# Improve the Quality of Product Recommendation based on Multi-channel CRM for E-commerce

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*Abstract*—**In Internet age, more and more Web applications and services are developed for electronic commerce (EC). However, the quality of product recommendations is still not good for electronic commerce. There are hundreds of thousands products placed on EC websites, but low percentage of those products were purchased by customers even though they still purchased many products. Because the scattered products customers purchased, customer-product matrix is also very sparse. It is difficult to find customers with the similar product preferences and the quality of the traditional product recommendation – the collaborative filtering method is not good. In this paper, we tried to propose a multi-channel customer relationship management (CRM) approach to solve the sparse problem of customer-product matrix, which results in the poor quality of product recommendations due to the difficulty of finding customers with the similar product preferences. We considered not only the similar users of the Web channel, but also the similar users of the other channels (e.g. television and catalog) in a multi-channel retailer. By these similar users from the multiple channels, the recommended products were ordered by the weighted frequent counts of the most frequent items purchased by the similar users with the hybrid weights for the Web target user.**

## I. INTRODUCTION

As the Internet becomes more popular, Web services and applications are getting more for electronic commerce (EC). However, the quality of product recommendations is still not good for electronic commerce. There are hundreds of thousands products placed on EC website, but low percentage of those products are purchased by customers even though they still purchased many products. Because the scattered products customers purchased, customer-product matrix is also very sparse. It is difficult to find customers with the similar product preferences and make good product recommendation.

Recommender systems are widely used to recommend various items, such as movies and music, to customers according to their interests [1, 2]. Generally, recommender systems are based on either 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 [3, 4]. In contrast, content-based filtering (CBF) method derives recommendations by matching customer profiles with content features [5, 6]. Some studies have combined collaborative filtering and content-based filtering techniques as a hybrid recommendation method [7, 8].

The typical CF method relies on finding users with similar interests to make recommendations. However, it suffers from the sparsity problem, which arises because users rate very few items and the user–item rating matrix is very sparse; thus, the recommendation quality is poor due to the difficulty of finding users with similar interests [4]. For example, we could find the sparse customer-product matrix on the Web channel as shown in Fig. 1. Customer (C5) only purchased products (P3, P8) on Web channel. It is hard to find similar users by the sparse customer-product matrix, so the recommendation quality may be poor.
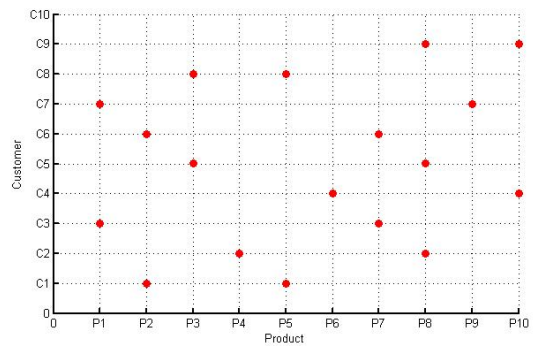


Fig. 1 Sparse customer-product matrix on the Web

In this paper, we tried to solve the sparsity problem on the Web by considering the consumption behaviors of multiple channels' users first. Customers could purchase products on the Web as well as the other channels (e.g. television, catalog) in a retailer. If we consider the consumption behaviors of all channels in a retailer, the customer-product matrix of all channels is more condensed than the individual Web channel, which is shown on Fig. 2. For example, customer (C5) purchased products (P3, P4, P5, P7, P8, P10) on all channels (e.g. Web, television and catalog channels) in a retailer. We could find more users with the similar interests in all channels. Thus, the recommendation quality of all channels may be better than the individual Web channel.

Furthermore, customer could purchase the different products in the individual channel (e.g. Web, television and catalog channel). For example, customers purchased products in multiple channels are shown in Fig. 3 as follows. Customer
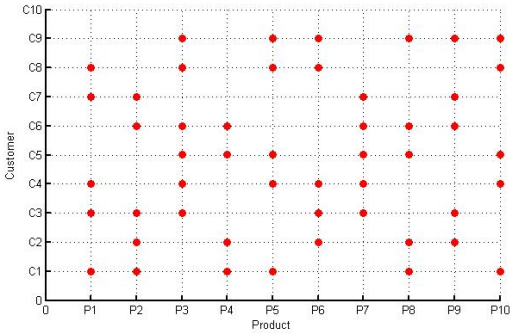
Fig. 2 Condensed customer-product matrix in all channels
(C5) purchased products (P3, P8) on the Web channel, purchased products (P4, P7) on the television channel, and purchased products (P5, P10) on the catalog channel. We could find similar users individually in each channel (e.g. Web, television and catalog channel) first, and then hybridize their consumption behaviors of the multiple channels.

It is interesting that the similar users of all channels might be not the same as the similar users of individual channel by considering the channel factor. The multiple channels' users might have the similar product preferences to the Web target user by their consumption behaviors on the multiple channels with the different weights. The hybrid weights indicate the relative importance of the consumption behaviors of the multiple channels' similar users to the Web channel users. The recommendation quality of the hybrid effect from the multiple channels might be better than all channels.
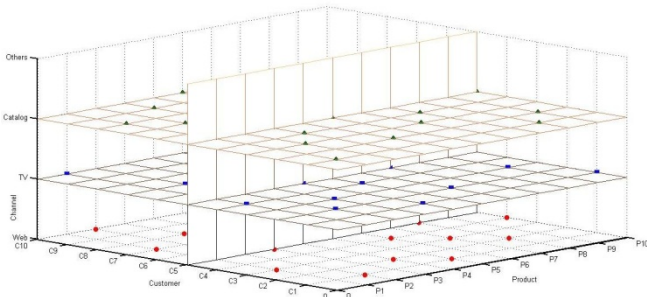


Fig. 3 Customers purchased products in multiple channels
Finally, we tried to propose a hybrid multi-channel method which adjusts the weights of the individual channel to address the difficulty of finding similar users on Web due to the sparsity problem inherent in typical CF systems for electronic commerce. The method finds the similar preference users of the multiple channels based on the similar product preferences, and the most frequent items of the individual channel similar users for the target Web user. Thus, the products were sorted by the frequencies of the frequent items with the hybrid weights of the individual channel to recommend to the target Web user.

The remainder of this paper is organized as follows. In Section II, we discuss the related work of our research. In Section III, we describe the proposed recommendation scheme and engine. In Section IV, we present the experiment evaluation. In Section V, we draw some conclusions.

## II. RELATED WORK

### A. Multiple channels

Multiple channels can be divided into physical channels (e.g., department stores) and virtual channels (e.g., the Web, catalogs, and television) [9]. In the past, most companies only provided single sales channels for customers to purchase products. However, because of advances in information technology and increased demand, companies now use multiple channels, i.e., physical and virtual channels, to provide customers with seamless services. In this way, companies create more value for their customers, e.g., greater choice and convenience. The channels can also be designed to allow customers to move from one channel to another seamlessly by reducing transaction costs during the purchase process [9-12]. Existing studies do not provide product recommendations for electronic commerce based on the consumption behavior of the multiple sales channels' similar preference users.

### B. Customer Relationship Management (CRM)

CRM represents the abbreviation of "customer relationship management", some other studies use the terms "customer relationship marketing" or "information-enabled relation marketing" as the abbreviations [13]. CRM could identify, attract significant and profitable customers by managing relationships with them and develop their long-term relationships strategically [14, 15]. CRM could also be an e-commerce application of database marketing [16]. CRM is how businesses manage their customer relationship by interacting with their customers based on customers' past transactions; it could be a methodology, technology, and e-commerce application to manage their customer relationships [17]. CRM is also an one-to-one marketing for each customer based on how much you know about your customers [18]. Besides, multichannel integration could be one of key cross functional processes in CRM strategy development. Payne and Frow [19] discuss the strategic role of multiple channel integration in CRM.

### C. Most Frequent Item-based Recommendation Method

The most frequent item-based recommendation method [4] 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.

### D. Collaborative Filtering

Collaborative filtering (CF) [2, 3] utilizes the nearest-neighbor principle to recommend products to a target audience. The neighbors are identified by computing the similarity between customers' purchase behavior patterns or tastes. The similarity is measured by Pearson's correlation coefficient, which is defined as follows:

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

where $\overline{r_{C_i}}$ and $\overline{r_{C_j}}$ denote the average number of products purchased by customers $C_i$ and $C_j$ respectively; variable I denotes the mix of the set of products; and $r_{ci,s}$ and $r_{cj,s}$ indicate, respectively, that customers $C_i$ and $C_j$ purchased product item S.

The $k$NN-based CF method utilizes k-nearest neighbors ($k$-NN) to recommend $N$ products to a target user [4]. The k-nearest neighbors are identified by computing the similarity between customers' purchase behavior or tastes. The similarity is measured by Pearson's coefficient, as shown in (1). After the neighborhood has been formed, the $N$ recommended products are determined by the k-nearest neighbors as follows. The frequency count of products is calculated by scanning the data about the products purchased by the $k$-nearest neighbors. The products are then sorted based on the frequency count, and the $N$ most frequently occurring products that have not been purchased by the target customers are selected as the top-$N$ recommendations.

## III. METHODOLOGY

### A. Multiple Channel CF (MC-CF) based approach

In Fig. 4, the similar users of multiple channels were found based on their product preferences and then provide recommendations by their product transactions for Web target user. The similar users of the other existing channels could be used to provide more transactions for the Web channel user. First, we found the similar users of each channel based on the users' similarity, which is measured by Pearson's correlation coefficient (1) of users' product preferences. For each target Web channel user, similar users are selected from the television, catalog, and Web channel users based on their product preferences in the corresponding channel. The method could find more similar users for the Web target user and would solve the sparsity problem of the Web channel to improve the quality of recommendations. The system then finds the most frequent items of the similar users of each channel based on their purchased transactions on each channel. The most frequent items of the hybrid multiple channels are determined, respectively, from the items of multiple channels using the weighted sum of the frequent counts with the different hybrid weights $w_T$, $w_C$, and $w_W$. The hybrid weights indicate the relative importance of the consumption behaviors of the multiple channels' similar users to the Web channel users on the Web, and are determined according to the best recommendation quality derived from the preliminary analytical data. Finally, the method uses the hybrid weights ($w_W$, $w_T$, $w_C$) to recommend products based on the most frequent-items approach.
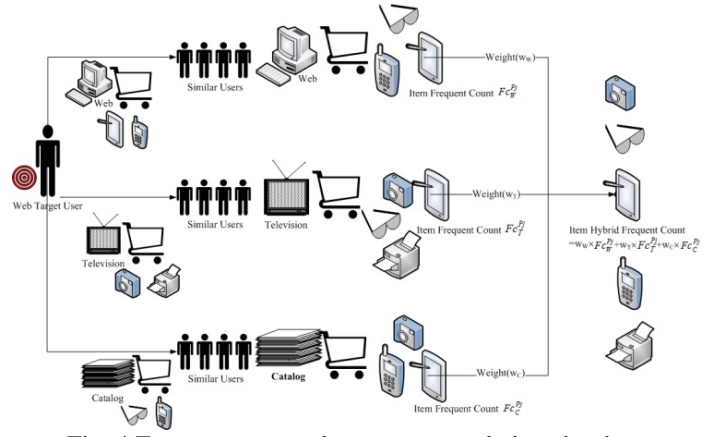


Fig. 4 E-commerce product recommendations by the similar users of the multiple channels (MC)

### B. All Channels CF (AC-CF) based approach

We could solve the sparsity problem by considering the similar users of all channels in a multichannel retailer, which is shown on Fig. 5. The customer-product matrix of all channels could be more condensed than the individual Web channel. We could find more users with the similar interests in all channels. Thus, the recommendation quality of all channels may be better than the single Web channel.
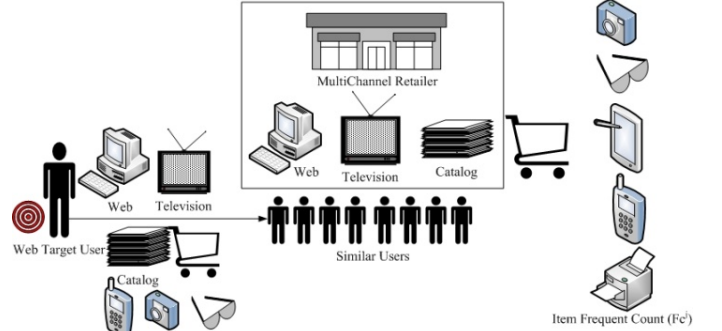


Fig. 5 E-commerce product recommendations by the similar users of all channels (AC) in a retailer

### C. The Recommendation Engine

The proposed method derives recommendations based on the most frequent items approach. For the similar users of the multiple channels, the most frequent items are extracted from the product transactions in the individual channel. The recommendation engine is comprised of the most frequent items $Y_M^{MF}$, which is shown in Fig. 6. In the figure, M represents either T, C, or W, which denote the television, catalog and Web channels respectively.

Let $Y_M^{MF}, M \in \{T,C,W\}$ denote the set of most frequent items derived from the similar users in multiple channels for the target user u on the Web. Let $Fc_T^{P_j}, Fc_C^{P_j}$, and $Fc_W^{P_j}$ represent the frequency counts of an item Pj in $Y_M^{MF}$, respectively. Let $Y_u^{MF}$ be the set of candidate products generated from the union of $Y_M^{MF} - X_u^{MF}$. The products in $Y_u^{MF}$ are ranked according to the weighted sum of their frequency counts calculated as (2).

$$Fc^{P_j} = w_T \times Fc_T^{P_j} + w_C \times Fc_C^{P_j} + w_W \times Fc_W^{P_j} \qquad (2)$$

Finally, the selected products are the most frequent items ranked according to the frequency count of products purchased by the similar users in multiple channels. Then, products in $Y_u^{MF}$ that have not been purchased by the user $u$ are added to the recommended product list as the top-N recommendations.
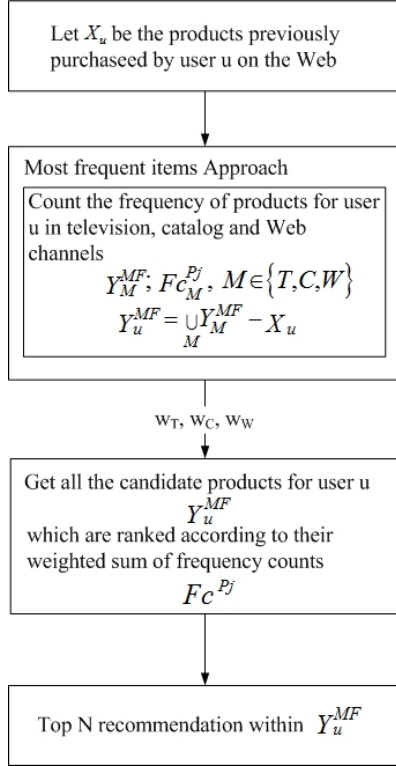


Fig. 6 The recommendation engine

## IV. EXPERIMENTAL EVALUATION

### A. Experiment Dataset

We use a data set obtained from a multi-channel company to conduct our experiment evaluation. The company is a home shopping company that owns television, catalog, Web and mobile channels in Taiwan. For the television channel, products are introduced on the channel and viewers can purchase the products by calling a toll-free number.

The experiment dataset were extracted from CRM system of the case company in 2007. To reduce the data quantity, the threshold of item purchased frequency is set to 10. There are 1,455 users who purchased 2,863 products on the Web. The products offered on the Web channel were also available on the other channels.

### B. Evaluation Metrics

Two metrics, precision and recall, are commonly used to measure the quality of a recommendation. They are also used in the field of information retrieval [20, 21]. Product items can be classified into products that customers are interested in purchase and those that are of no interest. The recommendation method then suggests products of interest to the customers accordingly. The recall metric indicates the effectiveness of a method in locating products of interest, while the precision metric represents customers' levels of interest in the recommended product items.

Recall is the fraction of interesting product items located:

$$Recall = \frac{number\ of\ correctly\ recommended\ items}{number\ of\ interesting\ items} \quad (3)$$

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

$$Precision = \frac{number\ of\ correctly\ recommended\ items}{number\ of\ recommended\ items} \quad (4)$$

The items deemed interesting to customers are the products that the customers purchased in the test set. Correctly recommended items are those that match the interesting items. Because increasing the number of recommended items tends to reduce the precision and increase the recall, the F1 metric is used to balance the tradeoff between precision and recall [21]. The F1 metric, which assigns equal weights to precision and recall, is calculated as follows:

$$F1 = \frac{2 \times recall \times precision}{recall + precision} \quad (5)$$

### C. The hybrid effect of the other channels on the Web

We compared the F1-metric qualities of one-channel with two-channel recommendation scheme. The scheme is a typical k-nearest neighbors (k-NN, k similar users) CF method, which finds similar users in individual channel and recommends top-N products are ranked according to their frequency counts of the most frequent items purchased by these similar users from one or two channels. We choose k = 20 as the number of nearest neighbors (NN) to find rapidly the hybrid effect of the other channels on the Web channel.

Fig. 7 demonstrated the hybrid effect of the other channels (Catalog and TV) on the Web channel. In the figure, the Web channel recommendation quality became better after considering the additional TV channel, but the quality became worse after considering the additional catalog channel. The recommendation quality of the products provided from the similar users of TV channel is better than the similar users from the catalog channel. The purchased transactions on TV channel are more important to the Web users than the catalog channel. Thus, the hybrid weight of TV channel for the Web channel may be larger than the catalog channel.
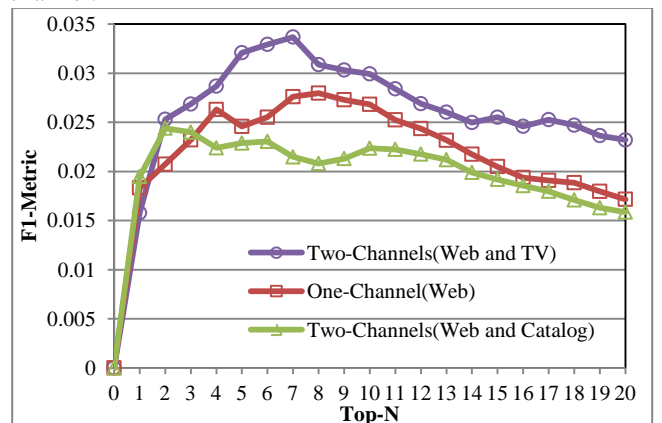


Fig. 7 The hybrid effect of the other channels on the Web

## D. Determining the hybrid weights for the multi-channel recommendation scheme

The hybrid channel recommendation scheme is based on the weight ratios of the Web ($w_W$), television ($w_T$), catalog ($w_C$) channels (i.e., $w_W + w_T + w_C = 100\%$). The weights are derived as follows. First, the dataset is divided into a training dataset (55%), preliminary analytical dataset (25%) and a testing dataset (20%). We use the training dataset to derive the most frequent items, and use the preliminary analytical data to derive the weights. Second, the weights are determined according to the best recommendation quality that can be achieved under the different combinations of weight assignments for the preliminary analytical data. Because the monthly average number of products purchased on the Web is 5.7, which is calculated from the dataset. We use the top 6 recommendations to determine the hybrid weights of the multiple channels. We adjust the values of the channel weights systematically in increments of 10%. The qualities of the top 6 hybrid recommendations according to different hybrid weight combinations ($w_W$, $w_T$, $w_C$) are shown in Fig. 8. The best recommendation quality F1-metric of 0.02568 for the top 6 recommendations is derived when ($w_W$, $w_T$, $w_C$) = (90%, 10%, 0%). We use the weight ratios of the hybrid recommendation scheme in the experiment next section.
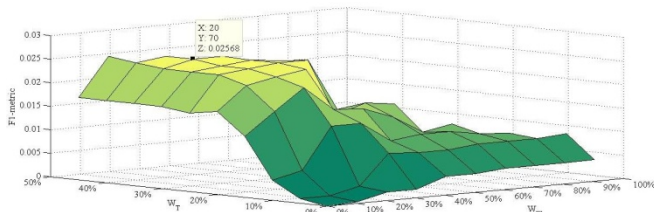


Fig. 8 Weight combinations of the hybrid recommendation

## E. Evaluation of the multi-channel recommendation method

Figure 9 shows the evaluation results of the three recommendation methods. We compare the proposed multi-channel CF (MC-CF) recommendation method, with two methods, namely, all channels CF (AC-CF), and single channel CF (SC-CF) methods. The MC-CF method is a CF-based method to recommend products which are ranked by the weighted frequency counts of the most frequent items of the similar users from the multiple channels with the different weights as described in Section III-A. The AC-CF method is an all-channel CF-based approach to recommends products which are ranked by the frequency counts of the most frequent items of the similar users from all the channels as described in Section III-B. The SC-CF method is a typical single channel CF-based approach that recommends products which are ranked by the frequency counts of the most frequent items of the similar users from only one single Web channel as described in Section II-D.

The AC-CF method performs well than the SC-CF method because all channels user–product preference matrix is more condensed than single channel user–product preference matrix. Thus, it is possible to find more similar users by using all channels user–product preference matrix. The MC-CF method generates recommendations with the hybrid

weighting ratio set at ($w_W$, $w_T$, $w_C$,) = (90%, 10%, 0%) for the top-N recommendations, as described in Section IV-D. The experiment results demonstrate that the proposed multi-channel CF-based (MC-CF) method performs well than the all channels (AC-CF) method and single channel (SC-CF) method for most of top-N recommendations.
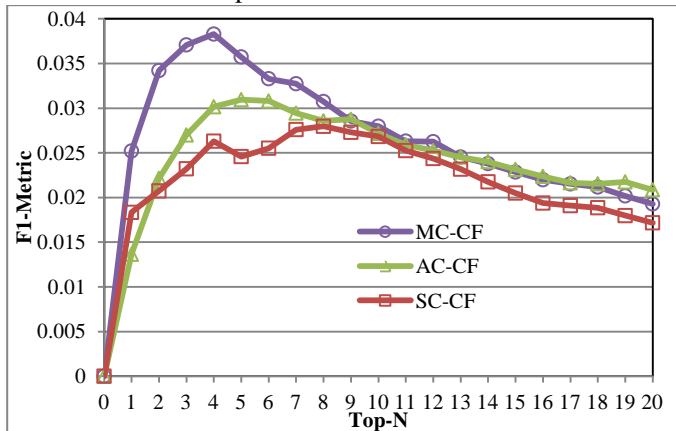


Fig. 9 Evaluation of MC-CF, AC-CF, and SC-CF recommendation methods

## V. CONCLUSION

As the Internet age comes, Web services and applications are getting more for electronic commerce (EC). However, the quality of product recommendations is still not good for electronic commerce. There are hundreds of thousands products placed on EC websites, but low percentage of those products are purchased by customers even though they still purchased many products. Because the scattered products customers purchased, customer-product matrix is also very sparse. It is difficult to find customers with the similar product preferences from a single channel and provide good product recommendations.

Some multi-channel companies often use advertising and marketing campaigns to gather information about users' consumption behavior on the specific channel. However, businesses could also obtain such information from the CRM systems of existing channels. In this paper, we have proposed a multi-channel CRM method to solve the difficulty of finding similar users for electronic commerce. It is assumed that the consumption behavior of Web channel users correlates with the consumption behavior of the similar users from the multiple channels with the different weights.

Experiments were conducted to compare the multiple channel CF-based (MC-CF) method, all channel CF-based (AC-CF) method, and single channel CF-based (SC-CF) method. The AC-CF method performs well than the SC-CF method because all channels user–product preference matrix is not as sparse as single channel user–product preference matrix. Thus, it is possible to find more similar users by using all channels product preference matrix. The experiment results demonstrate that the proposed multiple channels (MC-CF) method performs well than AC-CF and SC-CF methods. The proposed method mitigates the sparsity problem and improves the recommendation quality by finding more similar users based on the consumption

behavior patterns of users in multiple channels. The hybrid weighting ratio set at $(w_W, w_T, w_C) = (90\%, 10\%, 0\%)$ for the top-N recommendations. The consumption behaviors of the Web channel are most important to Web channel itself, and TV channel is more important than the catalog channel. It would be beneficial for the Web channel users by considering the additional consumption behaviors of TV channel users.

Our study has some limitation. For example, we did not consider the hybrid weight of the mobile channel because the purchased transactions of the mobile channel were not sufficient. The hybrid effect was not obvious and the weight of the mobile channel could be neglected. In the future, we will try more methods to apply other data mining techniques, e.g., clustering and association rules, to improve the qualities of product recommendations for e-commerce.

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