Frequency (%)	Video	Frequency (%)	Mobile phone features	Phone type
0	449	442	98	368	82	400	89	442	98	439	98	Java, Video, Bluetooth, Card slot, Flash light	Camera phone
1	319	0	0	7	2	13	4	318	100	301	94	Java, Video	Simple phone
2	162	156	96	162	100	8	5	156	96	146	90	Java, Video, Bluetooth, Card slot	Feature phone
Total	930	598	64	537	58	421	45	916	98	886	95		

quality achieved using the preliminary analytical data set. We use the product category frequency count with at threshold of 20% to identify the characteristics of each product preference cluster, as shown in Table 4. The frequency count of a product category is defined as the number of users that browse the product category divided by the total number of users.

4.3.3. Determining the MPF and preference weights of the hybrid recommendation scheme The hybrid recommendation scheme is based on the hybrid weighting ratios w_M and w_P ($w_P = 1 - w_M$) of the mobile phone and product preference clusters. Hybrid recommendation becomes pure preference-based recommendation when w_M equals zero, and pure MPF-based recommendation when w_M equals one.

The top-*N* recommendations are divided into two segments. One segment is from the top-1 to the top-10 recommendations and the other is from the top-11 to the top-20 recommendations. We choose the top-5 and top-15 recommendations to represent the first and second segments, respectively. The quality of the top-5 and top-15 hybrid recommendations with different MPF weights (w_M) is shown in Figure 4. The best recommendation quality for the top-5 and top-15 occurs when $w_M = 0.9$ and $w_M = 0.6$, respectively. We use these weights as the hybrid weighting ratios of the hybrid recommendation scheme in Section 4.3.4.

4.3.4. Evaluation of MPF-preference hybrid recommendation methods We compare two proposed methods, namely, MPF-based and Hybrid MPF-Preference methods, with the other two methods, preference-based and CF methods. MPF-based method cluster users into groups based on users' MPF and recommend products according to the association rules and most frequent items extracted from user groups. Preference-based method makes recommendations based on user groups that are clustered according to the users' product preferences.

Table 4: *Product preference cluster identification*

Cluster ID	*Users*	*Product category*
0	185	Lingerie, pants
1	336	Mobile phones, cordless phones, digital cameras
2	179	Hotels, travel coupons, food, domestic travel
3	230	Skin care, MP3, cosmetics, living products
Total	930	

Hybrid MPF-Preference recommendations are generated by a combination of the MPF-based and preference-based recommendation schemes with the hybrid weighting ratio described in Section 3.3. The hybrid weighting ratio described in Section 4.3.3 is set at $w_M = 0.9$ for the first top-N segment (top1-10) and $w_M = 0.6$ for the second top-N segment (top11–20). The CF method is a typical k-NN CF method that recommends the top-N most frequently occurring products of the k-NN (similar users). Because the average number of users in the product clusters is 232.5($=930/4$), we choose $k = 200$ as the number of nearest neighbours. Table 5 presents the precision, recall and F1-metric evaluation of k-NN CF, Preference-based, MPF-based and Hybrid MPF-Preference methods.

The F1 values of all methods are low, since the user-item matrix of our experiment data is very sparse. Although the F1 values of our proposed methods are still low, our methods

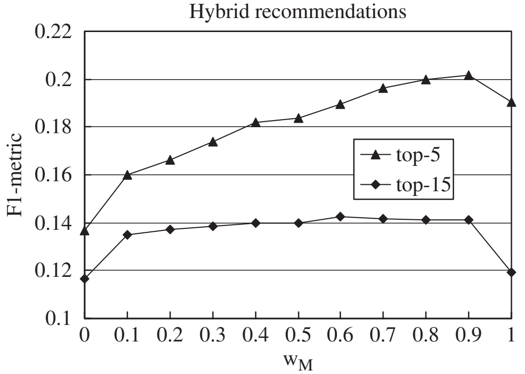

Figure 4: *The weighting ratio* w_M *of the hybrid recommendations.*

can achieve better improvement over conventional methods. For example, as listed in Table 5, the average F1-metric of the MPF-based method is 11% better than the preference-based method. Furthermore, the average F1-metric of the hybrid MPF-Preference method, which combined MPF-based and preference-based methods, is 33% better than the preference-based method. The F1-metric of the hybrid MPF-Preference, MPF-based, Preference-based and k-NN CF methods are shown in Figure 5.

As shown in Figure 5, the recommendation quality of all the methods declines after the top-4 recommendations, as the number of recommended products increases. Recall that association rule-based recommendations are based on the items users browsed previously. There are only a few recommended products because the average number of previously browsed products was 3.87. Therefore, the most frequent item recommendations are used to support the association rule recommendations if the number of recommended products is not sufficient. However, most frequent item-based recommendations are not better than association rule-based recommendations, so the recommendation quality deteriorates after the top-4 recommendations.

4.3.5. The effect of the hybrid method on mobile phone and product preference clusters Figure 6 shows that the mobile phone cluster 0 (camera phones with java, video, Bluetooth, card slot and flash light functions) achieves the best recommendation quality, followed by cluster 1 (simple phones with java and video functions),

Table 5: *Evaluation of k-NN CF, Preference-based, MPF-based and hybrid methods*

TopN	*k-NN CF*			*Preference-based*			*MPF-based*			*Hybrid MPF-preference*		
	Precision	*Recall*	*F1*	*Precision*	*Recall*	*F1*	*Precision*	*Recall*	*F1*	*Precision*	*Recall*	*F1*
2	0.015	0.004	0.006	0.153	0.085	0.092	0.161	0.088	0.099	0.176	0.100	0.110
4	0.026	0.017	0.017	0.104	0.113	0.089	0.122	0.128	0.106	0.140	0.157	0.125
6	0.036	0.055	0.035	0.080	0.124	0.080	0.096	0.156	0.100	0.113	0.186	0.118
8	0.039	0.098	0.045	0.072	0.146	0.081	0.079	0.165	0.091	0.092	0.195	0.106
10	0.035	0.107	0.044	0.063	0.156	0.076	0.067	0.172	0.082	0.081	0.212	0.100
12	0.030	0.109	0.040	0.057	0.165	0.072	0.058	0.178	0.075	0.072	0.221	0.094
14	0.027	0.111	0.036	0.051	0.171	0.066	0.051	0.180	0.069	0.064	0.227	0.087
16	0.023	0.112	0.033	0.046	0.174	0.062	0.045	0.181	0.063	0.058	0.236	0.081
18	0.021	0.112	0.030	0.042	0.179	0.059	0.043	0.197	0.062	0.053	0.244	0.077
20	0.019	0.112	0.028	0.040	0.187	0.057	0.041	0.210	0.061	0.049	0.248	0.073
Average	0.027	0.084	0.032	0.071	0.150	0.073	0.076	0.165	0.081	0.090	0.203	0.097

and cluster 2 (feature phones with java, video, Bluetooth and card slot functions). Among all the phone types, camera phones with the flash light feature yield the best recommendation quality. The owners of camera phones like to browse for digital cameras and travel products because they like to travel and take photographs. We also evaluate the effect of the hybrid method on the recommendation quality of MPF-based clusters. Figure 6 shows that the recommendation quality of the hybrid method (hybrid 0–2) is better than that of the MPF-based method (mphone 0–2) for each MPF-based cluster. In other words, the effect of combining MPF-based recommendations with preference-based recommendations is positive.

From Figure 7, we observe that product cluster 0 (lingerie, pants and skincare products) achieves the best recommendation quality in terms of product preferences, followed by product cluster 2 (hotels, travel coupons, food and domestic travel), product cluster 1 (mobile phones, digital cameras, cordless phones and notebooks), and product cluster 3 (skincare, mp3, cosmetics and consumer products). Users who prefer lingerie and underwear products receive better quality recommendations than users who prefer other products. We also

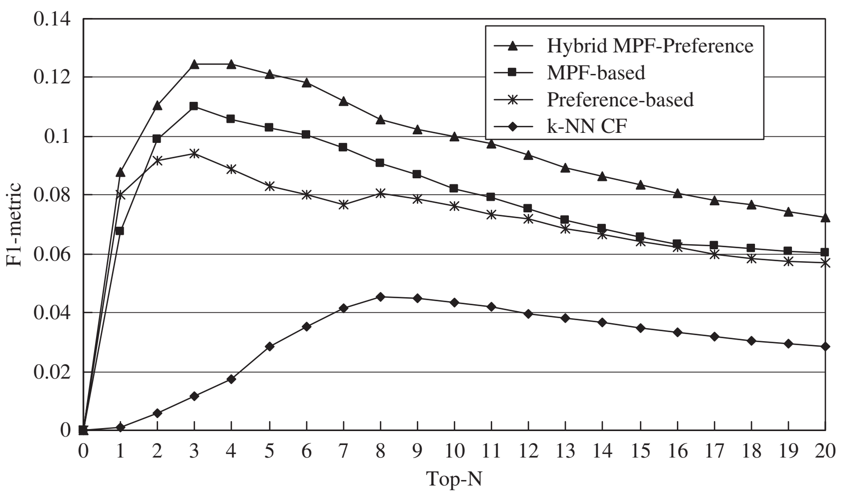

Figure 5: *Evaluation of hybrid, MPF-based, preference-based and* k-*NN CF methods.*

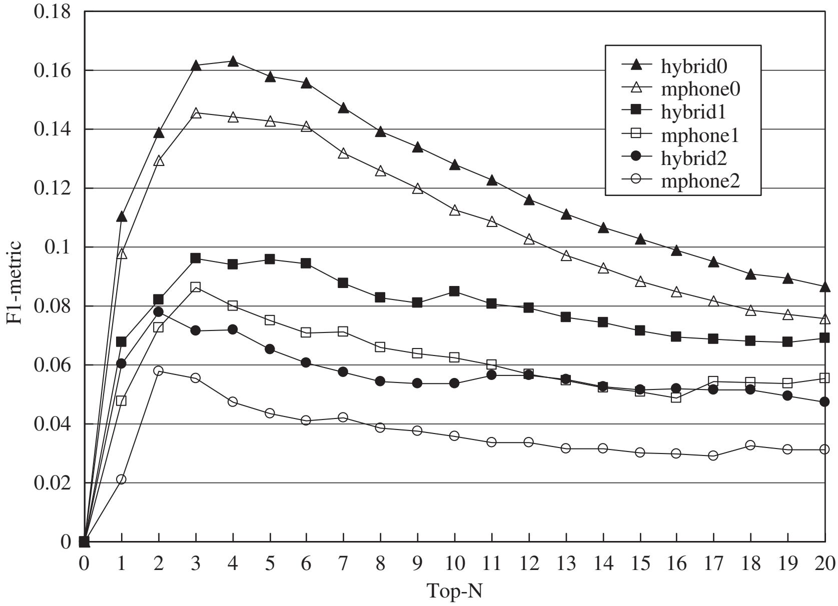

Figure 6: *Effect of the hybrid method on the recommendation quality for mobile phone clusters.*

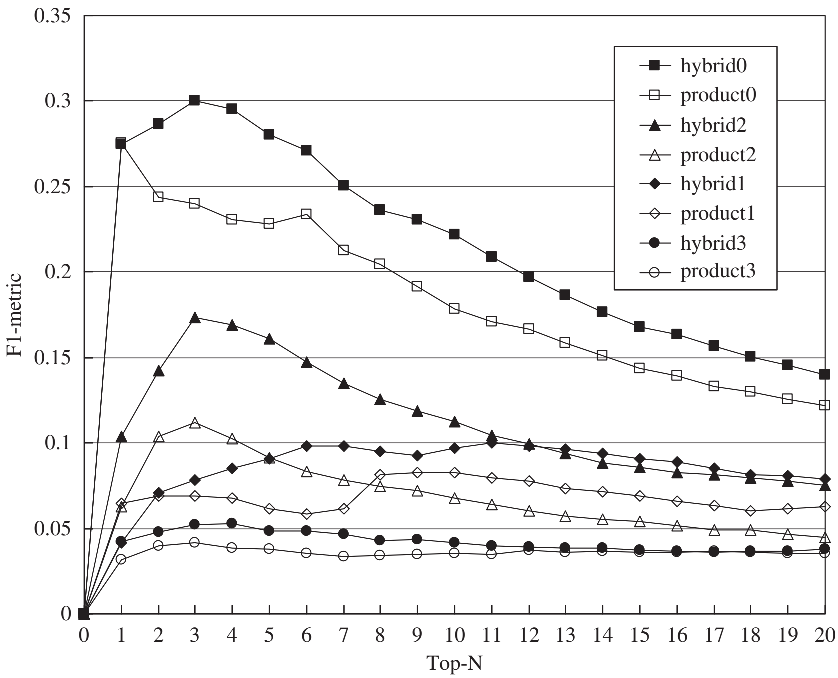

Figure 7: *Effect of the hybrid method on the recommendation quality for product clusters.*

evaluate the effect of the hybrid method on the recommendation quality of preference-based clusters. Figure 7 shows that the recommendation quality of the hybrid method (hybrid 0–3) is better than that of the preference-based method (product 0–3) for each preference-based cluster. Hence, combining the preference-based method with the MPF-based method can improve the quality of recommendations.

5. Conclusion

We have proposed a MPF-based hybrid method to resolve the sparsity issue of the typical CF method in mobile environments. We assume that the MPF preferred by users indicate their interest in particular m-commerce products and services; thus, they can be used to group users with similar interests. The hybrid method combines the MPF-based method and preference-based method, which uses association rule mining to extract recommendation rules from user groups and make recommendations.

Experiment results show that the quality of MPF-based recommendations is better than that of the preference-based method and the typical k-NN CF scheme. However, the hybrid method outperforms the MPF-based, preference-based and the typical k-NN CF methods.

According to the cluster analysis results, mobile phone cluster 0 (camera phones with Bluetooth, card slot, flash light, java and video functions) yields the best recommendation quality among the mobile phone clusters; product cluster 0 (lingerie, pants and skincare products) achieves the best recommendation quality in terms of product preference clusters. The hybrid method, which combines recommendations derived by the MPF-based and preference-based methods, improves the recommendation quality of MPF-based clusters and preference-based clusters.

Acknowledgements

This research was supported in part by the National Science Council of the Taiwan under grant NSC 96-2416-H-009-007-MY3.

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