國 立 交 通 大 學

資訊管理研究所

博 士 論 文

行動商務產品推薦方法

Product Recommendation Approaches for Mobile Commerce

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摘　要

隨著第三代行動通訊(3G)的用戶數增加，使得行動資料傳輸量增大，因此促使行動商務的形成。但多通路的公司想要發展行動商務往往遇到困難，因為缺乏對新行動通路使用者消費行為的了解。而傳統協同過濾推薦法因很少產品在行動網站上被瀏覽到所以可能產生資料稀疏的問題。

在這篇研究中，我們首先提出一個以手機特徵為基礎的混合推薦法去解決傳統協同過濾法在行動環境下資料稀疏的問題，我們運用手機的特徵去辨認使用者的偏好，然後依其特性將使用者分群。此混合推薦法結合了手機特徵和產品偏好，並且運用了用戶群產生關聯規則來推薦產品。

接著，我們提出一個混合多通路方法去解決對於新通路使用者消費行為的未知問題，與傳統協同過濾法中因找不到相似使用者所產生的資料稀疏問題。推薦給新行動通路的產品是基於新行動通路的瀏覽行為與既有通路的消費行為以不同的權重混合而成。

最後，我們結合了手機特徵與多通路法成為一個手機特徵多通路混合法，利用關聯規則與最頻繁項目集來推薦產品。我們的實驗顯示手機特徵多通路混合法的推薦品質比手機特徵法和混合多通路法好，亦比傳統協同過濾法好。

關鍵字： 產品推薦，行動商務，協同過濾法，手機特徵法，混合多通路法。

Product Recommendation Approaches for Mobile Commerce

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Abstract

Mobile data communications have evolved as the number of third generation (3G) subscribers has increased to conduct mobile commerce. Multichannel companies would like to develop mobile commerce but meet difficulties because of lack of knowledge about users' consumption behaviors on the new mobile channel. Typical collaborative filtering (CF) recommendations may suffer from the so-called *sparsity problem* because few products are browsed on the mobile Web.

In this study, we first propose a mobile phone feature-based (MPF) 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 employs association rule mining to extract recommendation rules from user groups and make recommendations.

Second, we propose a hybrid multiple channels (HMC) method to resolve the lack of knowledge about users' consumption behaviors on the new channel and the difficulty of finding similar users due to the *sparsity* problem of typical CF. Products are recommended to the new mobile channel users based on their browsing behaviors on the new mobile channel as well as the consumption behaviors on the existing multiple channels according to different weights.

Finally, we combine MPF with HMC approach into a hybrid MPF-HMC method, which utilizes association rules of product categories and products as well as most frequent items to recommend products. Our experiment results show that the hybrid MPF-HMC combined method performs well compared to the pure MPF-based and HMC-based methods as well as the typical kNN-based CF method.

Keywords: product recommendation, mobile commerce, collaborative filtering (CF), mobile phone features (MPF), hybrid multiple channels (HMC)

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終於畢業了，在人生寶貴的十年間，工作、唸書、結婚、生子。在四十不惑之年拿到學位，應是給自己最好的生日禮物!

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劉純和
于 新竹 交通大學
2010 年庚寅 秋

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Chapter 1. Introduction

1.1 Background and Motivation

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 that of 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 [31, 45]. M-commerce covers a large number of services, one of which is mobile shopping (m-shopping) [47]. Retailers have increased their investment in mobile shopping channels to deliver content, products, and promotions to customers. However, it is hard to determine consumption behaviors since there are very few purchase orders in the early stages of the development of m-shopping. The number of product recommendations is also low due to the small number of consumption behaviors that have been identified.

In the mobile commerce environment, the screens of mobile devices are small and have limited resolution, and the input mechanisms are poor [15, 45]. Moreover, fewer products are browsed on the mobile Web because Internet fees for mobile communications are still high; hence, one-to-one product recommendations are important [5]. Recommender systems are widely used to recommend various items such as movies and music to customers based on their interests [14, 40]. Generally, the techniques of 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 [36, 38]. In contrast, content-based filtering (CBF) derives recommendations by matching customer profiles with content features [21, 34]. In addition, some studies have combined collaborative filtering and content-based filtering techniques as a hybrid recommendation method [4, 11].

The typical CF method relies on finding users with similar interests to make recommendations. It suffers from the *sparsity* issue in which users rate very few items and the user–item rating matrix is very sparse, and thus the recommendation quality is poor due to the difficulty of finding users with similar interests [38]. In mobile shopping environments, active users may browse and purchase very few items on the mobile Web, and thus it is difficult to find users with similar interests on the mobile Web based on the product preferences that are derived from users' browsing and purchasing histories.

On the other hand, multichannel companies may meet difficulties when they develop new channels due to lack of knowledge about the new channel users' consumption behaviors. Most existing companies use advertisement and marketing campaigns to understand users' consumption behaviors of the new channel. However, when we observed the customer transaction data from customer relationship management system (CRM), we could find customers purchasing products across channels with different percentages. The customers of the existing channels may show migration behaviors between one channel and another channel [3, 41]. Hence, some of new channel users may be old customers who have migrated from the existing channels. In addition, the consumption behaviors of new mobile channel users may be partially correlated to the behaviors of the other channel users (e.g. television, catalog, and Web) with different overlapping percentages as shown in Figure 1.

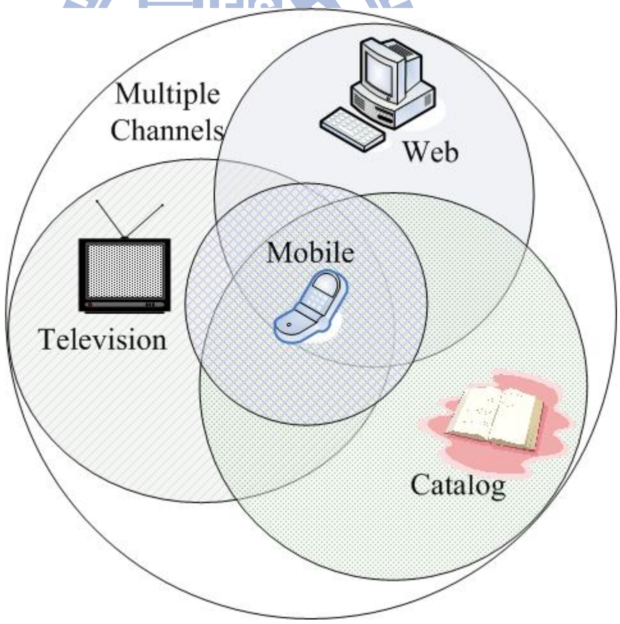

Figure 1 Hybrid multiple channels concept

1.2 Goals

According to the above motivations, this dissertation proposed a mobile phone features-based (MPF) recommender, which combined preference-based method as a hybrid recommender to resolve the sparsity issue of the typical CF method used in mobile environments. We also proposed a hybrid multiple channels method based on users product preference to enhance the quality of recommendation to resolve the lack of knowledge about the consumption behaviors of the new channel users and the difficulty of finding similar users due to the sparsity problem of typical CF.

1.3 Approaches

We propose a mobile phone features-based (MPF) 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 mobile phone features 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 mobile phone features 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 mobile phone features 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.

On the other hand, we propose a hybrid multiple channels method to resolve the lack of knowledge about the consumption behaviors of the new channel users and the difficulty of finding similar users due to the *sparsity* problem of typical CF. Existing multiple channels' (e.g. television, catalogs, and Web) heavy users who spend a large amount of money to purchase products frequently and recently are valuable customers to represent users' consumption behaviors of each channel based on 80/20 rule. The related study suggested the RFM model (Recency, Frequency and Monetary) as a market segmentation tool to quantify customer behaviors. Based on Pareto Principle (80/20 rule), a small portion of customers frequently contribute to the majority of revenue [30]. Other studies have similar definitions of heavy users. For example, heavy users are defined as those customers whose average monthly purchase quantity is above the median monthly purchase quantity [13, 24]. Internet heavy users spend more time to surf the WWW than the other users [43]. Heavy users of the existing channels could provide sufficient transaction instances that could be used to find more similar users for the new channel, which could solve the sparsity problem of the new channel and derive more association rules to improve the recommendation quality. The proposed hybrid method recommends products to the new channel users based on mobile users' browsing behaviors as well as heavy users' consumption behaviors for the existing multiple channels using different weights.

Finally, we integrate two approaches, MPF-based and HMC-based recommenders into a new recommender. The new recommender cluster users into groups based on MPF and HMC groups, and the association rules and the most frequent items are derived from MPF and HMC groups. Products are recommended by the derived association rules and the most frequent items to the new mobile channels.

This dissertation makes contributions on one-to-one marketing and customer relationship management of mobile commerce. Enterprises can focus on target market to reduce costs of advertisements to strengthen their profit and market competitive.

1.4 Organization

The dissertation is composed of five chapters. The research architecture is organized as shown in Figure 2 and described as follows.

Chapter 1: Introduction

This chapter details the backgrounds behind the development of various recommender systems. Furthermore, the motivations for studying recommender systems are elucidated in this chapter.

Chapter 2: Related work

This chapter presents the related works on mobile phone features (MPF), multiple channels, market segmentation, the association rule-based recommender, the typical collaborative filtering (CF), and CF recommenders for e-commerce and m-commerce. This chapter also described the evaluation metrics used to evaluate the accuracy of recommendations.

Chapter 3: Mobile phone features-based (MPF) recommender

In this chapter, we describe the proposed MPF-based, preference-based, and hybrid recommendation methods. We also present the experiment results and summarize our findings.

Chapter 4: Hybrid multiple channels-based (HMC) recommender

In this chapter, we explain how we select the heavy users of a channel. We also describe the proposed recommendation scheme and the recommendation engine, as well as the experimental results including the derivation of the hybrid weights of the multiple channels and the evaluations of the four recommendation methods. Finally, we present some explanations and implications concerning the derived hybrid weights of the multiple channels.

Chapter 5: MPF-HMC combined recommender

In this chapter, we combine MPF-based with HMC-based recommender into a hybrid recommender. The recommendation quality of the combined recommender is better than the pure MPF-based and HMC-based recommenders.

Chapter 6: Conclusions and future works

In this chapter, we draw some conclusions which summarize our findings and discuss the limitations of the study and future research.

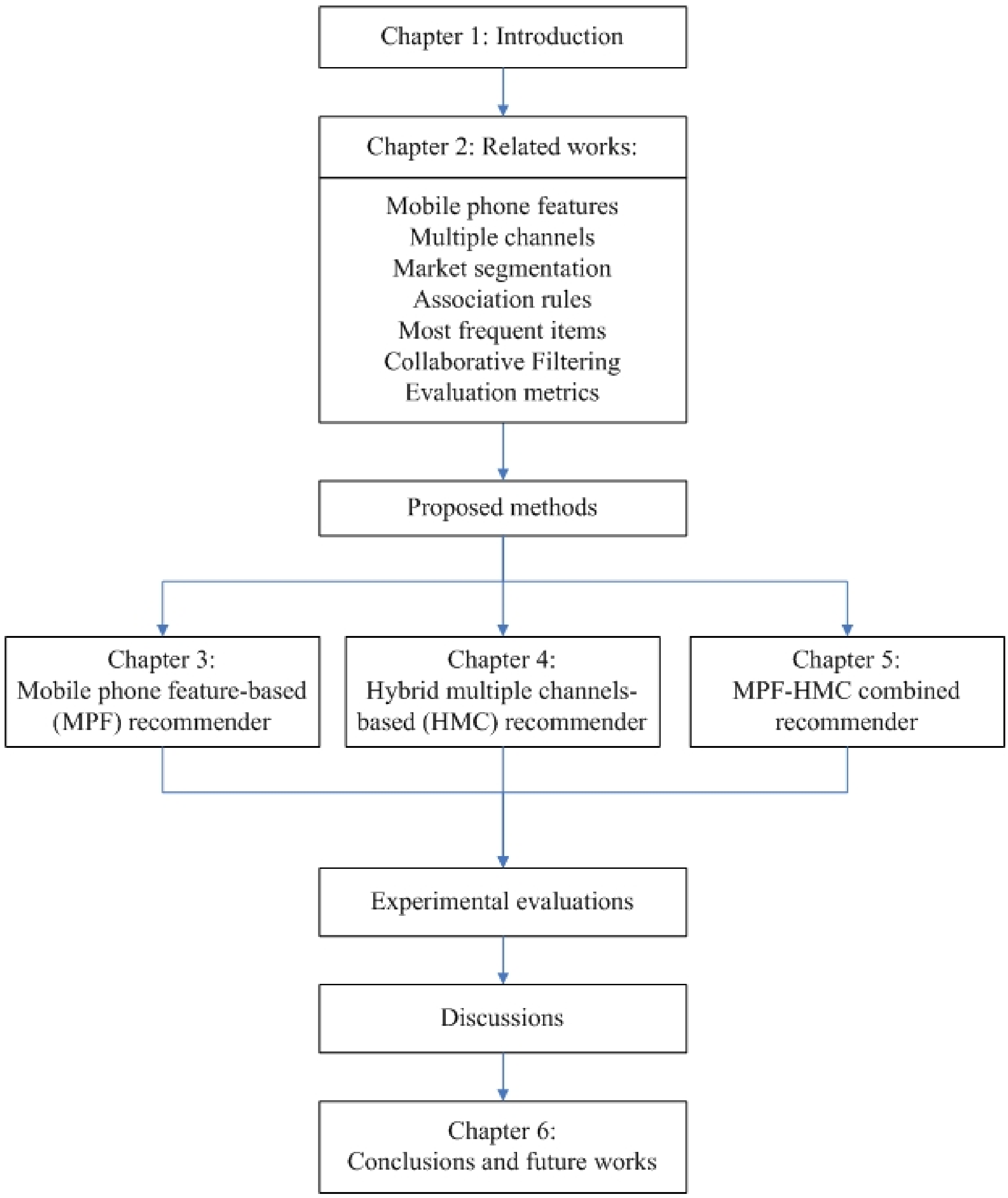

Figure 2 The research architecture

Chapter 2. Related Work

2.1 Mobile Phone Features (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 [32]. These features enable users to access related mobile services, e.g., download MP3 files, upload photos to blogs, video streaming and on-line shopping [20]. Ling et al. [27] investigated the impact of mobile phone features on user satisfaction and analyzed the feature preferences of diverse ethnic groups as well as preferences based on gender. Virvou and Savvopoulos [46] 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 mobile phone features 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 Multiple Channels

Multiple channels could be roughly divided into physical (store) and virtual (e.g. Web, catalog, and television) channels [42]. In the past, most companies only provided single store channels to customers for purchasing products. Nowadays, owing to information technology and customer need, companies provide multiple channels comprising physical and virtual channels to customers with seamless services which could create more customer value including choice and convenience. The channels could also be designed to allow customers to move from one channel to another seamlessly by reducing transaction cost during the purchase process [8, 39, 42]. Existing work viewed multiple channels as the ability to reduce transaction cost and create more customer value rather than as an auxiliary channel to understand the new channel users' product preferences which could assist in recommending products to consumers.

2.3 Market Segmentation

Clustering techniques, which are usually used to segment markets [7, 35], seek to maximize the variance among groups while minimizing the variance within groups. A number of clustering algorithms have been developed, such as K-means, hierarchical, and fuzzy c-means algorithms [33]. K-means clustering [29] is a widely used similarity grouping method that partitions a dataset into k groups. The K-means algorithm assigns instances to clusters based on the minimum distance principle. An instance is assigned to a cluster based on the minimum distance to the center of the cluster over all *k* clusters.

The Recency, Frequency and Monetary (RFM) framework is used to analyze customer behavior and define market segments. It is widely used in direct marketing and database marketing [17, 30]. Bult and Wansbeek [6] defined the framework's terms as follows: (1) R (Recency): the period since the last purchase. A lower value corresponds to a higher probability that the customer will make a purchase in the near future. (2) F (Frequency): the number of purchases made within a certain period; higher frequency indicates greater loyalty. (3) M (Monetary): the amount of money spent during a certain period; the higher the amount, the more the company should focus on that customer. Most direct marketing firms target market segments that have lower recency (R) higher frequency (F) and higher monetary (M) values [17, 30]. Miglautsch [30] suggested using the RFM model as a market segmentation tool to quantify customer behavior. His findings showed that a relatively small percentage of customers frequently contribute most of the revenue based on the Pareto Principle (80/20 rule).

2.4 Association Rules for Product Recommendation

Association rule mining is a widely used data mining technique to generate recommendations in recommender systems. Accordingly, this work employs association rule mining to discover the relationships among product items based on patterns of co-occurrence across customer transactions.

2.4.1 Association Rule Mining

Association rule mining tries to find the associations between two sets of products in a transaction database. Agrawal et al. [1] 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 $X \cap Y = \Phi$. 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, among all transactions that contain X, the fraction that also contains Y. An example of an association rule in the basket market analysis domain is: "80% of transactions that contain bread also contain milk; 20% of all transactions contain the two of them". Herein, X = {bread}, Y = {milk}, 80% is called the confidence of the rule, and 20% the support of the rule.

The support of an association rule indicates how frequently the rule applies to the target data. A high level of support corresponds to a strong correlation between the product items. The confidence score is a measure of the reliability of an association rule. The higher the level of confidence, the more significant will be the correlation between the product items. The Apriori algorithm [2] is normally used to find association rules by discovering frequent item sets of product items. An item set is considered to be frequent if its support exceeds a user-specified minimum support threshold. Association rules that meet a user-specified minimum confidence threshold can be generated from the frequent item sets.

2.4.2 Association Rule-based Recommendation Method

Sarwar et al. [38] described the association rule-based recommendation method as follows. For each customer, a customer transaction is created to record all the products that he or 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 purchased by *u* previously. 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 to be 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.

2.5 Most Frequent Item-based Recommendation Method

The most frequent item-based recommendation method [38] counts the purchase frequency of each product by scanning the products purchased 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 by the target customer.

2.6 Collaborative Recommendation

2.6.1 Definition

Collaborative recommendation (or collaborative filtering) predicts user preferences for items in a word-of-month manner. That is, user preferences are predicated by considering the opinions (in the form of preference ratings) of other "like-minded" users. In particular, one can define a similarity measure between a pair of user preference ratings to define the like-mindedness between users. As preference ratings are used instead of domain-specific features, the applicability of collaborative recommender systems is more universal. For instance, if the system finds that you like computer books and at the same time are similar in taste to a group of users who like both computer books and science fictions, it will then recommend science fictions to you.

2.6.2 Typical KNN-based CF Method

Collaborative filtering is a successful recommendation method, which has been widely used in various applications. A typical KNN-based collaborative filtering (CF) method [36, 38, 40] employs nearest-neighbor algorithm to recommend products to a target customer *u* based on the preferences of *neighbors*. That is, those customers having similar preferences as customer *u*. Notably, preferences generally are defined in terms of customer purchasing behavior, namely, purchased/non-purchased (binary choice) of shopping basket data, or taste, namely, preference rating on product items.

The typical KNN-based CF method is detailed as follows. Customer preferences, namely, customer purchase history, are represented as a customer-item matrix ***R*** such that, r_{ij} is one if the ith customer purchased the jth product; and is zero otherwise. The similarity of preferences among customers can be measured in various ways. A common method is to compute the Pearson correlation coefficient defined as Eq. (1):

$$corr_P(c_i, c_j) = \frac{\sum_{s \in I} (r_{c_i,s} - \bar{r}_{c_i})(r_{c_j,s} - \bar{r}_{c_j})}{\sqrt{\sum_{s \in I} (r_{c_i,s} - \bar{r}_{c_i})^2 \sum_{s \in I} (r_{c_j,s} - \bar{r}_{c_j})^2}} \quad (1)$$

The notations $\bar{r}_{c_i}$ and $\bar{r}_{c_j}$ denote the average number of products purchased by customers c_i and c_j, respectively. Moreover, the variable I denotes the set of products. Additionally, the $r_{ci,s}$ and $r_{cj,s}$ indicate whether customers c_i and c_j purchased product item s. Customers are ranked by their similarity measures in relation to the target customer u, as determined using the Pearson correlation coefficient. The k most similar (highest ranked) customers are selected as the k-nearest neighbors of customer u. Finally, the top-N recommended products are determined from the k-nearest neighbors of u, as follows. The frequency count of products is calculated by scanning the purchase data of the k-nearest neighbors. The products then are sorted based on frequency count. The N most frequent products that have not yet been purchased by target customer u are selected as the top-N recommendations.

2.6.3 Collaborative Filtering for E-commerce and M-commerce

In electronic commerce, several applications have been used the collaborative filtering technique to provide recommendations. GroupLens is a netnews recommendation system based on collaborative filtering technique which assists people to find news articles they will like. The system predicts scores based on the opinions of the other readers who have already rated articles [36]. Sarwar [38] proposed a recommendation method which incorporates collaborative filtering and association rule mining technique to recommend movies from MovieLens databas. Amazon.com provides recommendations of those products that are similar to the customer's purchased products based on an item-based collaborative filtering technique [26]. Cho et al. [9] suggested a new methodology which combines collaborative filtering and clustering technique to recommend products for customers of a department store based on their sequential purchase patterns. However, the typical CF suffers from the data sparsity problem due to few products purchased by customers. Several studies have been proposed to solve the data sapasity problem. For example, Zeng et al. [49] suggested a class-based collaborative filtering technique to recommend movies from EachMovie database to solve the data sparsity.

Huang and Huang [16] developed a foods recommendation system based on two-stage technique, which discovered the sequential patterns in product category to reduce the sparsity problem. Kim et al. [19] proposed a collaborative filtering method based on collaborative tagging to recommend webpages on a social bookmark website, which could solve the data sparsity problem.

In mobile commerce, several applications have been used the collaborative filtering technique to provide recommendations. Li et al. [23] proposed a two-stage collaborative filtering method which incorporates clustering and sequential pattern technique for mobile service (product advertising and ring tone download) based on users' profile, preferences and location. Liou and Liu [28] combined the mobile phone features (MPF) and product preference methods based on collaborative filtering technique to provide product recommendations on the mobile Web. In addition, mobility information about user locations obtained from global positioning systems (GPS) is usually used to combine with the recommendation methods in m-commerce [48]. For example, PILGRIM is a location-based collaborative filtering system which recommends webpages to users who are in ellipsoid area [5]. VISCOR is a mobile wallpaper recommender system that combines collaborative and content-based filtering to reduce users' search costs and provide better wallpaper recommendations [18]. MONERS, a news hybrid recommender system, determines news article preferences based on the importance of the news event, news recentness, changes in user preferences, user segments, and article preferences [22]. MCORE considers users' context data to recommend mobile services [10]. These methods use a single channel (mobile phone) to collect users' preferences and make recommendations, but few studies have investigated multiple channels (e.g. television, catalogs, and Web) to recommend products.

Our study proposed the multiple channels based collaborative filtering technique to recommend products on a mobile shopping website for mobile commerce. The proposed method successfully integrated two heterogeneous databases of the CRM system and the mobile website. A summary of applications based on collaborative filtering (CF) recommendations are presented in Table 1.

Table 1 Collaborative filtering recommendation for e-commerce and m-commerce

Channel	e-commerce	m-commerce
Single	Techniques: • Item-based: e.g. [26] • User-based: e.g. [36] • Clustering: e.g. [9] • Association rules: e.g. [38] • Sequential pattern: e.g. [16] Applications: • News: e.g. [36] • Movies: e.g. [38, 49] • Products: e.g. [9, 16, 26] • Bookmarks: e.g. [19]	Techniques: • User-based: e.g. [18] • Clustering: e.g. [22] • Association rules: e.g. [28] • Sequential pattern: e.g. [23] • Location-based: e.g. [5] Applications: • Webpages: e.g. [5] • Wallpaper images: e.g. [18] • Products: e.g. [28] • News: e.g. [22] • Ringtone: e.g. [23]
Multiple		• Products: Our study

2.7 Evaluation Metrics

Two metrics, precision and recall, are commonly used to measure the quality of a recommendation. These are also used measures in information retrieval [37, 44]. Product items can be classified into products that customers are interested in purchasing, and those that they are not interested in purchasing. A recommendation method may recommend interesting or uninteresting products. The recall-metric indicated the effectiveness of a method for locating interesting products. The precision-metric represented the extent to which the product items recommended by a method really are interesting to customers.

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

$$\mathit{Recall} = \frac{\mathit{number\ of\ correctly\ recommended\ items}}{\mathit{number\ of\ interesting\ items}} \tag{2}$$

Precision is the fraction of recommended products (predicted to be interesting) that are really found to be interesting.

$$\mathit{Precision} = \frac{\mathit{number\ of\ correctly\ recommended\ items}}{\mathit{number\ of\ recommended\ items}} \tag{3}$$

Items interesting to customer u were those products purchased by u in the test set. Correctly recommended items were those that match interesting items. However, increasing the number of recommended items tended to reduce the precision and increase the recall. An F1-metric [44] could be used to balance the trade-off between precision and recall. F1 metric assigned equal weight to precision and recall and was given by,

$$F1 = \frac{2 \times recall \times precision}{recall + precision} \tag{4}$$

Each metric was computed for each customer, and the average value computed for each cluster, as well as the overall average (over all customers) as measures of the quality of the recommendation.

Chapter 3. Mobile Phone Features-based (MPF) Approach

3.1 MPF-based Hybrid 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 3. 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' mobile phone features. 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 products to users. Similar to the MPF-based method, the preference-based method, shown on the right-hand side of Figure 3, 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 Section 3.1.2 and Section 3.1.3 respectively.

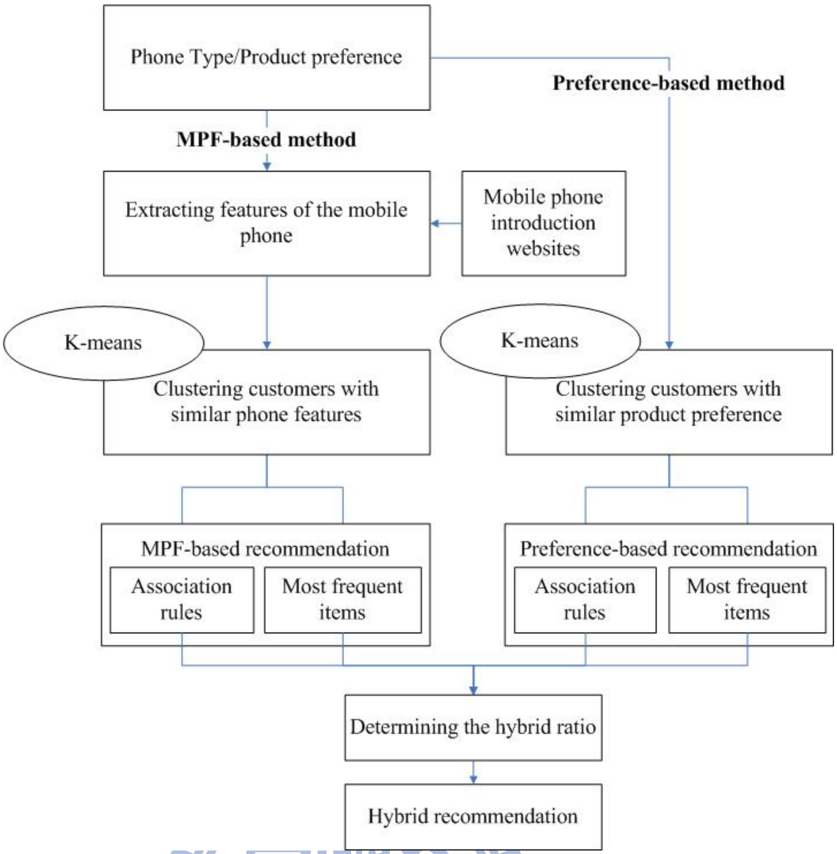

Figure 3 An overview of the proposed hybrid recommendation scheme

3.1.1 Data Pre-processing and Clustering

We obtained the features of each mobile phone from one of the mobile phone web sites. There are more than 100 features on a mobile phone. it is hard to analyze 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 2 lists the selected features, including Bluetooth 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 8 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 3 discrete data type features including screen size, color and material. These values of the display features are missing and are difficult to collect. Thus, we do not select the display feature.

Table 2 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)

We calculate the similarity of users based on the selected features. The camera quality feature, which is a discrete data type, and the other 7 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 Eq. (5) [25]. Therefore, we use the following 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.

$$Z_{camera} = \frac{X_{camera} - M(X_{camera})}{\sigma_{Xcamera}} \tag{5}$$

where X_{camera} is the camera quality; and $M(X_{camera})$ and $\sigma_{Xcamera}$ 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 3. In the matrix, the values of the camera resolution mega-pixels are transformed into semantic values based on Eq. (5), with $Z_{camera} < -0.8$, $-0.8 \leqq Z_{camera} \leqq 0.8$, and $Z_{camera} > 0.8$, 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 mobile phone features.

Table 3 User-mobile phone feature matrix

User ID	Phone type	Bluetooth	Camera			Card slot	Flash light	Java	MP3	Radio	Video
			H	M	L						
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

User product preference clustering is more intuitive than user mobile phone feature 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.

3.1.2 The MPF-based and Preference-based Recommendation Phase

After clustering users into groups based on similar mobile phone features 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 4 and described as follows. Let X_u represent the set of products previously browsed 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 $Y^k{}_u$, 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 $c(Y_u{}^k)$, i.e., the associated confidence of the association rule (AR) $X^k \rightarrow Y^k$.

We compare the number of candidate products $|Y_u{}^{AR}|$ and the top-N recommendations. If the former is greater than the latter, the system recommends the top-N products among the products in $Y_u{}^{AR}$. On the other hand, if the number of candidate products $|Y_u{}^{AR}|$ is less than the number of top N recommendations ($|Y_u{}^{AR}|<N$), the remaining N-$|Y_u{}^{AR}|$ 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 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.

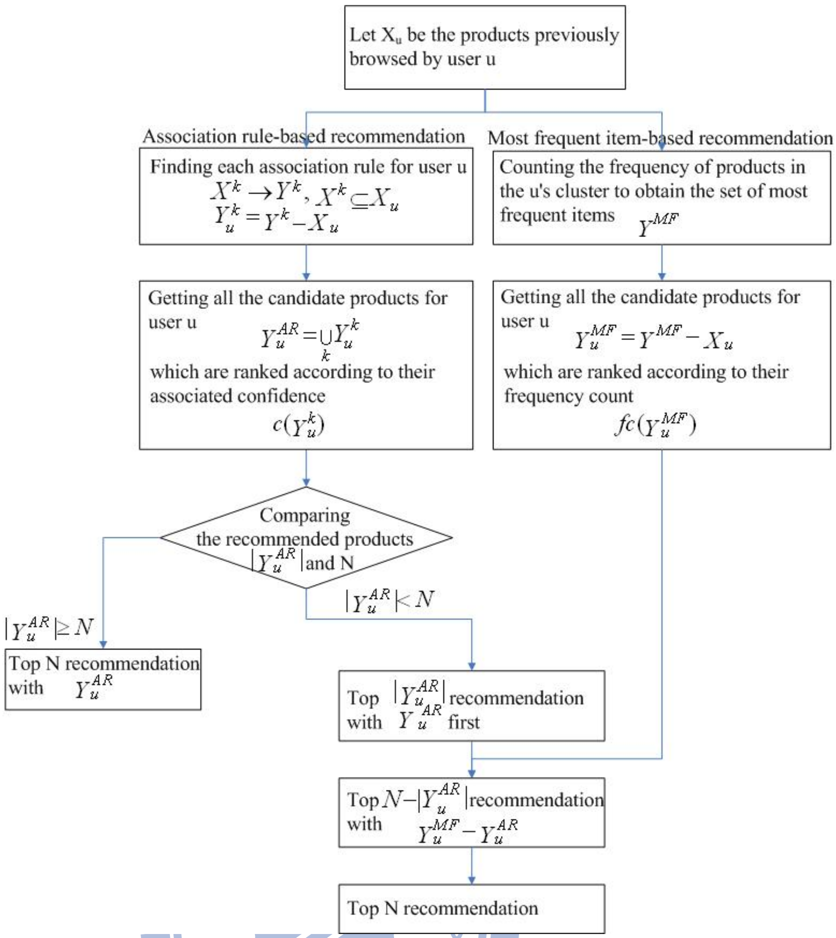

Figure 4 The MPF-based and preference-based recommendation phase

3.1.3 The Hybrid Recommendation Phase

The hybrid recommendation phase combines the MPF-based method and the preference-based method, as shown in Figure 5. 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.

$$c^H = w_M \times c^{Mi} + w_P \times c^{Pj} \tag{6}$$

where w_M and w_P are the weights assigned to the MPF-based approach and the preference- based approach respectively.

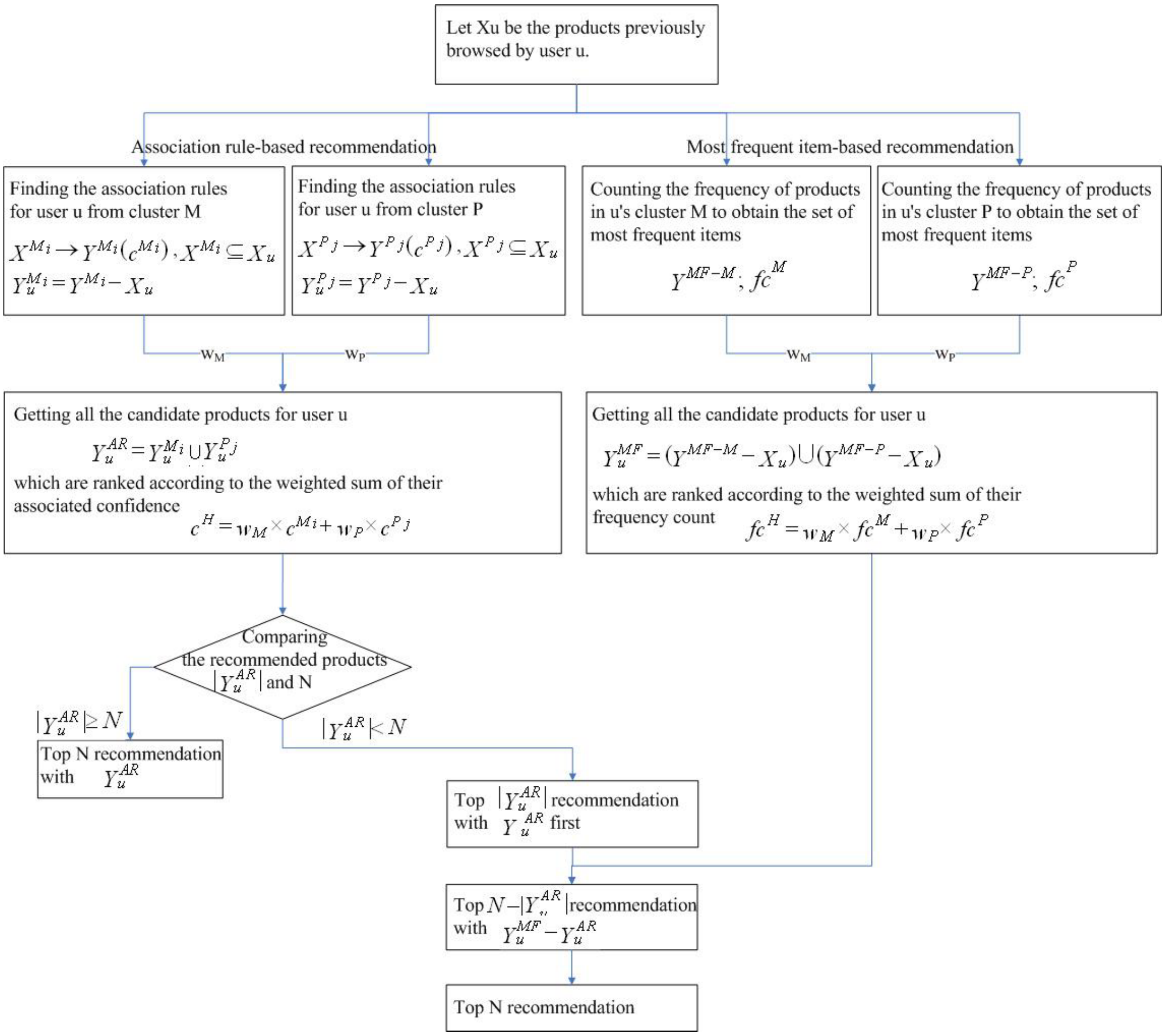

Figure 5 The hybrid recommendation phase

Similar to the MPF-based method and the preference-based method, if the number of candidate products $|Y_u^{AR}|$ is less than the number of top N recommendations ($|Y_u^{AR}|<N$), the remaining $N-|Y_u^{AR}|$ 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 $Y^{MF\text{-}M}$ and $Y^{MF\text{-}P}$ 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 $Y^{MF\text{-}M}$ and $Y^{MF\text{-}P}$ respectively. Products in Y_u^{MF} that have not been browsed by the target user and have not been included in Y_u^{AR} are

recommended based on the ranking order of the weighted sum of their frequency counts.

$$fc^{H} = w_{M} \times fc^{M} + w_{P} \times fc^{P} \tag{7}$$

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.

3.2 Experimental Setup and Datasets

Data for the mobile web log was collected between Oct. 2006 and Jan. 2007. The dataset, which contained information about 1,692 users, 1,416 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 1,353 users and 165 mobile phones in the training data set, and 339 users and 93 mobile phones in the test data set. The minimum support was set at 0.004, and the minimum confidence level was set at 0.6.

3.3 Experimental Results

3.3.1 Mobile Phone Features and Cluster Number Selection

Although we selected 8 mobile phone features in Section 3.1.1, the recommendation quality may not be the best if we combine all the features. Therefore, we try all possible combinations of the 8 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 3.1.2, we try various mobile phone feature combinations and various numbers of clusters between 2 and 8. 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 3. Hence, we use these five features with 3 clusters as the parameters for MPF-based recommendation.

3.3.2 Mobile Phone and Product Preference Custer Identification

Based on the results derived in the previous section, we divide the training users into 3 clusters according to the five selected phone features, as shown in Table 4. 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.

Table 4 Mobile phone cluster classification

Cluster ID	Users	Blue-tooth	Freq	Card slot	Freq	Flash light	Freq	Java	Freq	Video	Freq	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%		

Based on Table 4, we can calculate the feature frequency of each cluster by considering the frequency count and the representative mobile phone features 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 mobile phone features. 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, i.e., products browsed by users. We cluster users into four groups based on the best recommendation 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 5. 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.

Table 5 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	

3.3.3 Association of Mobile Phones and Product Preference Clusters

We use association rules to find the relationships between various mobile phone features and product categories. Retailers want to know two types of information: 1) the kinds of products that are suitable for the mobile channels; and 2) the types of users that use mobile phone channels to purchase products. Because the features of the mobile phones owned by the users included in our study can be extracted from the mobile web, we can determine the relationships between the product categories and various mobile phone features. Knowing users' mobile phone types could help retailers select suitable products for the mobile channels and recommend appropriate products on-line.

We derive the association rules between the type of mobile phone and specific product categories, as shown in Table 6. The support and confidence scores are defined in Eq. (8) and Eq (9).

$$\text{Support}(\text{M} \rightarrow \text{P}) = \frac{\text{Number of users that use phone(M) to browse product category(P)}}{\text{Number of users}} \quad (8)$$

$$\text{Confidence}(M \rightarrow P) \equiv \frac{\text{Number of users that use phone(M) to browse product category(P)}}{\text{Number of users that use phone(M)}} \quad (9)$$

The minimum support and confidence scores are set at 0.05 and 0.2 respectively. The table shows that all the mobile phone owners in our study like to browse mobile phones and skin care products. Users who own camera phones like to browse travel products, while users who own simple phones like to browse lingerie products. The owners of simple phones and camera phones browse all types of products, whereas the owners of feature phones only browse skincare, mp3, cosmetics, and consumer products.

Table 6 Association rules between mobile phone type and product categories

Association rules (Mobile phone→Product category)				
Rule	Mobile phone	Product category	Support	Confidence
1	Camera phone	Mobile phones, cordless phones, digital cameras	0.18	0.37
2	Camera phone	Hotels, travel coupons, food, domestic travel	0.10	0.21
3	Camera phone	Skin care, mp3, cosmetics, living products	0.11	0.23
4	Simple phone	Lingerie, pants, skin care	0.08	0.24
5	Simple phone	Mobile phones, cordless phones, digital cameras	0.11	0.33
6	Simple phone	Skin care, mp3, cosmetics, living products	0.09	0.25
7	Feature phone	Mobile phones, cordless phones, digital cameras	0.07	0.40
8	Feature phone	Skin care, mp3, cosmetics, living products	0.05	0.28

3.3.4 Determining the 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 6. 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 3.3.5.

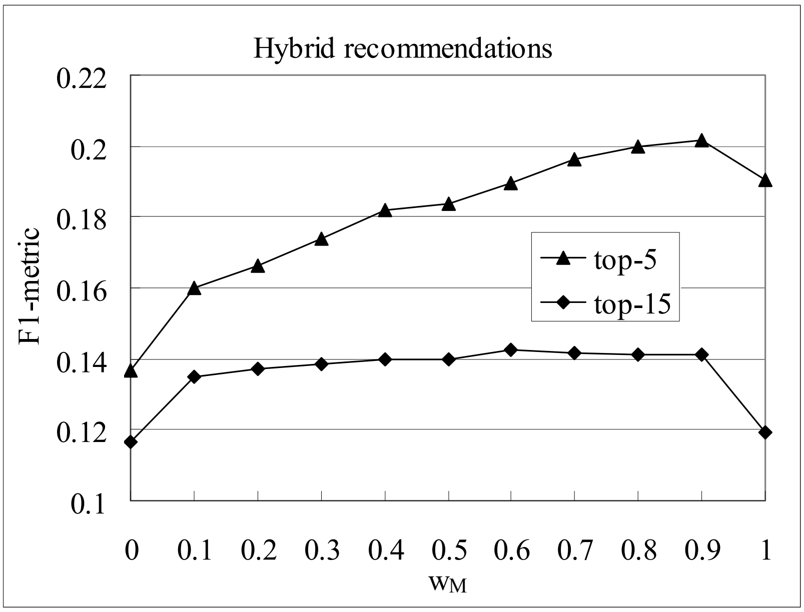

Figure 6 The weighting ratio w_M of the hybrid recommendations

3.3.5 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' mobile phone features 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. 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 3.1.3. The hybrid weighting ratio described in Section 3.3.4 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-nearest neighbors (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 neighbors. Table 7 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 can achieve better improvement over conventional methods. For example, as listed in Table 7, 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-mertic of the hybrid MPF-Preference, MPF-based, Preference-based and k-NN CF methods are shown in Figure 7.

Table 7 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
Avg.	0.027	0.084	0.032	0.071	0.150	0.073	0.076	0.165	0.081	0.090	0.203	0.097

As shown in Fig 7, 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.

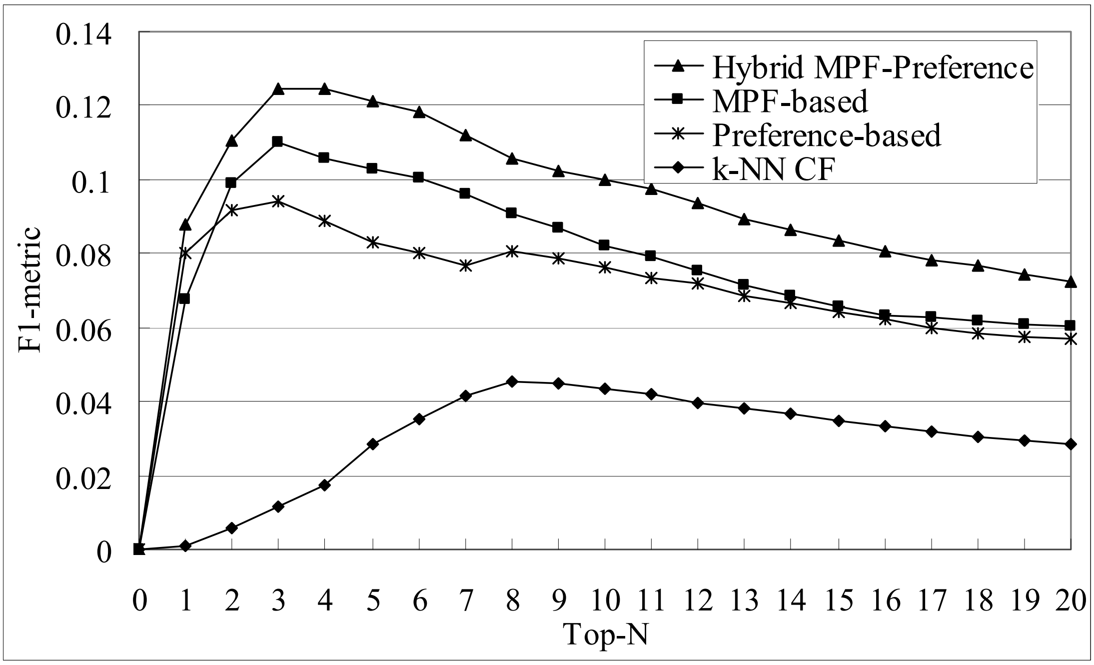

Figure 7 Evaluation of the hybrid, MPF-based, preference-based and k-NN CF methods

3.4 Discussions

Figure 8 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), 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 8 shows that the recommendation quality of the hybrid method (hybrid0 – 2) is better than that of the MPF-based method (mphone0 – 2) for each MPF-based cluster. In other words, the effect of combining MPF-based recommendations with preference-based recommendations is positive.

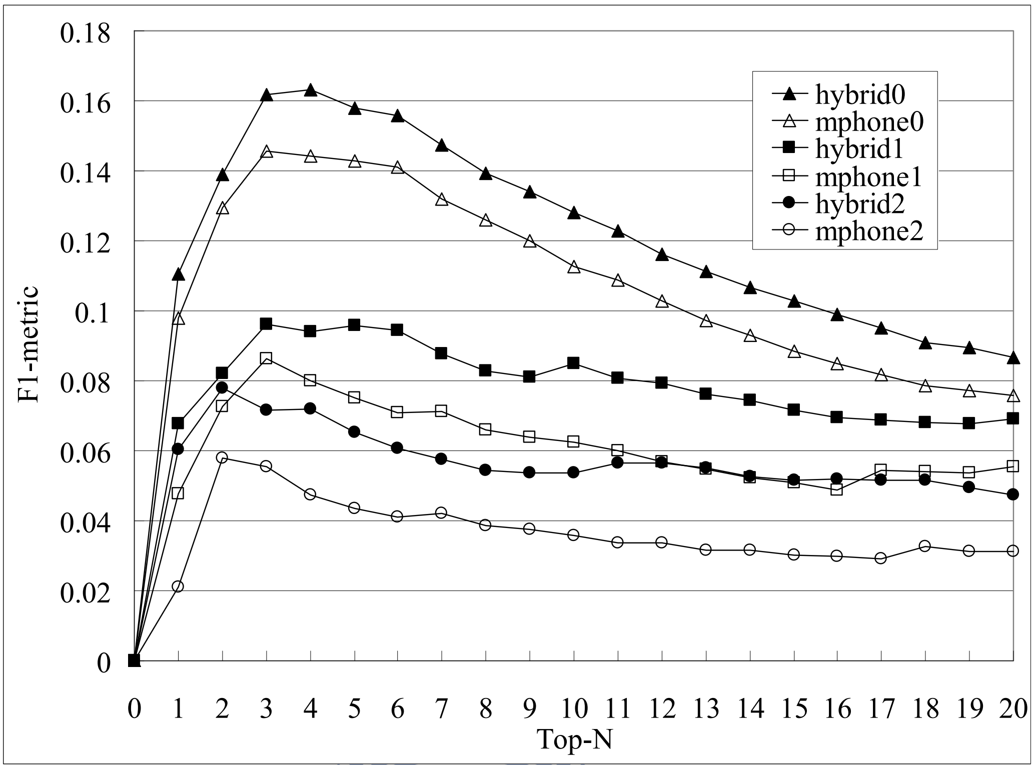

Figure 8 Effect of the hybrid method on the recommendation quality for mobile phone clusters

From Figure 9, 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 evaluate the effect of the hybrid method on the recommendation quality of preference-based clusters. Figure 9 shows that the recommendation quality of the hybrid method (hybrid0 – 3) is better than that of the preference-based method (product0 – 3) for each preference-based cluster. Hence, combining the preference-based method with the MPF-based method can improve the quality of recommendations.

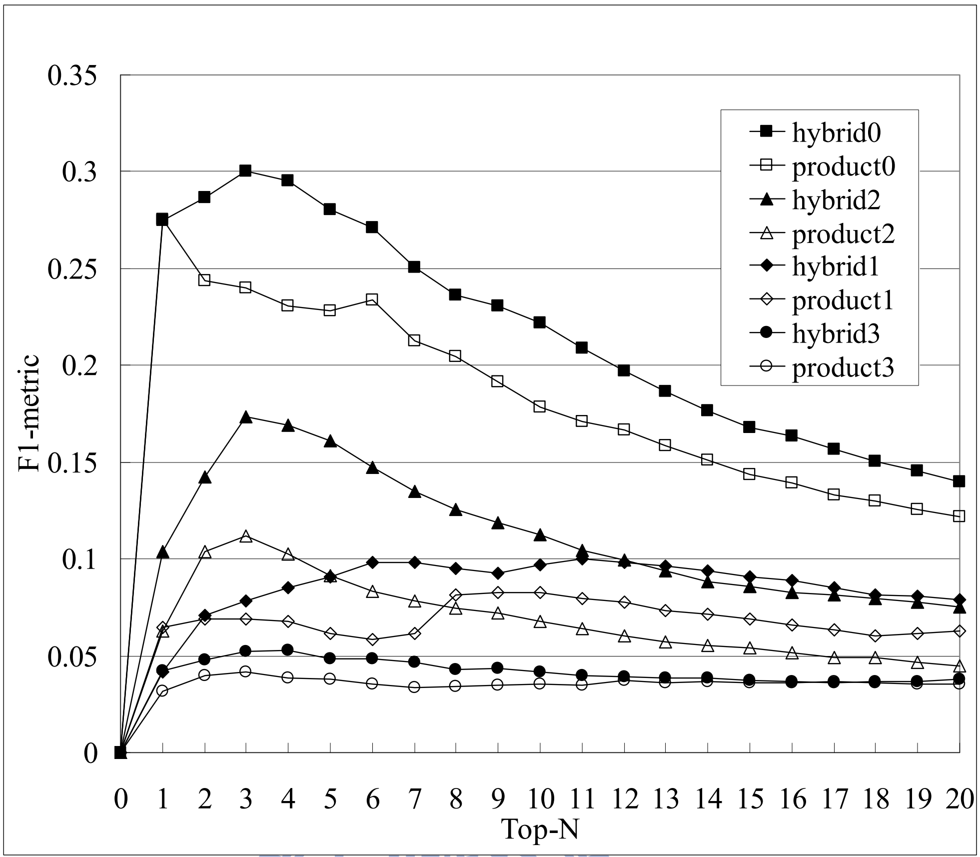

Figure 9 Effect of the hybrid method on the recommendation quality for product clusters

Chapter 4. Hybrid Multiple Channels-based (HMC) Method

4.1 Hybrid Multiple Channels-based (HMC) Method

In this section, we describe the proposed recommendation method based on the hybrid multiple channels, which are composed of mobile, television, catalog, and Web channels, as shown in Figure 10. Users of the multiple channels are divided into RFM groups to find heavy users based on their recency (R), frequency (F) and monetary (M) values; then these heavy users are divided into preference groups based on their product category preferences to provide recommendations for the new channel users. First, we use the K-means clustering method to cluster existing channel users into RFM groups based on the Euclidean distance of R, F, and M values and compare the average R, F, and M values of the clusters to the average R, F, and M values of all users. Heavy users who were selected by the clusters of the lower R values but the higher F and M values, provides more transaction instances that could be used to find more similar users for the new channel. Second, we use the K-means clustering method to cluster the heavy users of each channel into preference groups based on users' similarity which is measured by Pearson's correlation coefficient of users' product category preferences. Heavy users in the preference group could find more similar users for the new channel, which could solve the sparsity problem of the new channel and derive more association rules to improve the recommendation quality. For every target mobile channel user, similar users are selected from the clusters of mobile, television, catalog, and Web channels based on product category preferences. The system then finds the association rules of products and product categories as well as the most frequent items of the similar users of each channel. The association rules and most frequent items of the hybrid multiple channels are determined from the rules and items of multiple channels using the weighted sum of the associated confidence scores and frequent counts with different hybrid weights of w_M, w_T, w_C, and w_W. The hybrid weights are the relative importance of the multiple channels to the mobile channel, which are determined by the best recommendation quality of the recommendation engine based on the preliminary analytical data, which will be described in Section 4.1.2. Finally, the method recommends products based on the association rules and most frequent items by using the hybrid weights (w_M, w_T, w_C, w_W).

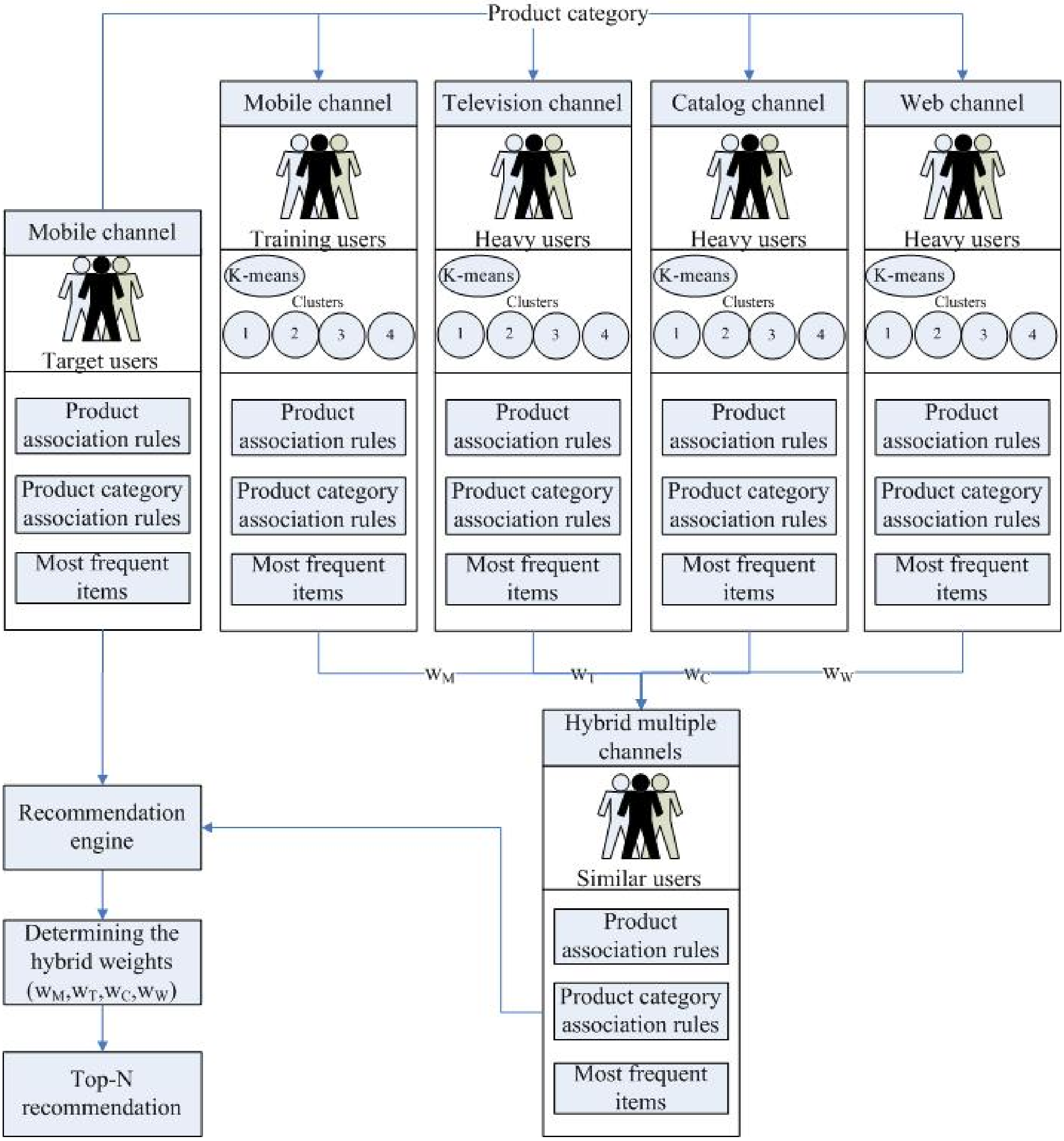

Figure 10 An overview of the proposed recommendation scheme

4.1.1 User Selection and Clustering of the Existing Channels

Heavy users are valuable customers who spend a large amount of money to purchase products frequently and recently in a channel. Figure 11 shows the selection of the heavy users with lower recency (R), higher frequency (F) and monetary (M) values. First, we calculate the R, F, and M values of each user in a channel. Second, we cluster users into groups by the K-means clustering method based on the

Euclidean distance of R, F, and M values, and compare the average R, F, and M values of clusters to the average R, F, and M values of all users in a channel. Finally, the clusters of heavy users in a channel are selected by the lower recency (R) values but the higher frequency (F) and monetary (M) values.

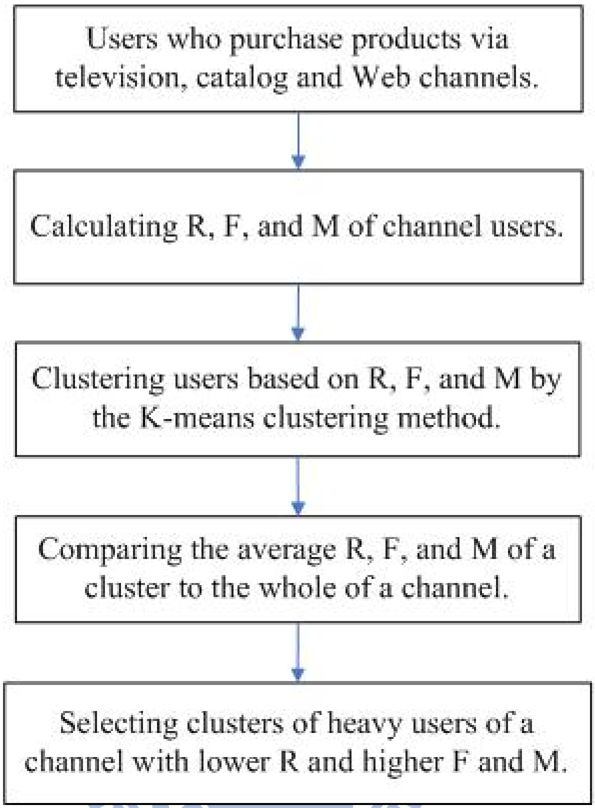

Figure 11 Selection of heavy users of a channel

After selected the existing channel heavy users to represent consumption behavior of users of a channel, the mobile, television, catalog, and Web channel users are clustered by the K-means clustering method into groups based on users' similarity which is measured by Pearson's correlation coefficient of the user–product category rating matrix as shown in Table 8.

Table 8 User–product category rating matrix

User ID	Cosmetics	Perfumes	Skincare	Pants	Shoes	Toys	Shirts	Notebooks	…
1	1	0	1	1	1	0	0	1	…
2	0	1	1	0	1	1	0	0	…
3	1	0	0	1	0	0	1	1	…
4	0	1	1	1	0	1	1	0	…
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	…

4.1.2 The Recommendation Engine

The proposed hybrid multiple-channel method derives recommendations based on the association-rule and most-frequent items approaches. For each group of users, two kinds of association rules are extracted, namely, product-level association rules and category-level association rules. The former are extracted from the product transactions; and the latter are extracted from category-level transactions, which are derived by replacing the products in product transactions with their respective categories. The recommendation engine is comprised of three components: the product association rules $(X_H^{PR_i} \rightarrow Y_H^{PR_i})$ component, the product category association rules $(X_H^{CR_j} \rightarrow Y_H^{CR_j})$ component, and the most frequent items (Y_H^{Mf}) component, as shown in Fig. 12. In the figure, *H* represents either *M, T, C,* or *W*, which denote the mobile, television, catalog and Web channels respectively.

In the multiple channel approach, let $X_H^{PR_i} \rightarrow Y_H^{PR_i}, H \in \{M, T, C, W\}$ be the product-level association rules extracted from the product transactions of a group of channel users, comprised of mobile, television, catalog, and Web channel users; and let their associated confidence scores be $cf_M^{PR_i}, cf_T^{PR_i}, cf_C^{PR_i}$, and $cf_W^{PR_i}$ respectively. In addition, let X_u represent the previous set of products that the target user *u* browsed in the mobile channel; and let Y_u^{AR} be the set of candidate products generated from the union of $Y_H^{PR_i} - X_u$ according to all the association rules $X_H^{PR_i} \rightarrow Y_H^{PR_i}$ that satisfy $X_H^{PR_i} \subseteq X_u$. The products in Y_u^{AR} are ranked according to the weighted sum of their confidence scores.

$$cf^{PR_i} = w_M \times cf_M^{PR_i} + w_T \times cf_T^{PR_i} + w_C \times cf_C^{PR_i} + w_W \times cf_W^{PR_i}, \tag{10}$$

where w_M, w_T, w_C, and w_W are the weights assigned to the mobile, television, catalog, and Web channels respectively.

Let $Y_H^{Mf}, H \in \{M, T, C, W\}$ denote the set of most frequent items derived from the user groups of target user *u* in multiple channels. The frequency count of an item *v* for a user group U_g is equal to the number of users in U_g that had browsed/purchased item *v*. Let $f_{v,M}^{Mf}, f_{v,T}^{Mf}, f_{v,C}^{Mf}$, and $f_{v,W}^{Mf}$ represent the frequency counts of an item *v* in Y_H^{Mf}, respectively. Let Y_u^{Mf} be the set of candidate products generated from the union of $Y_H^{Mf} - X_u$. The products in Y_u^{Mf} are ranked according to the weighted sum of their frequency counts calculated as Eq. (11).

$$f_v^{Mf} = w_M \times f_{v,M}^{Mf} + w_T \times f_{v,T}^{Mf} + w_C \times f_{v,C}^{Mf} + w_W \times f_{v,W}^{Mf} \tag{11}$$

Let $X_H^{CR_j} \rightarrow Y_H^{CR_j}, H \in \{M, T, C, W\}$ be the category-level association rules extracted from the category-level transactions of a group of channel users, comprised of mobile, television, catalog, and Web channels; and let their associated confidence scores be $cf_M^{CR_j}, cf_T^{CR_j}, cf_C^{CR_j}$, and $cf_W^{CR_j}$ respectively. In addition, let X_u^C represent the set of product categories that the target user *u* browsed previously from the mobile channel; and let Y_u^C be the set of candidate product categories generated from the union of $Y_H^{CR_j}$ according to all the category-level association rules $X_H^{CR_j} \rightarrow Y_H^{CR_j}$ that satisfy $X_H^{CR_j} \subseteq X_u^C$. The categories in Y_u^C are ranked according to the weighted sum of their confidence scores (Eq. 12).

$$cf^{CR_j} = w_M \times cf_M^{CR_j} + w_T \times cf_T^{CR_j} + w_C \times cf_C^{CR_j} + w_W \times cf_W^{CR_j} \tag{12}$$

Let Y_u^{CMf} denote the set of most frequent candidate items derived from the candidate product categories Y_u^C and most frequent candidate items Y_u^{Mf}. We note that Y_u^{Mf} is derived from the user groups of target user *u* in multiple channels. Y_u^{CMf} is the set of items in Y_u^{Mf} that also belong to the candidate categories in Y_u^C. Each item *v* in Y_u^{CMf} is associated with a pair of (cf^{C_k}, f_v^{Mf}), where cf^{C_k} is the associated confidence score of *v*'s category C_k derived using Eq. (12), and f_v^{Mf} is the frequency count of item *v* calculated using Eq. (11). The product items in Y_u^{CMf} are ranked as follows. The items with the highest frequency counts in each category of Y_u^C are selected first and ranked according to their associated confidence scores. Then, the items with the highest frequency counts among the remaining items in each category are selected and ranked according to their associated confidence scores. The process repeats to select and rank items in Y_u^{CMf} by recommending most frequent items from diverse candidate categories.

We compare the number of candidate products $|Y_u^{AR}|$ and the top-N recommendations. Note that Y_u^{AR} is the set of candidate products generated from the product-level association rules. If the number of candidate products $|Y_u^{AR}|$ is higher than the number of top-N recommendations $(|Y_u^{AR}| \geq N)$, the system will recommend the top-N products from Y_u^{AR}. If the number of candidate products $|Y_u^{AR}|$ is less than the number of top-N recommendations $(|Y_u^{AR}| < N)$, but $|Y_u^{AR} \cup Y_u^{CMf}|$ is larger than the number of top-N recommendations $(|Y_u^{AR} \cup Y_u^{CMf}| \geq N)$, the system will recommend $|Y_u^{AR}|$ products from Y_u^{AR}. The remaining $N - |Y_u^{AR}|$ products for recommendation are selected from Y_u^{CMf}. Note that Y_u^{CMf} is the set of most frequent product items belonging to the associated product categories in Y_u^C .

If $|Y_u^{AR} \cup Y_u^{CMf}|$ is less than the number of top-N recommendations $(|Y_u^{AR} \cup Y_u^{CMf}| < N)$, the remaining $N - |Y_u^{AR} \cup Y_u^{CMf}|$ products for recommendation are selected from Y_u^{Mf} - ($Y_u^{AR} \cup Y_u^{CMf}$), which is the set of most frequent items that the target user *u* has not browsed in the mobile channel and are not in $Y_u^{AR} \cup Y_u^{CMf}$. The products are ranked according to the weighted sum of the frequency counts of the products.

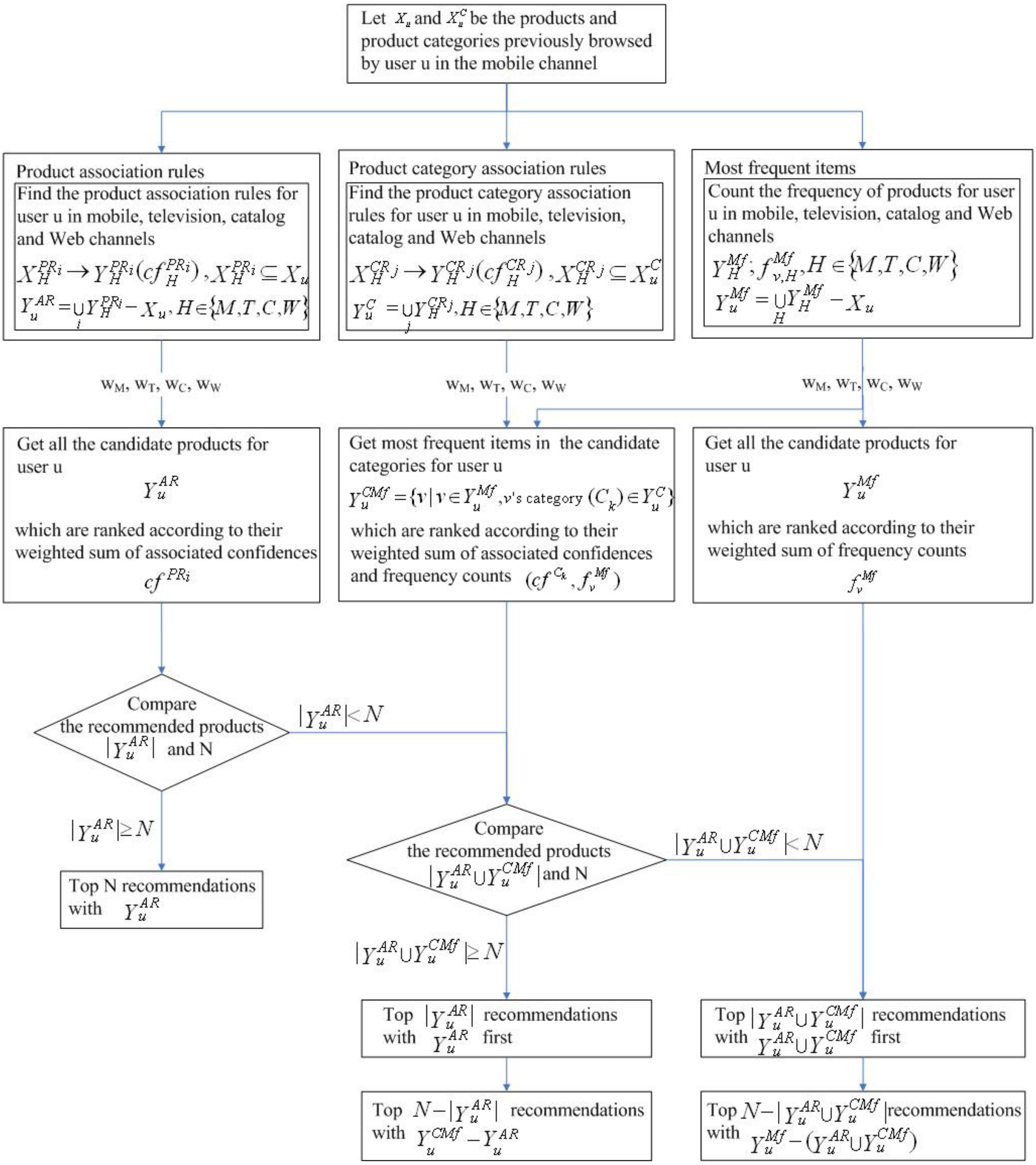

Figure 12 The recommendation engine

4.2 Experimental Setup and Datasets

The multichannel company is a home shopping company which has owned the television, catalog and Web channels in Taiwan. Because of the rapid development of 3G mobile network, the company would develop the new mobile channel. The television channel is a sale channel of the home shopping company. The products are introduced in television channel and people can purchase products by a toll-free telephone.

The mobile channel is an on-line experimental mobile shopping website which tried to find the consumption behaviors of the new mobile channel users. Users could access the mobile website by their own mobile phones via 2G, 3G, 3.5G and Wi-Fi networks. Data for the mobile channel and the existing channels were collected from the mobile website and CRM system of a retailer from October 2006 to January 2007, which contained information of about 1,692 users who own 184 different models of the mobile phones and offered 1,416 products which are included in 194 product categories. The product categories which are frequently browsed are mobile phones, lingerie, digital cameras, skincare, MP3 players, watches, living products, cosmetics, cordless phones and travel coupons. The products offered by the mobile channel were also provided in the other three channels.

The dataset was divided up as follows: 80% was used for training and 20% for testing. The training set was also used as the dataset 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 dataset to determine the hybrid weights assigned to mobile, television, catalog, and Web channels based on the quality of the recommendations. There were 1,353 users in the training dataset and 339 users in the test dataset.

The consumption behaviors of the applications in e-commerce are different, so the datasets are different. The support and confidence of the association rules are set to retrieve the interesting patterns in datasets. Based on the characteristics of our dataset, the minimum support and confidence of the association rules were set at 0.004 and 0.4 to find the interesting rules, which were both higher than the study by Cooley et al. [12] but lower than the study by Cho et al. [9].

4.3 Experimental Results

4.3.1 Heavy Users' Selection of the Existing Channels

The groups of heavy users were determined by comparing the group average of RFM values to the total average of RFM values in a channel. The heavy user groups are those groups with group average R smaller than and group average FM larger than the total average RFM in each channel. First, the R, F, and M values of every user of television, catalog, and Web channels were calculated. Users of a channel were clustered into groups. By comparing the group average to the total average in a channel, the group average may be larger (↑) or smaller (↓) than the total average. Because each R, F, and M value of a group can have two alternative values, larger (↑) or smaller (↓) than the total average, we cluster users based on three R, F, and M values into 8 groups (2 × 2 × 2). Second, the heavy user groups were checked (✓) in Table 9 due to their average R were smaller (↓) but F, M were larger (↑) than the total average in each channel. The clustering results are considered significant ($p<0.05$) based on R, F and M variable differences for television, catalog and Web channels. For example, the clusters of heavy users in the television channel are clusters 4 and 5 because their average R were smaller (↓) than the total average R, their average F were larger (↑) than the total average F, and their average M were larger (↑) than the total average M in the television channel. Similarly, based on the selection criteria, the clusters of heavy users in the catalog channel are clusters 3 and 6, and the clusters of heavy users in the Web channel are clusters 2 and 7 as checked in Table 9.

Table 9 R, F, and M values of users in each channel by clusters

Channel	Television*				Catalog*				Web*			
Cluster ID	Users	R	F	M	Users	R	F	M	Users	R	F	M
0	1,156	80↑	2↓	3,932↓	132	54↑	2↓	3,951↓	26	82↑	2↓	2,677↓
1	4,844	40↓	4↑	10,366↓	187	40↓	3↑	5,990↓	235	40↑	3↓	5,174↓
2	562	93↑	2↓	3,059↓	61	63↑	2↓	2,917↓	✓ 216	16↓	14↑	38,158↑
3	2,013	69↑	3↓	4,969↓	✓ 83	19↓	7↑	23,019↑	155	52↑	3↓	4,260↓
4	✓ 5,694	32↓	5↑	16,831↑	21	68↑	2↓	2,566↓	321	28↓	4↓	9,822↓
5	✓ 4,534	23↓	9↑	40,772↑	101	60↑	2↓	3,331↓	262	37↑	3↓	7,610↓
6	4,032	47↑	3↓	7,556↓	✓178	32↓	4↑	9,101↑	67	61↑	2↓	3,069↓
7	2,765	60↑	3↓	6,287↓	140	47↑	3↑	4,577↓	✓ 325	22↓	6↑	16,012↑
Total	25,600	44	4	15,431	903	44	3	7,067	1,607	33	5	12,909

* Significant at the 0.05 level

We note that there are exactly two heavy user groups for each channel based on the selection criteria. For other dataset, there may exist more than two heavy user groups. The final selection result is shown in Table 10. In our study, we are interested in the major consumption behaviors which are contributed by heavy users in channels. Users are selected due to their heavy consumption behaviors in channels.

Table 10 Clusters of heavy users selected in each channel

Television		Catalog		Web	
Cluster ID	Users	Cluster ID	Users	Cluster ID	Users
4	5,694	3	83	2	216
5	4,534	6	178	7	325
(4,5)	10,228	(3,6)	261	(2,7)	541

4.3.2 Determining Channel Weights for the Hybrid Recommendation Scheme

The hybrid multiple channel recommendation scheme is based on the hybrid weighting ratios of mobile (w_M), television (w_T), catalog (w_C), and Web (w_W) channels ($w_M + w_T + w_C + w_W = 100\%$). The derivation of these weights is as follows. First, the dataset is divided into 80% training dataset and 20% testing dataset. The training dataset trains a model to evaluate the testing dataset. In the 80% training dataset, 55% is used to derive the association rules and 25% is used as the preliminary analytical data to derive the weights. Second, these weights are determined by the best recommendation quality of the recommendation engine based on the preliminary analytical data. Because the average number of browsed products is 3.87 in the mobile channel, we choose the top four recommendations to determine the hybrid weights of multiple channels. We systematically adjust the values of channel weights in increments of 1%. The qualities of the top four hybrid recommendations according to different hybrid weight combinations (w_M, w_T, w_C, w_W) are shown in Figure 13. The best recommendation quality F1-metric of 0.1573 for the top four recommendations occurs when (w_M, w_T, w_C, w_W) = (60%, 1%, 33%, 6%). We use these weights as the hybrid weighting ratios of the hybrid recommendation scheme in the experiments described in Section 4.3.3.

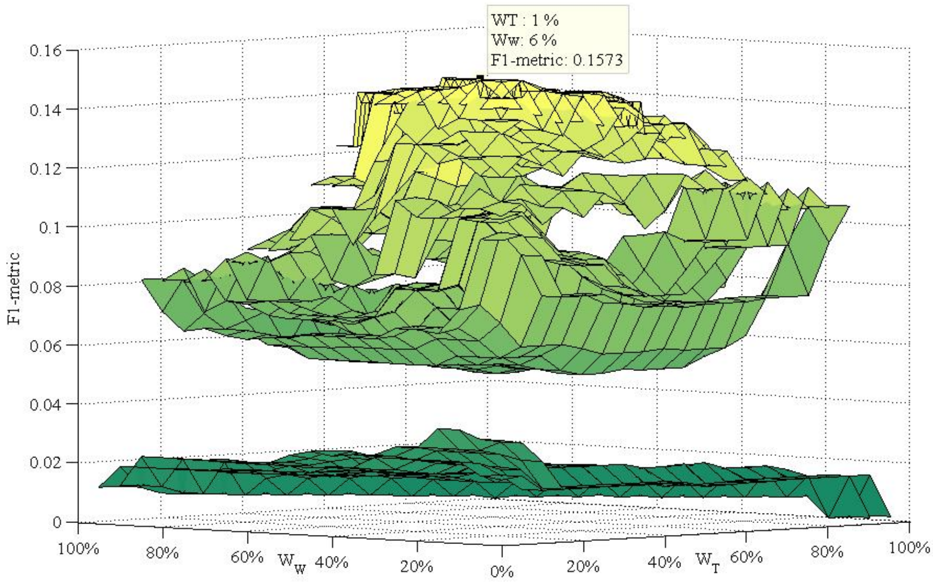

Figure 13 The hybrid weight combinations of the hybrid recommendations

The weight of the television channel is the smallest. We conduct further analysis on the data set to get an insight on the weighting ratios of channels by comparing the overlap of consumed products between each channel and the mobile channel. Let S_M be the set of products that had been browsed by the users in mobile channel. Let S_T be the set of products that had been purchased by the heavy users in television channel. The product overlapping ratio between the television channel and mobile channels is the ratio of the number of products in both S_M and S_T to the number of products in S_M. The product overlapping ratio between other channel and the mobile channels is derived similarly. The product overlapping ratio between the television and mobile channels is 10.9%. The product overlapping ratio between the Web and mobile channels is 13.9%, while the ratio between the catalog and mobile channels is 18.4%. Because the product overlapping ratio between the television and mobile channels is the lowest among all the channels, it implies that the consumption behaviors of the television and mobile channels are the most dissimilar. Thus, the television channel contributes least on the enhancement of the recommendation quality for the mobile channel. Consequently, the weight of the television channel is the smallest.

4.3.3 Evaluation of the Hybrid Multiple Channel Recommendation Method

We compare the proposed hybrid multiple channel (HMC) recommendation method, with three methods, namely, SC-PCAR, SC-PAR, and KNN-MFI methods. The HMC method recommends products based on the product-level and category-level association rules extracted from multiple channels as described in Section 4.1.2. The SC-PCAR method is a single channel approach that recommends products based on the product-level and category-level association rules extracted from the mobile channel. The SC-PAR method is a single channel approach that recommends products based on the product-level association rules derived from the mobile channel. Note that if the number of candidate products selected from the association rules is less than *N* for the top-N recommendations, the HMC, SC-PCAR and SC-PAR methods recommend remaining products based on the most frequently occurring items. The KNN-MFI method is a typical k-NN CF method that recommends the top-*N* most frequently occurring products of the k-nearest neighbors (similar users) in the mobile channel. Because the average number of users in a user group is 232.5 (= 930/4), we choose k = 200 as the number of nearest neighbors. Note that the HMC and SC-PCAR methods cluster users into groups based on the users' similarity derived from the user-product category preference matrix; while the SC-PAR and KNN-MFI methods cluster users into groups based on the users' similarity derived from the user-product preference matrix.

Figure 14 shows the evaluation results of the four recommendation methods. The SC-PCAR method outperforms the SC-PAR method because the user–product category preference matrix is not as sparse as the user–product preference matrix. Thus, it is possible to find more similar users by using the category preference-based approach. The HMC method generates recommendations based on multiple channels, i.e., the mobile, television, catalog, and Web channels, with the hybrid weighting ratio set at (w_M, w_T, w_C, w_W) = (60%, 1%, 33%, 6%) for the top-N recommendations, as described in Section 4.3.2.

As shown in Figure 14, the HMC method outperforms the SC-PCAR, SC-PAR and KNN-MFI methods. In general, the recommendation quality of HMC, SC-PCAR and SC-PAR methods declines after the top four recommendations, i.e., as the number of recommended products increases. Recall that association rule-based recommendations are based on the items users browsed previously. In our study, there are only a few recommended products because the average number of products browsed previously 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, the most frequent item-based method does not perform better than the association rule-based recommendation methods, so the recommendation quality deteriorates after the top four recommendations.

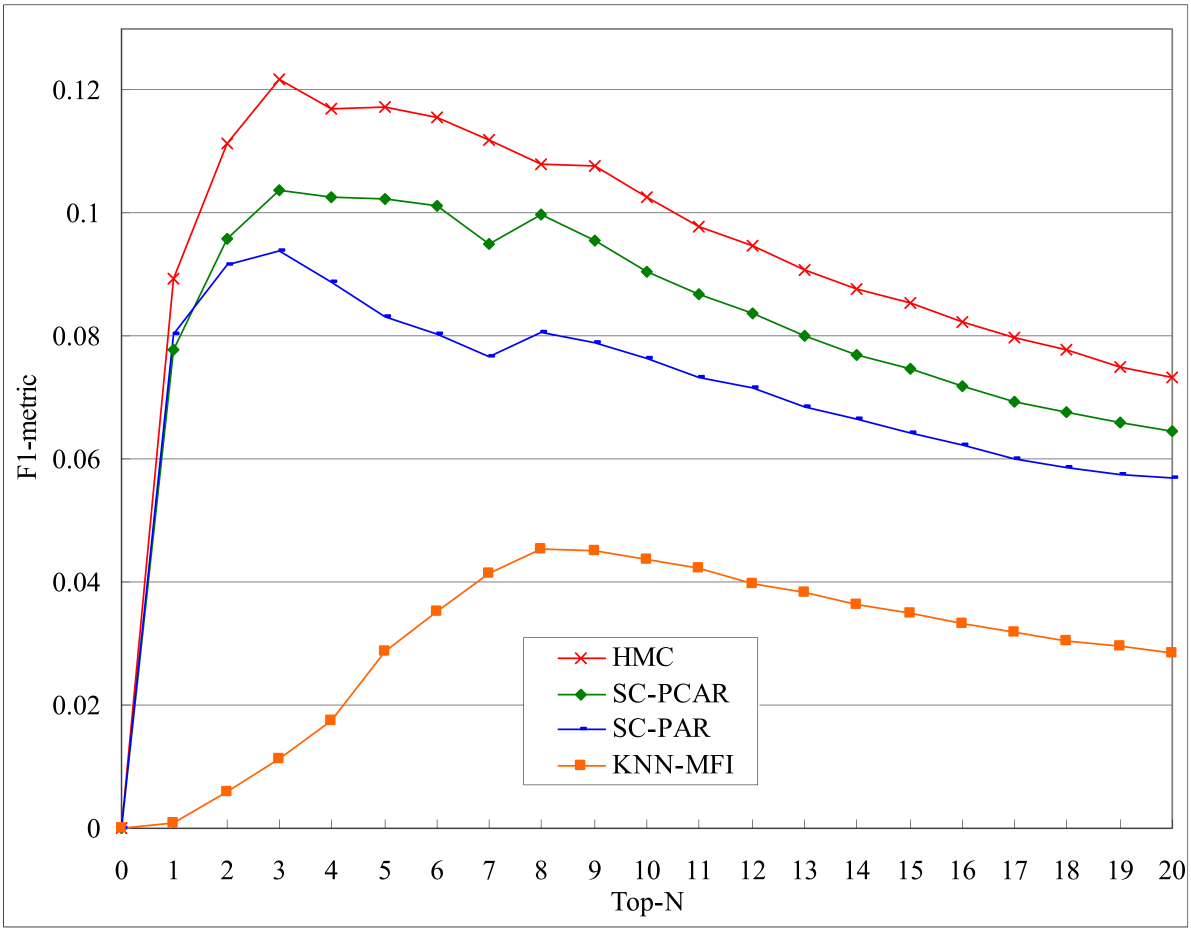

Figure 14 Evaluation of the HMC, SC-PCAR, SC-PAR, and KNN-MFI methods

4.4 Discussions

To provide recommendations for new mobile channel users, the hybrid weights are determined by the best recommendation quality of the recommendation engine based on the preliminary analytical data, which was described in Section 4.3.2. The derived hybrid weight combination (w_M, w_T, w_C, w_W) of the multiple channels is (60%, 1%, 33%, 6%). The weight of the mobile channel is the largest (60%) because users in the mobile environment have the highest similarity in browsing behaviors corresponding to users in the other channels. The recommendation quality for the mobile users can be enhanced by referring to the consumption behaviors of other channel users, for example, television (1%), catalog (33%) and Web (6%). The weight of the catalog channel is larger than the Web channel because of the following possible reasons. First, the catalog advertising provided promotion campaigns, while the Web channel did not provide the promotion of the mobile channel. Thus, more mobile channel users may be migrated from the catalog channel than from the Web channel. Another possible reason is the mobile phone's limited interface. The Web channel users would like to surf website freely with the large screen of the computer, rather than browse the same product webpages costly with the small screen of the mobile phone. Furthermore, the product overlapping ratio of the consumed products between the catalog and mobile channels is 18.4%, which is higher than the ratio (13.9%) between the Web and mobile channels. It implies that the consumption behaviors of the catalog and mobile channels are more similar than the consumption behaviors of the Web and mobile channels. Thus, the catalog channel contributes more than the Web channel on the enhancement of the recommendation quality for the mobile channel. Consequently, the weight of the catalog channel is larger than the web channel.

This experimental platform provides a good trial run environment to avoid investing too much money (e.g. advertisement and marketing campaigns) in the initial stage and collects users' consumption behaviors as references to develop the commercial run in the future. In the trial run, a retailer did not know about users' product preferences in the early stages of new channel development. By knowing the weights composition of multiple channels (e.g. 60%, 1%, 33%, 6%) for the new channel users (e.g. mobile channel) from the CRM analysis, it is easier to place products in the new channel based on the weights. For example, the selection of products in the new channel from television, Web and catalog should be in proportion with 1%, 6% and 33%; the remaining 60% products are the new products developed from the other suppliers outside the retailer. Furthermore, when the retailer decides to develop the new channel in the commercial run, the retailer could form a task force to operate the new channel. Because each existing channel department is familiar with the favorite products and marketing campaigns for its own channel users, the new task force could be formed based on the weights of departments of the existing channels. For example, the selection of manpower in the new channel from television, Web and catalog should be in proportion with 1%, 6% and 33%; the remaining 60% manpower is the new employees recruited from the mobile industry (e.g. telecommunication industry) outside the retailer.

Although the hybrid multiple channel method outperforms all the other methods, it is more computationally intensive. We compared the tradeoff between recommendation quality and computational time across the four methods. The recommender system includes two subsystems: the off-line batch run and on-line recommendation subsystems. The off-line subsystem deals with data pre-processing, user clustering and association rule mining. When a target user browses the mobile Web, the system will recommend products based on the stored association rules of clusters in the on-line recommendation subsystem. The computation times were compared based on the on-line recommendation phase, as shown in Table 11.

The evaluation was performed on a PC with an Intel Core 2 Quad 2.4GHz CPU and 4GB RAM. Table 11 shows the average recommendation qualities and computation times per target user from the top-1 to the top-20 recommendations. The computation times of the HMC, SC-PCAR, SC-PAR and the KNN-MFI methods were 0.27, 0.16, 0.09 and 0.36 seconds respectively. The computation time of the HMC method was longer than those of the single channel methods, but shorter than that of the KNN-MFI method. The multiple channel method - HMC required more time because it needed to match more association rules for the multiple channels. The recommendation quality of the hybrid multiple channel method is better than the single channel methods, but the tradeoff for better recommendation quality is an increase in the computation time. However, as the recommendation quality is important to a recommender, the additional computation time is acceptable.

Table 11 Computation times and recommendation qualities of the compared methods

Method	Computation Time	Recommendation Quality
HMC	0.27	0.10
SC-PCAR	0.16	0.09
SC-PAR	0.09	0.07
KNN-MFI	0.36	0.03

Chapter 5. Combine MPF with HMC Approach

5.1 MPF and HMC Combined Method

5.1.1 System Overview

In this section, we describe the proposed hybrid recommendation method, which combines an MPF-based method and a HMC-based method, as shown in Figure 15. First, the MPF-based method combines user mobile phones' features (MPF) and users' product preferences as user profiles to find similar users for the target users in the mobile channel, as shown on the left-hand side of the figure. Next, the association rules and frequently browsed products are extracted from similar users. 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 products to users.

Similar to the MPF-based method, HMC-based method, shown on the right-hand side of Figure 15, clusters users by the K-means clustering method based on Pearson's correlation coefficient of users' product preferences and finds similar users from multiple channels (i.e. television, catalog and web channels). 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 HMC-based recommendations with the hybrid ratio determined by the preliminary analytical data to recommend products. We discuss the recommendation engine of the hybrid recommendation schemes in Section 5.1.2.

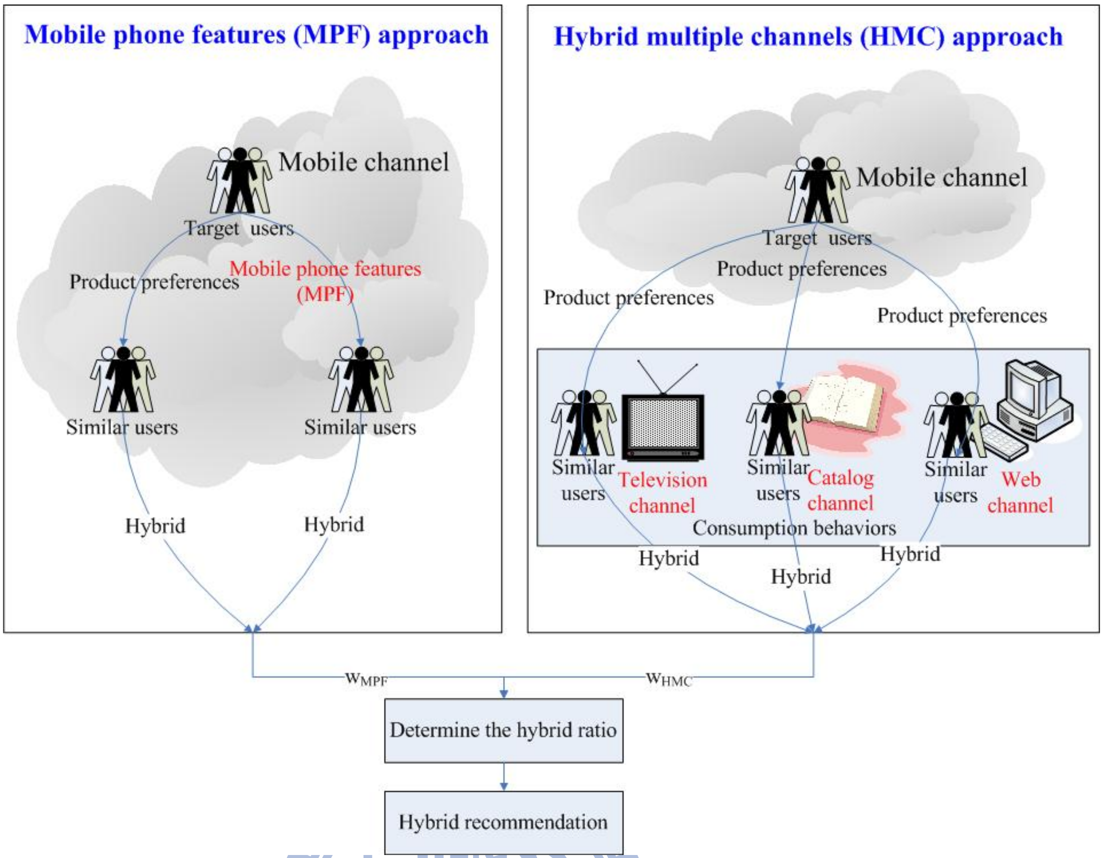

Figure 15 An overview of the combined MPF and HMC hybrid recommendation

5.1.2 The Recommendation Engine

The proposed hybrid multiple-channel method derives recommendations based on the association-rule and most-frequent items approaches. For each group of users, two kinds of association rules are extracted, namely, product-level association rules and category-level association rules. The former are extracted from the product transactions; and the latter are extracted from category-level transactions, which are derived by replacing the products in product transactions with their respective categories. The recommendation engine is comprised of three components: the product association rules $(X_H^{PR_i} \rightarrow Y_H^{PR_i})$ component, the product category association rules $(X_H^{CR_j} \rightarrow Y_H^{CR_j})$ component, and the most frequent items (Y_H^{Mf}) component, as shown in Fig. 16. In the figure, *H* represents either *MPF* or *HMC* which denote mobile phone features (MPF) or hybrid multiple channels (HMC) respectively.

In the multiple channel approach, let $X_H^{PR_i} \rightarrow Y_H^{PR_i}, H \in \{MPF, HMC\}$ be the product-level association rules extracted from the product transactions of a group of channel users, comprised of mobile, television, catalog, and Web channel users; and let their associated confidence scores be $cf_{MPF}^{PR_i}$ and $cf_{HMC}^{PR_i}$ respectively. In addition, let X_u represent the previous set of products that the target user u browsed in the mobile channel; and let Y_u^{AR} be the set of candidate products generated from the union of $Y_H^{PR_i} - X_u$ according to all the association rules $X_H^{PR_i} \rightarrow Y_H^{PR_i}$ that satisfy $X_H^{PR_i} \subseteq X_u$. The products in Y_u^{AR} are ranked according to the weighted sum of their confidence scores.

$$cf^{PR_i} = w_{MPF} \times cf_{MPF}^{PR_i} + w_{HMC} \times cf_{HMC}^{PR_i}, \tag{13}$$

where w_M, w_T, w_C, and w_W are the weights assigned to the mobile, television, catalog, and Web channels respectively.

Let $Y_H^{Mf}, H \in \{MPF, HMC\}$ denote the set of most frequent items derived from the user groups of target user u in multiple channels. The frequency count of an item v for a user group U_g is equal to the number of users in U_g that had browsed/purchased item v. Let $f_{v,MPF}^{Mf}$ and $f_{v,HMC}^{Mf}$ represent the frequency counts of an item v in Y_H^{Mf}, respectively. Let Y_u^{Mf} be the set of candidate products generated from the union of $Y_H^{Mf} - X_u$. The products in Y_u^{Mf} are ranked according to the weighted sum of their frequency counts calculated as Eq. (14).

$$f_v^{Mf} = w_{MPF} \times f_{v,MPF}^{Mf} + w_{HMC} \times f_{v,HMC}^{Mf} \tag{14}$$

Let $X_H^{CR_j} \rightarrow Y_H^{CR_j}, H \in \{MPF, HMC\}$ be the category-level association rules extracted from the category-level transactions of a group of channel users, comprised of mobile, television, catalog, and Web channels; and let their associated confidence scores be $cf_{MPF}^{CR_j}$ and $cf_{HMC}^{CR_j}$ respectively. In addition, let X_u^C represent the set of product categories that the target user u browsed previously from the mobile channel; and let Y_u^C be the set of candidate product categories generated from the union of $Y_H^{CR_j}$ according to all the category-level association rules $X_H^{CR_j} \rightarrow Y_H^{CR_j}$ that satisfy $X_H^{CR_j} \subseteq X_u^C$. The categories in Y_u^C are ranked according to the weighted sum of their confidence scores (Eq. 15).

$$cf^{CR_j} = w_{MPF} \times cf_{MPF}^{CR_j} + w_{HMC} \times cf_{HMC}^{CR_j} \tag{15}$$

Let Y_u^{CMf} denote the set of most frequent candidate items derived from the candidate product categories Y_u^C and most frequent candidate items Y_u^{Mf}. We note that Y_u^{Mf} is derived from the user groups of target user u in multiple channels. Y_u^{CMf} is the set of items in Y_u^{Mf} that also belong to the candidate categories in Y_u^C.

Each item v in Y_u^{CMf} is associated with a pair of (cf^{C_k}, f_v^{Mf}), where cf^{C_k} is the associated confidence score of v's category C_k derived using Eq. (15), and f_v^{Mf} is the frequency count of item v calculated using Eq. (14). The product items in Y_u^{CMf} are ranked as follows. The items with the highest frequency counts in each category of Y_u^C are selected first and ranked according to their associated confidence scores. Then, the items with the highest frequency counts among the remaining items in each category are selected and ranked according to their associated confidence scores. The process repeats to select and rank items in Y_u^{CMf} by recommending most frequent items from diverse candidate categories.

We compare the number of candidate products $|Y_u^{AR}|$ and the top-N recommendations. Note that Y_u^{AR} is the set of candidate products generated from the product-level association rules. If the number of candidate products $|Y_u^{AR}|$ is higher than the number of top-N recommendations $(|Y_u^{AR}| \geq N)$, the system will recommend the top-N products from Y_u^{AR}. If the number of candidate products $|Y_u^{AR}|$ is less than the number of top-N recommendations $(|Y_u^{AR}| < N)$, but $|Y_u^{AR} \cup Y_u^{CMf}|$ is larger than the number of top-N recommendations $(|Y_u^{AR} \cup Y_u^{CMf}| \geq N)$, the system will recommend $|Y_u^{AR}|$ products from Y_u^{AR}. The remaining $N - |Y_u^{AR}|$ products for recommendation are selected from Y_u^{CMf}. Note that Y_u^{CMf} is the set of most frequent product items belonging to the associated product categories in Y_u^C.

If $|Y_u^{AR} \cup Y_u^{CMf}|$ is less than the number of top-N recommendations $(|Y_u^{AR} \cup Y_u^{CMf}| < N)$, the remaining $N - |Y_u^{AR} \cup Y_u^{CMf}|$ products for recommendation are selected from Y_u^{Mf} - ($Y_u^{AR} \cup Y_u^{CMf}$), which is the set of most frequent items that the target user u has not browsed in the mobile channel and are not in $Y_u^{AR} \cup Y_u^{CMf}$. The products are ranked according to the weighted sum of the frequency counts of the products.

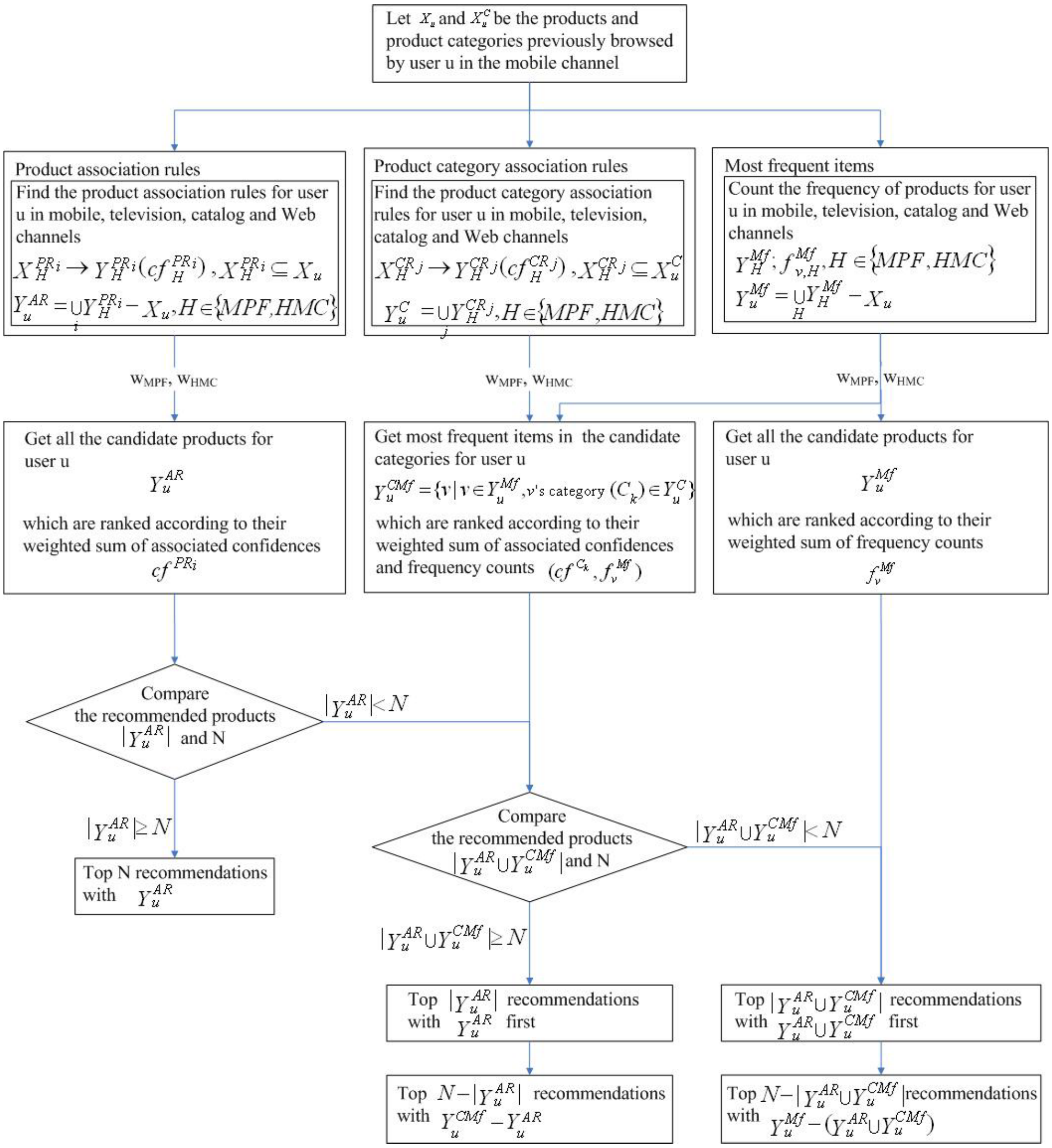

Figure 16 The recommendation engine

5.2 Experimental Setup and Datasets

The multichannel company is a home shopping company which has owned the television, catalog and Web channels in Taiwan. Because of the rapid development of 3G mobile network, the company would develop the new mobile channel. The television channel is a sale channel of the home shopping company. The products are introduced in television channel and people can purchase products by a toll-free telephone.

The mobile channel is an on-line experimental mobile shopping website which tried to find the consumption behaviors of the new mobile channel users. Users could access the mobile website by their own mobile phones via 2G, 3G, 3.5G and Wi-Fi networks. Data for the mobile channel and the existing channels were collected from the mobile website and CRM system of a retailer from October 2006 to January 2007, which contained information of about 1,692 users who own 184 different models of the mobile phones and offered 1,416 products which are included in 194 product categories. The product categories which are frequently browsed are mobile phones, lingerie, digital cameras, skincare, MP3 players, watches, living products, cosmetics, cordless phones and travel coupons. The products offered by the mobile channel were also provided in the other three channels.

The dataset was divided up as follows: 80% was used for training and 20% for testing. The training set was also used as the dataset 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 dataset to determine the hybrid weights assigned to mobile, television, catalog, and Web channels based on the quality of the recommendations. There were 1,353 users in the training dataset and 339 users in the test dataset.

The consumption behaviors of the applications in e-commerce are different, so the datasets are different. The support and confidence of the association rules are set to retrieve the interesting patterns in datasets. Based on the characteristics of our dataset, the minimum support and confidence of the association rules were set at 0.004 and 0.4 to find the interesting rules, which were both higher than the study by Cooley et al. [12] but lower than the study by Cho et al. [9].

5.3 Experimental Results

5.3.1 Determining the Weights for the Hybrid Recommendation Scheme

The hybrid recommendation scheme is based on the hybrid weighting ratios w_{MPF} and w_{HMC} (w_{MPF}=1-w_{HMC}) of the mobile phone features (MPF) and hybrid multiple channels (HMC) clusters. Hybrid recommendation becomes pure MPF-based recommendation when w_{MPF} equals one and pure HMC-based recommendation when w_{MPF} equals zero. The derivation of these weights is as follows. First, the dataset is divided into 80% training dataset and 20% testing dataset. The training dataset trains a model to evaluate the testing dataset. In the 80% training dataset, 55% is used to derive the association rules and 25% is used as the preliminary analytical data to derive the weights. Second, these weights are determined by the best recommendation quality of the recommendation engine based on the preliminary analytical data. Because the average number of browsed products is 3.87 in the mobile channel, we choose the top four recommendations to determine the hybrid weights of multiple channels. We systematically adjust the values of channel weights in increments of 0.1. The qualities of the top four hybrid recommendations according to different hybrid weight combinations (w_{MPF}, w_{HMC}) are shown in Figure 17. The best recommendation quality F1-metric of 0.2049 for the top four recommendations occurs when (w_{MPF}, w_{HMC}) = (0.7, 0.3). We use these weights as the hybrid weighting ratios of the hybrid recommendation scheme in the experiments described in Section 5.3.2.

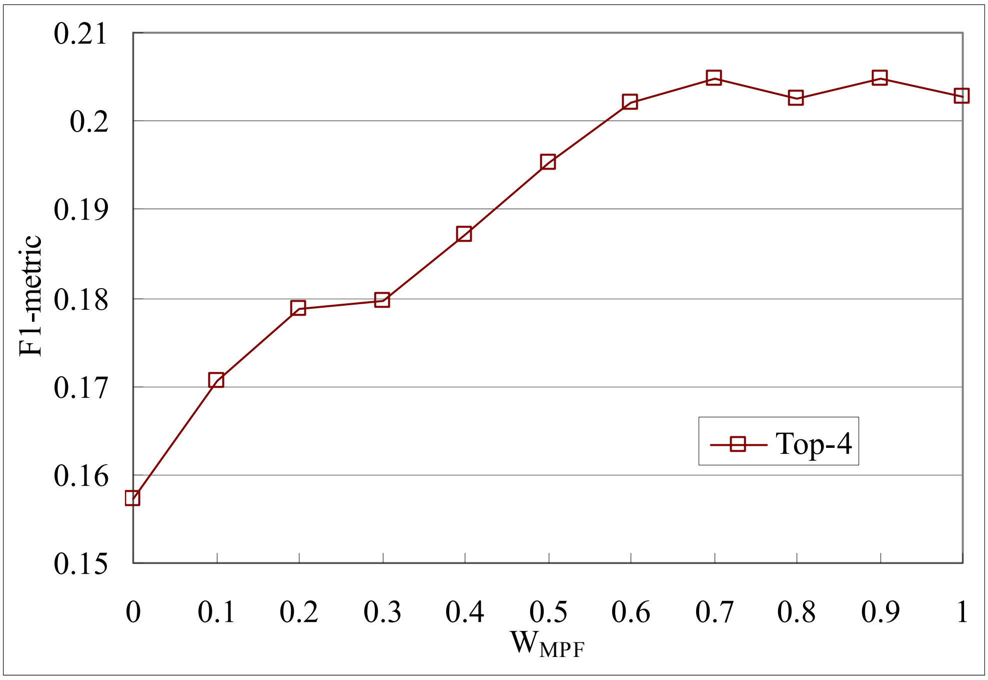

Figure 17 The weight combinations of the hybrid recommendations

5.3.2 Evaluation of the Recommendation Methods

We compare the MPF-HMC recommendation method, with five methods, namely, MPF, HMC, SC-MPF, SC-PAR, and KNN-MFI methods. The MPF-HMC method recommends products by combining MPF and HMC methods based on the product-level and category-level association rules extracted from multiple channels as described in Section 5.1. The MPF method is a single channel approach which combines MPF and product preferences to recommend products based on the product-level association rules extracted from the mobile channel. The HMC method is a multiple channels approach which combines users' consumption behaviors of the multiple channels to recommend products based on the product-level and category-level association rules extracted from the multiple channel. The SC-MPF method is a single channel approach which uses MPF as user profile to recommend products based on the product-level association rules extracted from the mobile channel. The SC-PAR method is a single channel approach which uses product preferences as user profile to recommend products based on the product-level association rules derived from the mobile channel.

Note that if the number of candidate products selected from the association rules is less than *N* for the top-N recommendations, the MPF-HMC, MPF, and HMC, SC-MPF, SC-PAR methods recommend remaining products based on the most frequently occurring items. The KNN-MFI method is a typical k-NN CF method that recommends the top-*N* most frequently occurring products of the k-nearest neighbors (similar users) in the mobile channel. Because the average number of users in a user group is 232.5 (= 930/4), we choose k = 200 as the number of nearest neighbors. Note that the MPF-HMC, MPF and HMC methods cluster users into groups based on the users' similarity derived from the user-product category preference matrix; while the SC-MPF, SC-PAR and KNN-MFI methods cluster users into groups based on the users' similarity derived from the user-product preference matrix.

Figure 18 shows the evaluation results of these recommendation methods. The category-based method outperforms the product-based method because the user–product category preference matrix is not as sparse as the user–product preference matrix. Thus, it is possible to find more similar users by using the category preference-based approach. The MPF-HMC method generates recommendations based on the MPF and HMC parts, with the hybrid weighting ratio set at (w_{MPF}, w_{HMC}) = (0.7, 0.3) for the top-N recommendations, as described in Section 5.3.1.

As shown in Figure 18, the MPF-HMC method outperforms the MPF, HMC, SC-MPF, SC-PAR and KNN-MFI methods. In general, the recommendation quality of MPF-HMC, MPF, HMC, SC-MPF and SC-PAR methods declines after the top four recommendations, i.e., as the number of recommended products increases. Recall that association rule-based recommendations are based on the items users browsed previously. In our study, there are only a few recommended products because the average number of products browsed previously 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, the most frequent item-based method does not perform better than the association rule-based recommendation methods, so the recommendation quality deteriorates after the top four recommendations.

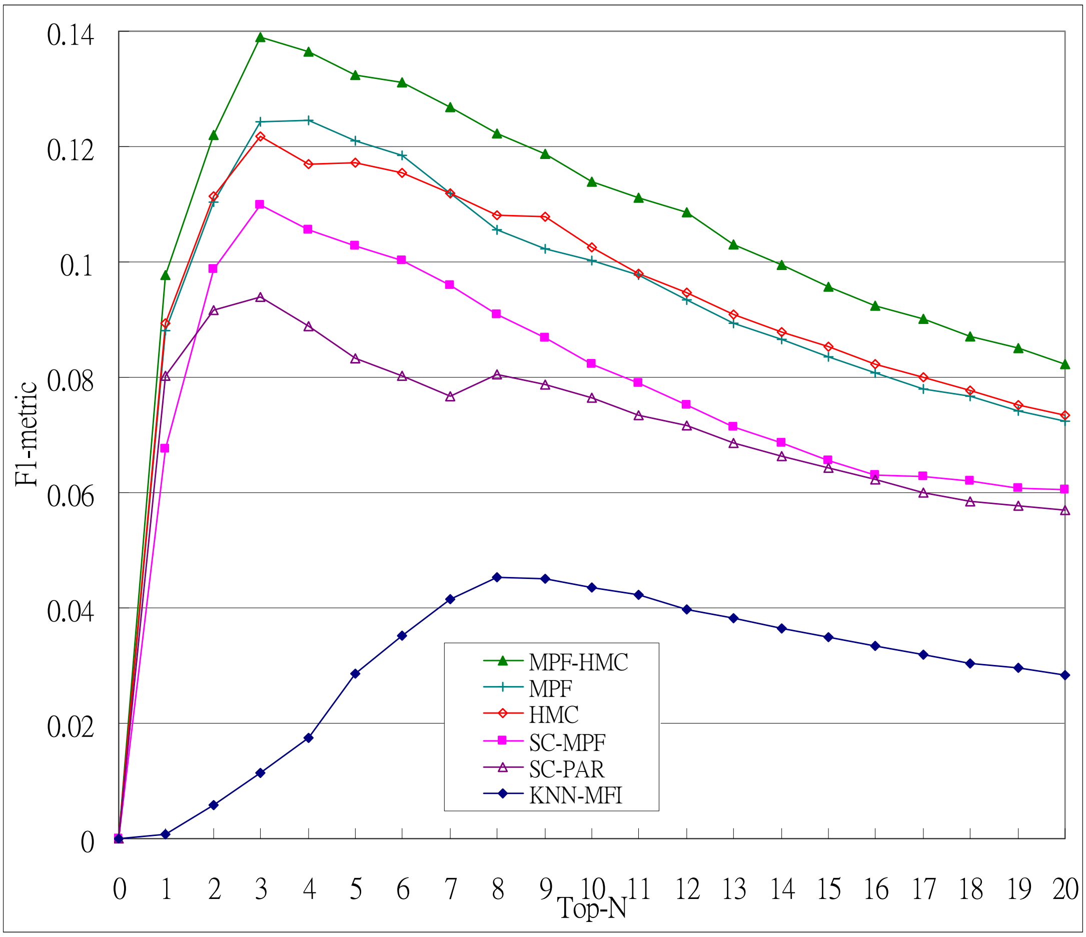

Figure 18 Evaluation of the MPF-HMC, MPF, HMC, SC-MPF, SC-PAR and KNN-MFI methods

Chapter 6. Conclusions and Future Works

6.1 Conclusions

We have proposed a mobile phone feature-based (MPF) hybrid method to resolve the sparsity issue of the typical CF method in mobile environments. We assume that the mobile phone features 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 employs 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.

On the other hand, multi-channel companies may meet difficulties when they develop the new channel due to lack of knowledge about users' consumption behaviors. Most existing companies use advertisement and marketing campaigns to understand users' consumption behaviors of the new channel. Compared to the costly advertisement and marketing campaigns, the businesses could also understand the consumption behaviors of the new channel users by the CRM system of the existing channels. However, in the early stages of new channel development, there were insufficient purchase orders to determine the consumption behaviors. Although the amount of browsing data for the mobile Web is greater, unfortunately the user–product rating matrix is very sparse because mobile Internet fees are still high;

similar users are difficult to find because of the *sparsity problem* of the typical CF method. In this study, we proposed a hybrid multiple channel method to resolve the lack of knowledge about the consumption behaviors with respect to the new channel and the difficulty of finding similar users. It is assumed that the browsing behaviors of new channel users are correlated with the browsing data of the new mobile channel as well as the consumption behaviors with respect to the existing multiple channels by the different weights.

Experiments were conducted to compare the hybrid multiple channels method, two single channel methods that use product category and product preferences, and the typical kNN-based CF method. The experimental results show that the proposed hybrid multiple channels method outperforms the two single channel methods and the typical kNN-based CF method. The hybrid multiple channels method successfully solved the *sparsity* problem by finding more similar users not only from its own channel but also from the other channels, which integrated two heterogeneous databases of the CRM system and the mobile website.

Finally, we combine MPF with HMC approach into a hybrid MPF-HMC method, which utilizes association rules of product categories and products as well as most frequent items to recommend products. Our experiment results show that the hybrid MPF-HMC combined method performs well compared to the pure MPF-based and HMC-based methods as well as the typical kNN-based CF method.

6.2 Future Works

This study has some limitations. First, we use the browsing data rather than the purchasing data because there are insufficient purchase orders in the mobile channel for analysis. With the purchase data, it could be easier to make recommendations since we would like to understand users' consumption behaviors. Second, the system could not identify the consumption behaviors of the different demographic groups in each channel because users' demographic data was unavailable. It could not derive the channel weight combinations for groups. Several future researches can be extended for this study such as investigations into the reasons why users migrate. What kind of factors such as channel advertisement or interface will affect users' channel migration behaviors? In addition, this study could be applied to existing channels (e.g. television and catalog) to make better recommendations for another existing channel (e.g. Web). Television and catalog channels could be the auxiliary channels to recommend products to Web channels. It could effectively improve the recommendation quality of electronic commerce by the other existing channels.

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