

# Using Temporal Information in Collaborative Filtering: An Empirical Study

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***Abstract** - Collaborative filtering is a widely used and proven method of building recommender systems that provide personalized recommendations on products or services based on explicit ratings from users. Recommendation accuracy becomes an important factor in some e-commerce environments (such as a mobile environment as a result of limited connection time and device size). As user preferences change over time, temporal information can improve recommendation accuracy.*

*In this paper, we present a variety of temporal information and investigate how such temporal information affects the accuracy of collaborative filtering-based recommender systems. The temporal information includes item launch time, user buying time, the time difference between the two, as well as several combinations of these three types of temporal information. We conducted several experiments on a collaborative filtering system for recommending character images (wallpapers) in a mobile e-commerce environment.*

*Empirical results show that the effectiveness of temporal information depends on the type of items and the user group of a given e-commerce environment. Our findings give insights on how to incorporate temporal information to maximize the efficiency of collaborative filtering in various e-commerce environments.*

**Keywords:** E-commerce, recommender system, collaborative filtering, temporal information, recommendation accuracy

## 1 Introduction

Recommender systems help users find relevant information, products or services by providing personalized recommendations to users based on their profiles [1]. Recommender systems have been proven especially useful in the e-commerce environment. Collaborative Filtering (CF) is a widely used method of providing recommendations based on item ratings from the user and other users. User-based CF algorithms focus on the similarity among users and experience

problems with scalability as the number of users grows. Item-based CF algorithms improve scalability by focusing on the similarity among items using user ratings rather than among the users themselves. A number of user-based and item-based collaborative filtering algorithms have been developed [2].

The quality of personalized recommendations is important in order to collect better ratings from more users. Recommendation accuracy becomes especially significant in some e-commerce environments. In a mobile environment, for example, it needs to recommend a relatively short list of highly relevant items due to limited connection time and device size [3]. Based on the observation that user preferences change over time, temporal information was proposed as a tool to improve the accuracy of collaborative filtering. Movie production time information was used to improve the performance and the accuracy of the collaborative filtering-based movie recommender system [4]. User rating time was considered to improve the precision of item-based collaborative filtering [5].

In this paper, we present types of temporal information that can be used to improve accuracy in collaborative filtering-based recommender systems. We investigated the degree of improvement of such temporal information in collaborative filtering-based recommender systems through several experiments on such a system in a mobile e-commerce environment. Our empirical results provide insight on how to incorporate specific temporal information in building more effective collaborative filtering in e-commerce environments with various items and user groups.

## 2 Temporal Information

The temporal information we used in our experiments includes item launch time, user purchase time, and the time difference between these two.

**Launch Time:** Launch time is when the item is first released or produced. This information indicates the age of the item. In general, preference to older items tends to decrease (although it depends on the type of item). The product launch time was used to improve the

performance of the collaborative filtering-based recommender system [4]. It was also reported that the inclusion of the production year improved the accuracy of the recommender system.

In a mobile e-commerce environment (as in the case of our experiment), the items are fashionable character images (wallpapers) appealing to younger people. This user demographic is more likely to buy newer items.

**Buying/rating Time:** Buying/rating time is when the user buys or rates an item. This information roughly indicates the age of the user's preference. More recent preferences tend to have a greater effect on future preferences, although this depends on the type of user. User rating time was considered to improve the precision of item-based collaborative filtering [5]. In our experiment, the users are mostly younger people that are easily influenced by their peers.

**Time Difference between Buying/rating and Launch Times:** Time difference is the temporal gap between when an item is released and when a user buys or rates it. This information indicates the duration for which an item is being considered by some users. A larger time difference means that the item is relatively old yet favored for a longer time by some users. This implies that even though the item is older, it still has the potential to appeal to users in the future.

**Combinations of Temporal Information:** Any combinations of these three types of temporal information can be used.

### 3 Experiments and Results

We have conducted several experiments using real-world data in a mobile e-commerce environment. We compared various collaborative filtering systems using temporal information with the pure collaborative filtering system. All simulations were implemented by VBA (Visual Basic for Applications) on Excel worksheets.

#### 3.1 The Data Set

As the data set for our experiments, we used a transaction data from June 2004 to August 2004 in which users purchased and downloaded character images (wallpaper) to their mobile devices via the Internet. The total number of users who purchased at least one image is 1,922. The total number of character images is 9,131. The total number of transactions is 65,101. We used 80% of the total transaction data as training data. We built a time-based recommender

system using these training transactions. The remaining 20% of the total transaction data was used as test data for demonstrating the effectiveness of our time-based recommender system. This was done by comparing the accuracy of our recommendations with those of a pure collaborative filtering-based recommender system for the users in the test transactions.

#### 3.2 Experiment Design

**Types of Collaborative Filtering Systems:** We can devise many kinds of Collaborative Filtering (CF) systems by combining different types of temporal information. In this experiment, we used seven representative cases as follows:

- Pure\_CF is collaborative filtering using original rating values. No temporal information is considered in Pure\_CF.

We construct three CF using single temporal information as follows:

- LTime\_CF: Original rating values are weighted by considering the item launch time.
- BTime\_CF: Original rating values are weighted by considering the user buying/rating time.
- DTime\_CF: Original rating values are weighted by considering the time difference between the user buying/rating time and the item launch time.

The following three are CF using combined temporal information:

- LBTime\_CF: LTime\_CF plus BTime\_CF, with more weight on LTime\_CF.
- BLTime\_CF: BTime\_CF plus LTime\_CF, with more weight on BTime\_CF.
- DLTime\_CF: DTime\_CF plus LTime\_CF, with more weight on DTime\_CF.

**Methods for Assigning Weights based on Temporal Information:** In Pure CF, the rating matrix is constructed by assigning 1 when the item is purchased and 0 otherwise. In other CF, we assign weights to the original rating values using the following weight assignment schemes:

- LTime\_CF: Recent launch times are weighted more.
- BTime\_CF: Recent buying times are weighted more.

- DTime\_CF: More time differences are weighted more.
- LBTime\_CF: Recent launch times and recent buying times are weighted more, but there is more emphasis on item launch time.
- BLTime\_CF: Recent buying times and recent launch times are weighted more, but there is more emphasis on user buying/rating time.
- DLTime\_CF: Greater time differences and recent launch times are weighted more, but there is more emphasis on the time difference.

We created three time groups,  $T_{old}$ ,  $T_{middle}$  and  $T_{recent}$  for the temporal information such as launch time, buying/rating time, and time difference, respectively. We then assigned 1, 2 and 3 to three groups, respectively. For the combined temporal information cases, we used -0.3, 0 and 0.3 as additional weights.

**Table 1. A Weight Assignment for LBTime\_CF**

buying time \ launch time	$T_{old}$	$T_{middle}$	$T_{recent}$
$T_{old}$	0.7	1	1.3
$T_{middle}$	1.7	2	2.3
$T_{recent}$	2.7	3	3.3

Table 1 shows an example weight assignment for LBTime\_CF. Note that the weights range from 0.7 to 3.3.

**Similar Neighbors and Recommended Items:** We used the Pearson correlation coefficient in order to find neighbors. We computed total 10 similar neighbors to the active user. We recommended total 10 items.

### 3.3 The Results

Each collaborative filtering system recommends 10 items. Of these 10 items, we count the number of actual purchases in the testing transaction data set. We can measure the accuracy of collaborative filtering by examining how many of the recommended items users actually buy.

**Table 2. Results of CF with Single Temporal Information**

ACCURACY	# of actual purchases from recommended items
<i>Pure_CF</i>	123
LTime_CF	155
BTime_CF	170
DTime_CF	81

The results of CF using single temporal information are given in Table 2. In the case of Pure CF, 123 items were actually purchased by the users from the set of recommended items.

In the collaborative filtering using the item launch time (LTime\_CF), the users purchased total 155 items among the items recommended. LTime\_CF showed a 26% improvement in accuracy compared with the pure CF.

BTime\_CF resulted in 170 actual purchases of the recommended items. This is a 38% increase in accuracy over the pure CF.

DTime\_CF resulted in 81 actual purchases. Its accuracy was worse than the pure CF by 34%.

**Table 3. Results of CF with Combined Temporal Information**

ACCURACY	# of actual purchases from recommended items
<i>Pure_CF</i>	123
LBTime_CF	171
BLTime_CF	180
DLTime_CF	88

Table 3 shows the results of CF using combined temporal information. 171 purchases were made in LBTime\_CF. LBTime\_CF shows a 39% increase in accuracy than the pure CF. LBTime\_CF is the combination of LTime\_CF and BTime\_CF with more weight placed on LTime\_CF. LBTime\_CF shows better accuracy than LTime\_CF and almost the same accuracy as BTime\_CF.

In BLTime\_CF, there were 180 actual purchases with a 46% improvement in accuracy over the pure CF. LBTime\_CF is the combination of BTime\_CF and LTime\_CF with more weight placed on BTime\_CF. BLTime\_CF shows significantly higher accuracy than both BTime\_CF and LTime\_CF.

Only 88 actual purchases were made in the case of DLTime\_CF. DLTime\_CF is the combination of DTime\_CF and LTime\_CF with more weight placed on

DTime\_CF. DTime\_CF showed a little improvement in accuracy over Pure\_CF, but is still worse than the pure CF in accuracy by 28%.

### 3.4 Discussion: Temporal Sensitivity

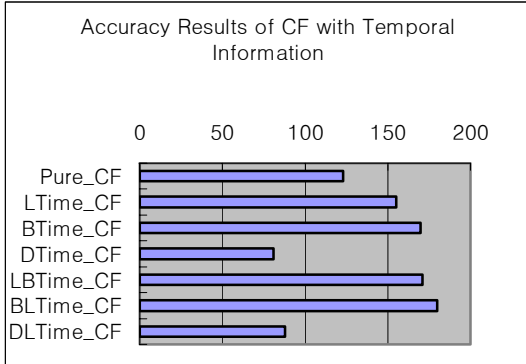


Figure 1. Accuracy Results of All CFs

Table 4. Accuracy Improvement over Pure\_CF

	Accuracy Improvement over Pure_CF
LTime_CF	26 %
BTime_CF	38 %
DTime_CF	- 34 %
LBTime_CF	39 %
BLTime_CF	46 %
DLTime_CF	- 28 %

From Figure 1 and Table 4, we can summarize the sensitivity of temporal information:

- Both the launch time and the buying time by themselves improved recommendation accuracy significantly. The buying time alone showed a better result.
- The time difference alone showed rather low accuracy. This is probably due to the characteristics of the items and users in this experimental e-commerce environment.
- Combing two types of temporal information increased the accuracy further than the single temporal information case, but not additively.

## 4 Conclusion and Future Work

We presented a variety of temporal information - item launching time, user buying time, and the time

difference between the two, as well as several combinations of these three types of temporal information. We showed empirical results on using a variety of temporal information to improve the recommendation accuracy of a collaborative filtering-based recommender system. The empirical results show the degree of effectiveness of temporal information.

Our results give a snapshot on how to use specific temporal information. This will be useful in developing more refined collaborative filtering-based recommender systems in various e-commerce environments.

As future work, we will conduct more experiments using data sets from various e-commerce environments, and identify possible correlations between item types and users groups and a variety of temporal information with respect to temporal sensitivity.

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