User based Collaborative Filtering with Temporal Information for Purchase Data

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Keywords: Item Recommendation, Collaborative Filtering, Temporal Recommendation.

Abstract: User based collaborative filtering algorithms are widely used for generating recommendations for users. Standard user based collaborative filtering algorithms do not consider time as a factor while measuring the user similarities and building the recommendation list. However, users' interests often shift with time. Recommender systems should therefore rely on recent purchases of the users to address this *user dynamics*. Items also have their own dynamics. Most of the items in a recommender system are widely popular just after their releases but do not sell that well afterwards. Giving more importance to the recent purchases of the *experts* may capture the item dynamics and hence result in better recommendation accuracy. We study the performances of different time-aware user based collaborative filtering algorithms on several benchmark datasets. The proposed algorithms use the time-of-purchase information for calculating user similarities. The time information is also used while combining the *purchase behaviors* of the *experts* and generating the final recommendation.

1 INTRODUCTION

In the recommendation problem, given a set of purchase records from different users, the task is to find a list of recommended or suggested items for the users. This list of items would be different for different users, as each user has his/her own personal choices of the items.

Users' purchase patterns for different products are different. For systems where a user may purchase/access the same item multiple times (e.g. music/video/article hosting systems, stores selling household items), past purchases by a user can be used as a basis for future recommendation. On the other hand, there are systems where the user generally does not purchase the same item more than once. Examples include purchases of books, music CDs, Movie DVDs etc. In such cases, the system can consider purchases or accesses made by users with similar purchase or access behaviors. User based collaborative filtering algorithms that use this concept of similar tastes of users can be used for recommending items for purchase stores where the same user does not purchase the same item more than once.

Traditional user based collaborative filtering algorithms do not consider time as a factor while finding similar users and generating the recommendation list. The basic user based collaborative filtering framework may not work well if the interest profile of the user changes with time. In reality, users' interests often shift over time. If the algorithm looks at the entire purchase history of the user, and gives equal importance to all the items purchased in the past, the recommended list may include items that are much similar to the ones the user liked in the past. Chances are that the user will not like those items as his interest has now shifted to different types of items. Such situations may be addressed by focusing more on the recent purchases of the users.

The items also have their own dynamics. Many items are *popular* in a narrow time window after their release. As the time progresses, their purchases decrease, and after some time, the item is not purchased much. The length of this window (which we call *popularity span*) may vary from item to item. We looked at the popularity spans of different items from sevaral real world datasets. It was observed that, for all the datasets, the popularity of majority of the items decay with time. Figure 1 shows the popularity span histogram for sample datasets from Amazon and Netflix.

One can use the information regarding the current selling trend of the items while generating the recommendations. If an item is currently popular, the item can be recommended to many users. However, if a system recommends items by looking at the popularity value only, then the recommendation will lose the

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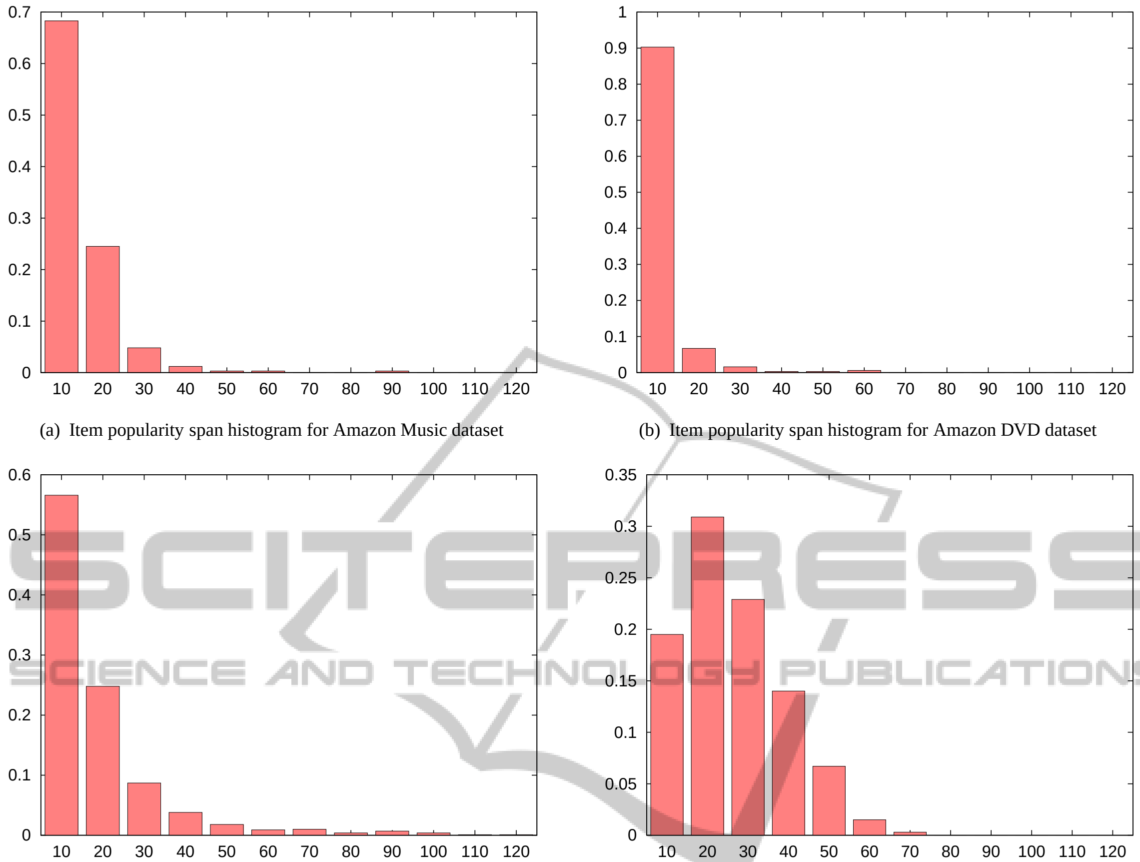


(a) Item popularity span histogram for Amazon Music dataset

(b) Item popularity span histogram for Amazon DVD dataset

(c) Item popularity span histogram for Amazon Book dataset

(d) Item popularity span histogram for Netflix dataset

Figure 1: Item popularity span histograms for different datasets. For each dataset, we considered the items that were purchased at least 20 times. If the *popularity score* of an item i in month m is at least 20, then we say that the product was *popular* in month m. The *largest popularity span* of an item is the largest time window (in months) in which the item was popular. Each graph represents the histogram of the *largest popularity span* for different items in a particular dataset. Y-axis shows the fraction of items that fall in a particular bin of the histogram.

personalization aspect. The system may recommend an item just because it is popular, but the user may not have any interest in that item. On the other hand, for a target user u, if an item is popular among many of the users who have interests similar to that of u, then the item might be of interest to u also. We try to incorporate the item dynamics in the user based collaborative filtering framework by looking at the recent purchases of the *similar users* or *experts*.

In this work, we explore several time-aware user based collaborative filtering algorithms for the recommendation problem on purchase data. We perform experimentation on Amazon and Netflix datasets and analyze the performances of the algorithms. We conduct experiments in a framework where the recommendation algorithms are run just prior to each purchase made by the user, and we see if the system is able to include the next purchase in its recommendation list. Experimental results indicate that recommendation performance can be improved by giving more importance to the recent purchases of both the user and the experts.

2 RELATED WORK

There has been some research work on designing time-aware collaborative filtering algorithms for solving the recommendation problem. (Kawamae et al., 2009) considers precedence information at user level and uses it for recommendation generation. A user who not only purchases many of the items that the target user also purchases, but also makes those purchases before the target user can be used as an *expert* for recommending items to the target user. It also considers other time specific factors such as launch time of items in the recommendation model. In (Lee et al., 2008), the authors proposed an algorithm that converts a purchase to an implicit rating by considering the launch-time of the item and the time of the purchase. This implicit rating is then used in collaborative filtering framework for recommendation. A recommender system based on tag and time information for social tagging systems is presented in (Zheng and Li, 2011). It uses a combination of a tag-weight matrix and a time-weight matrix for this purpose. For each user-tag pair, the tag-weight matrix stores the fraction of times the user has used the tag. The time-weight matrix, for a user-tag pair, stores a value that is dependent on the time when the user entered the tag.

Temporal algorithms have also been used for solving various other types of recommendation problems. In (Parameswaran et al., 2010), the authors propose a precedence mining model that estimates the probability of future consumption based on temporal patterns. The algorithm is used for a course recommendation application where depending on the past courses that a student has taken new courses are suggested to the student. There are algorithms that study temporality where there is a strict order or path followed by the user, and the goal is to predict the next step in that sequence. A typical example of such a task is the next-page prediction problem in which the system tries to predict the next web page a user will access given a sequence of pages visited up to now ((Deshpande and Karypis, 2004)). In (Shani et al., 2005), purchase sequences are viewed as states of a dynamic system. If one sequence leads to another sequence, then the system is considered to have made a transition to the new state. This state transition model is described as a Markov Decision Process and is used to generate recommendations. Algorithms based on precedence mining may not be appropriate for solving the recommendation problem in a more general case where such precedence information are not much useful. Two users who purchase the same set of products, but in different order, may have similar tastes of the items. One of these users can be used for generating recommendations for the other. (Rendle et al., 2010) uses a matrix factorization technique over personalized Markov chains representing sequential purchase patterns of users. This method called FPMC (Factorizing Personalized Markov Chains) is used for the *next basket recommendation* problem. The method assumes that a user may purchase the same item multiple times.

A related problem where time aware algorithms have also been used is the rating prediction problem. Rating prediction problem is used in systems where users give ratings to different items. In (Ding and Li, 2005; Ding et al., 2006), the authors assign time weights for items so that the recently rated items are able to contribute more to the prediction. (Campos et al., 2010) calculates the most similar users with all the available information from the dataset. After that, only the most recent ratings of the neighbors are used to find the predicted rating. (Koren, 2008) merges the factor and neighborhood models for collaborative filtering to solve the task of rating prediction. A factor model that looks at several temporal aspects from rating data is discussed in (Koren, 2009).

A combination of bias model and time weighted similarity model is presented in (Rongfei et al., 2010).

3 PRELIMINARIES AND PROBLEM DEFINITION

Let U and I be the set of users and items respectively. Let D be a collection of past purchase records. Each record in D is called a *purchase* or a *transaction*, and is of the form (u, i, t_{ui}) which represents the fact that user u has purchased item i at time t_{ui}.

Given a *target user* $u \in U$ and past purchase data D, the goal of a recommender system is to find a set $R_u \subseteq I$ of items that the target user may want to purchase in future.

4 OUR ALGORITHMS

For the systems where the same users generally do not purchase the same items multiple times, the user based collaborative filtering framework is widely used for generating the recommendations. Algorithms using this framework work in two phases: expert selection and recommendation generation. As discussed in Section 1, giving importance to the recent purchases of the user in the expert selection phase may address the issues related to the users' interest shift. Giving more importance to the recent purchases of the experts may capture the item dynamics. For both the target user and the experts, the system can look at their purchase histories in three different ways: (a) treat all items as equal, (b) consider items purchased in a small time window, or (c) look at the entire history but with discounted importance assigned to the items purchased long back. We explore four out of these nine different combinations and present those algorithms in this section.

4.1 Algorithm 1: Count (CNT)

The first among these four algorithms does not look at time information. We call this algorithm as Count, or CNT in short. We use this algorithm as the baseline. We estimate the Similarity weight of a user v for a target user u as the number of items that both u and v have purchased [1]. The top-K users according to the similarity weights are selected as the experts. In the second phase, the algorithm looks at the purchase histories of the experts. For each item, its score is given by the number of experts who have purchased it. The items are then sorted in non-increasing order of their scores, and the top N items are recommended to u.

4.2 Algorithm 2: Recent-k (RECK)

CNT looks at all the purchases made by the users in the past and treats them equally. However, users' interests often shift over time. To handle this situation, we do not look at the entire history of the target user's purchases. Our next algorithm RECK looks at a small window (say, of size k) of his/her recent purchases. Experts are selected based on how many of the items from this window they have bought.

Let the set of the k most recent purchases of user u be I_u^k. The expert selection and recommendation generation phases are performed as follows:

- For each user $v \in U \setminus i$, find weight $w_v = |I_u^k \bigcap I_v|$. Select top-$K$ experts according to similarity weights. Let this set be E.
- For each item $i \notin I_u$, score $s_i = \sum_{v \in E \wedge i \in I_v} w_v$. Recommend top-$N$ items with the highest scores.

4.3 Algorithm 3: Recent-k with Weight (RECKW)

The next algorithm, represented by RECKW, extends RECK by adding more time-dependent factors in the expert selection and recommendation generation processes. RECK looks at only the most recent purchases of the target user to find the experts. In RECK, if v purchased many items that the target user u has purchased recently, then v gets high similarity weight for u. However, all those purchases of v might be made long back. If this user v is selected as an expert, and v's interest has shifted recently, then the system may end up recommending many items that v has purchased recently, but those items do not match u's recent taste. This observation motivated us to look at v's recent interest, and give more weight to v if his/her recent purchases are similar to u's recent purchases. To calculate the item's contribution to the user's similarity weight, we take help of a decay function that we denote by $decay(t)$. There are two properties that the function should have: (a) It should be monotonically decreasing, and (b) for very large values of t, the value of the function should be small but non-zero. The first property ensures that recent purchases are more important than old purchases. The second property signifies that very old purchases are not completely ignored, but they have much lesser importance weight compared to recent purchases. We use the following decay function in our algorithms.

$$decay(t) = \frac{\gamma^t + \lambda}{1 + \lambda}. \quad (1)$$

γ and λ are constants and assume values from the continuous interval $[0, 1]$. It can be easily verified that the function is monotonically decreasing. Also, for very large t, the value of the function is $\frac{\lambda}{1+\lambda}$, which is non zero. This value can be controlled by choosing a value of λ that is suitable for the application. Hence, the function satisfies the above properties. Please note that there are several different choices of decay functions. However, our focus in this work is to show that recommendation performances can be improved by giving more importance on the users' and the experts' recent purchases. So we chose a function that satisfies above two properties and used it for generating recommendations. We did not do much experimentation regarding different forms of decay functions.

The steps used by RECKW for expert selection is similar to the steps used in RECK. The only difference is that each item in $C = I_u^k \bigcap I_v$ now contributes $decay(\tau - t_{vi})$ to v's similarity weight, where τ is the current time. So, items recently purchased by v are given more importance. In the second phase, for each item $i \in I_v$, expert v contributes a score of $w_v * decay(\tau - t_{vi})$. The scoring rule suggests that if there are many products that an expert has purchased, then the ones that are purchased more recently will get higher score. The top-N items with the highest score are recommended to the target user. The basic steps of the algorithm are outlined below:

- For each user $v \in U \setminus u$, find the co-purchased items $C = I_u^k \bigcap I_v$.
- Set v's weight $w_v = \sum_{j=1}^{|C|} decay(\tau - t_{vC(j)})$. Select top-$K$ users (E) as experts.
- For each item $i \notin I_u$, set score $s_i = \sum_{v \in E \wedge i \in I_v} w_v * decay(\tau - t_{vi})$. Output top-$N$ items as recommendations.

4.4 Algorithm 4: Entire History with Discounted Weight (DISCHIST)

RECK and RECKW look at k most recent purchases of the target user u. Though the most recent purchases

[1] Please note that the it is not necessary to normalize the similarity weights in a fixed range.

of a user are perhaps the most important and representative of the user's recent interest, the past purchases may not be totally unimportant. For users whose interests have remained the same over long periods of time, looking at some more purchases from the past may be useful. We wanted to see if we can improve the performance of recommendation by looking at all past purchases of u. However, treating all past purchases equally may decrease the performance of the algorithm for those users whose interests have changed over time. To avoid such a scenario, we use the concept of *importance weight*, where recent purchases are given more weight but old purchases are given less, but non-zero weight. The importance weight may be characterized by a decay function as defined in Equation 1. In algorithm DISCHIST, each purchase of user u of the form (u,i,t_{ui}) is assigned an importance weight of $decay(\tau - t_{ui})$, where τ is the current time. As the decay function is monotonically decreasing in nature, users who have purchased many of the items that u has purchased recently get higher weight than those who have purchased many items that u had purchased long back. The rest of the steps are similar to that in RECKW. A brief outline of the steps are given below.

- For each user $v \in U \setminus u$, find the co-purchased items $C = I_u \bigcap I_v$.
- Set v's weight $w_v = \sum_{j=1}^{|C|} decay(\tau - t_{uC(j)})$. Select top-$K$ users (E) as experts.
- For each $i \notin I_u$, set score $s_i = \sum_{v \in E \wedge i \in I_v} w_v * decay(\tau - t_{vi})$. Output top-$N$ items as recommendations.

5 EXPERIMENTAL RESULTS

5.1 Datasets Used

We used the Amazon product co-purchase metadata[2] and a sample of the Netflix data[3] for comparative evaluation of the recommendation algorithms. The Amazon dataset contains details of different products sold on amazon. The products are of five types: Book, Music, DVD, Video and Toy. There were not many products for the "Toy" and "Video" categories. We used the data for Music, DVD and Book categories for experimentation.

There are not many publicly available datasets for evaluating product recommendation algorithms. However, several datasets are available for evaluating rating prediction algorithms. We use one such dataset, the Netflix dataset, for for our experiments. In the Netflix dataset, users rate different movies that they have rented. If a user has rated a movie in this dataset, then it can be assumed that the user was interested in watching the movie. Hence if a recommender system could recommend that movie just before the user decided the watch the movie, the user could have accepted the recommendation. Based on this intuition, we converted the Netflix dataset into a purchase dataset. If a user has rated a movie, then we assume that the user has rented/purchased the movie. In (Kawamae et al., 2009), the authors used the Netflix dataset for evaluating the proposed recommendation generation algorithm.

5.2 Preprocessing the Datasets

For each product, the Amazon dataset mentions its product type, different categories that the product belongs to, and a list of reviewers who have reviewed the product. In most cases, a user reviewed a product only once. We considered these reviews as purchases. i.e., if user u has reviewed item i, we considered that u has purchased i. Also, for each review, the dataset mentions the date on which the review was entered. If user u has entered multiple reviews for product i, then we keep the earliest review and remove the rest from the dataset. We separated out data for each different product type from the dataset. So, we used three different datasets for the Amazon data, for the three different product categories namely Book, Music and DVD.

For the Netflix dataset, the sample was taken by considering the first 1500 movies as items and the persons who have rated those movies as users. If a user had rated a movie, we consider that the user has purchased the movie. In the Netflix dataset, each user rates a movie at most once.

For both Amazon and Netflix datasets, we removed from the datasets any transaction corresponding to a user with fewer than m_l total purchases. This preprocessing enabled us to remove some of the non-prolific users. Also, we removed from the dataset transactions corresponding to users who made more than m_u purchases. This was necessary so that we could fit the co-purchase network (as mentioned in Section 5.5) in the memory. For the Amazon datasets (Book, Music and DVD), values of m_l and m_u were set to 50 and 200 respectively. For the Netflix dataset, m_l and m_u were fixed at 20 and 400 respectively. For all datasets, time information was maintained in unit of months.

[2] http://snap.stanford.edu/data/amazon-meta.html
[3] http://www.netflixprize.com/

Table 1: Summary comparison of the algorithms. C is the items of importance. E is the set of experts. w_v is the weight of user v as computed during the *expert selection phase*. s_i is the score of item i as computed in *recommendation generation phase*.

Algorithm	CNT	RECK	RECKW	DISCHIST
Items of interest (C)	$I_u \bigcap I_v$	$I_u^k \bigcap I_v$	$I_u^k \bigcap I_v$	$I_u \bigcap I_v$
Contribution of $i \in C$ to w_v	1	1	$decay(\tau - t_{vi})$	$decay(\tau - t_{ui})$
Contribution of $v \in E$ to s_i	1	w_v	$w_v * decay(\tau - t_{vi})$	$w_v * decay(\tau - t_{vi})$

5.3 Experimental Setup

D is a dataset of product purchase transactions with purchase timestamps. Each record in D is of the form (u,i,t), which denotes that user u has purchased item i at time t. We sort D in non-decreasing order of the purchase timestamp t. The first 20% transactions from the dataset were kept aside initially. Let this set be denoted by $\widehat{D}$. Only those users who have at least 10 purchases in $\widehat{D}$ were selected as *test users*. The remaining data $\widetilde{D} = D \setminus \widehat{D}$ was used for testing purpose as follows.

For each purchase $(u,i,t_{ui}) \in \widetilde{D}$, we wanted to see if the algorithms were able to recommend the item i to the user u by looking at the past purchase records. The recommendation algorithms were allowed to view purchase records from D with $t < t_{ui}$ and were asked to come up with a list of N items as recommendation for the *test user* u. We call the transaction (u,i,t_{ui}) as a *test purchase* or *test transaction*. Item i is called the *test item*. The experimental setup is shown pictorially in Figure 2. We experimented with four different values of N: $20, 50, 80$ and 100. We ran the above prediction task for the first 40 test purchases of each *test user*. Relative performances of the algorithms were found to be similar for the different values of N. We report results for $N = 50$.

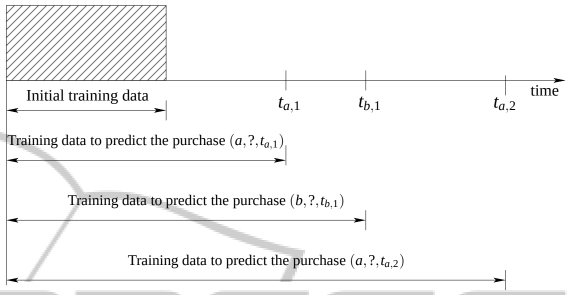


Figure 2: The experimental setup is shown graphically. The first 20% of the data is used only for training. Suppose there are only two test users a and b. a has purchased two items, at time $t_{a,1}$ and $t_{a,2}$. b has purchased one item at time $t_{b,1}$. We invoke the recommendation algorithm three times, at time steps $t_{a,1}, t_{a,2}$ and $t_{b,1}$. At time $t_{a,1}$, the algorithms use the entire data from the beginning to time step $(t_{a,1} - 1)$ as observed data or training data and produce recommendations for a. We then see whether the item that a purchased at $t_{a,1}$ is in the recommendation lists for a produced by the algorithms. Similarly, recommendations are generated for b (or a) at $t_{b,1}$ (or at $t_{a,2}$) by using the data from beginning to time step $t_{b,1} - 1$ (or time step $t_{a,2} - 1$) as training data.

5.4 Algorithms Compared

We compared the performance of the four algorithms described in the paper with two other algorithms from recent literature. The algorithms suggested in (Lee et al., 2008), (Kawamae et al., 2009) and (Zheng and Li, 2011) use time aware collaborative filtering for recommendation. (Lee et al., 2008) divides the items into several groups based on their launch time. The users also were grouped according to their interests in purchasing items from these different item groups. However, the grouping and parameters associated with the groups were set in ad hoc manner. It was not clear whether the same can be useful for generating recommendations for other datasets. We compare our algorithms with the algorithms proposed in the remaining two papers, viz. the algorithm based on Personal Innovator degree (PID) from (Kawamae et al., 2009) and the one based on Weighted Combination Model (WCM) from (Zheng and Li, 2011). Recommendation lists are generated by sorting the items based on the recommendation scores assigned to them by the algorithms.

We also considered the time-aware algorithm proposed in (Ding et al., 2006). Although it is a rating prediction algorithm, we considered using it as a baseline as it is also based on the collaborative filtering framework and gives more importance to the most recent ratings given by the users. We used it to predict the unknown ratings as the datsaets we have used for evaluation have rating information. Top-K items based on the predicted ratings were output as recommendation. However, after some preliminary experiments, we found that performance of this algorithm was poorer than PID and WCM. So we did not use this algorithm for detailed comparison.

5.5 Parameters and Optimizations

Algorithms RECK, RECKW and DISCHIST require two parameters λ and γ for specifying the decay function given in Equation 1. For all the experiments, the values of λ and γ were fixed at 0.1 and 0.6 respectively. The length of the most recent purchase window was set to 5. These values were selected after running experiments on small validation sets. 40 most similar users were selected as experts.

Early studies in user based collaborative recommender systems revealed that it is common for the target user to have highly correlated neighbors (with high user similarity scores) that are based on a very small number of co-purchased items. To address this issue, it was suggested to give more *significance weight* to users who have many co-purchased items with the target user (Herlocker et al., 2002). Following this observation, for each test transaction, we first selected the top-100 users with the maximum number of co-purchased items with the test user. We assigned similarity weights to these 100 users. Top-40 among these users were selected as experts. This made the implementations faster as it was not necessary to compute the similarity values for each user pair for each test transaction. This scheme was used for all the algorithms that we compared in the experimental section. A co-purchase network of users was kept for determining the number of co-purchased items. The network contained an edge between two users if they purchased at least one common item. The weight of the edge was set to the number of items co-purchased by them. This structure was updated in runtime after observing each new transaction from the test set.

5.6 Evaluation Metrics

We use *Hit Rate* and *Mean Reciprocal Rank (MRR)* metrics for comparing the performance of the algorithms. Definitions of the metrics are given below.

- **Hit Rate.** Hit Rate of an algorithm is defined as the fraction of test transactions ($\widetilde{D}$) for which the test item is present in the algorithm's recommendation list. Mathematically,

$$Hit\ Rate = \frac{1}{|\widetilde{D}|} \sum_{i \in \widetilde{D}} I(i \in R_i),$$

  where R_i is the recommendation list for the test transaction i. $I(p)$ is a boolean indicator function that evaluates to 1 if and only if the predicate p is true. Higher value of Hit Rate indicates better performance.

- **Mean Reciprocal Rank.** We use Mean Reciprocal Rank (MRR) to evaluate the ability of a recommendation algorithm to place a test item near the top of the recommendation list.

  If the test item i is at rank $r(i)$ of the recommendation list, then the Reciprocal Rank (RR) of the algorithm for i is $\frac{1}{r(i)}$. If i is not in the recommendation list, then $r(i)$ is considered as ∞. Hence the Reciprocal Rank is 0 in that case. MRR is defined as the mean of the reciprocal ranks over all test transactions ($\widetilde{D}$). Mathematically,

$$MRR = \frac{1}{|\widetilde{D}|} \sum_{i \in \widetilde{D}} \frac{1}{r(i)}.$$

For both Hit Rate and MRR, higher values indicate better performance.

5.7 Comparison

For all the algorithms used for comparison, four different sizes (20, 50, 80, 100) of the recommendation list were considered. The ordering of the algorithms according to their performances are similar for all these list sizes. We report the results for the top-50 recommendations.

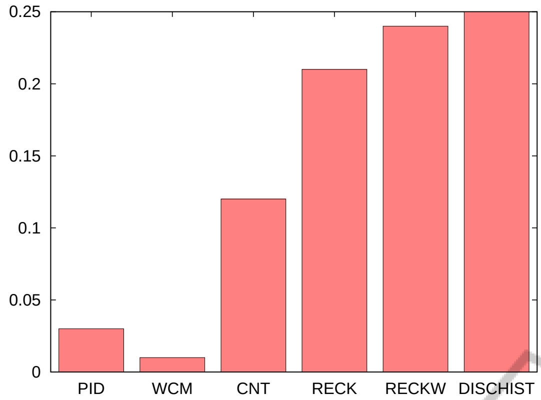
5.7.1 Amazon Music Dataset

Figure 3(a) and Figure 4(a) compare the *Hit Rate* and MRR for Amazon Music dataset. According to the results, the four algorithms defined in this paper perform better than the algorithms mentioned in Section 5.4 according to both the evaluation metrics. Among the algorithms defined in this paper, the simple baseline method CNT that does not look at the time information performs the worst. The RECK algorithm that considers the last few purchases of the target user for expert selection does better than CNT. Algorithm RECKW that builds upon RECK by using time weighting on the experts' purchases achieves even better Hit Rate for this dataset. The DISCHIST algorithm that looks at all purchases of all the users but with discounted importance on the old purchases achieves the highest Hit Rate.

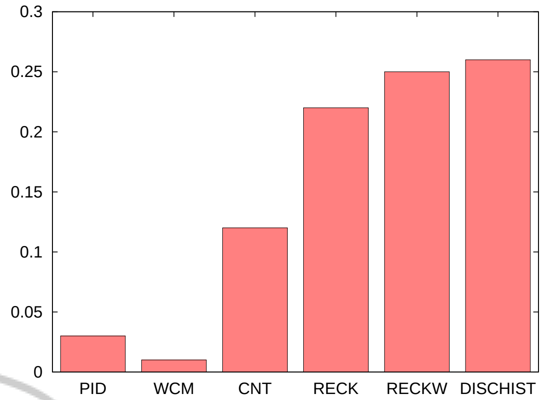
It can be seen from figure 4(a) that RECKW has maximum MRR, i.e. it is able to put maximum number of test items at the best (minimum) rank position among the competitor algorithms. DISCHIST comes next in terms of MRR. Ordering of the remaining algorithms for this measure is similar to the ordering obtained for the Hit Rate measure.

5.7.2 Amazon DVD Dataset

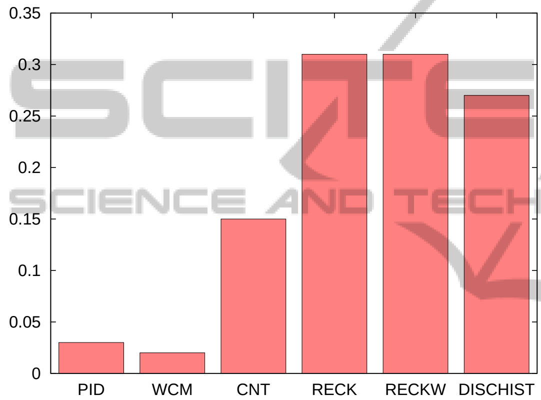
The results for this dataset are similar to the results obtained for the Amazon Music dataset. Hit Rates of the algorithms are shown in Figure 3(b). DISCHIST gives the best performance according to this measure and is closely followed by RECKW.



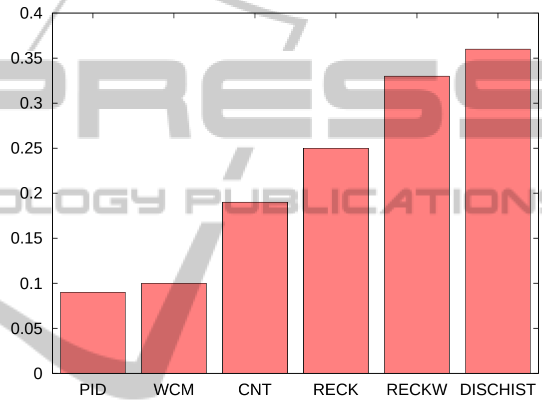
(a) *Hit Rate* for Amazon Music dataset



(b) *Hit Rate* for Amazon DVD dataset



(c) *Hit Rate* for Amazon Book dataset



(d) *Hit Rate* for Netflix dataset

Figure 3: Comparison of Hit Rate for different datasets.

Figure 4(b) compares the MRR for all the algorithms. It can be seen from the figure that RECKW achieves highest MRR. DISCHIST comes second according to this metric. It means that *ReckW* and *DiscHist* are able to put the test item near the top of the recommended list for most of the test transactions.

5.7.3 Amazon Book Dataset

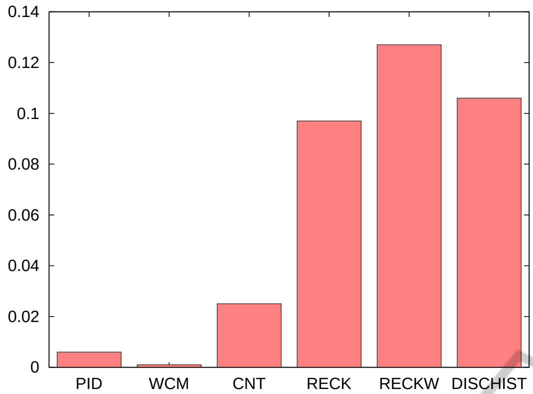
Hit Rate and MRR for the Amazon Book dataset are shown in Figure 3(c) and Figure 4(c) respectively. These results are somewhat different from the results obtained for the Amazon Music dataset and Amazon DVD dataset. Here we see that both RECKW and RECK perform best according to Hit Rate. For MRR, RECKW is the best algorithm and is closely followed by RECK. DISCHIST appears at the third position for this dataset, for both the metrics.

The results seem to indicate that for Amazon Book dataset, it might be wise to look at only the recent purchases of the target user. Looking at the entire purchase history of the user, even with time weighted discounted model as suggested in DISCHIST, might reduce the performance of the recommendation. A reason behind this might be that users have very focused interest for book items and this interest shifts over time. Users purchase books belonging to only the *type(s)* that they are currently interested in. As for music and DVDs, they might have interest in several *types* simultaneously and their recent purchases are mix of items belonging to all those types.

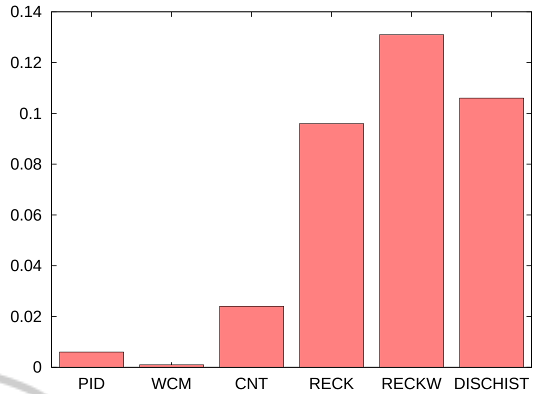
5.7.4 Netflix Dataset

Experiments on the Amazon datasets showed that the algorithms that give importance to the time-of-purchase information achieve better performances. This observation was corroborated by the results obtained on the Netflix dataset.

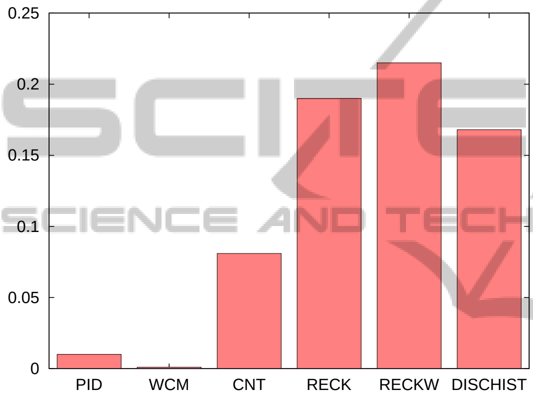
Hit Rate comparison for the Netflix dataset is shown in Figure 3(d). These results are similar to the results observed for the Amazon Music dataset and Amazon DVD dataset. DISCHIST performs best according to this metric. Comparison of MRR values



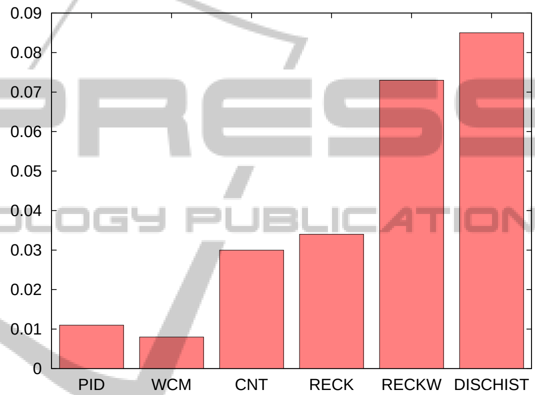
(a) *Mean Reciprocal Rank* for Amazon Music dataset



(b) *Mean Reciprocal Rank* for Amazon DVD dataset



(c) *Mean Reciprocal Rank* for Amazon Book dataset



(d) *Mean Reciprocal Rank* for Netflix dataset

Figure 4: Comparison of Mean Reciprocal Rank for different datasets.

is shown in Figure 4(d). For this dataset, DISCHIST is the best algorithm according to MRR. Performance of RECKW is also quite good as indicated by the figure. Performances of PID and WCM algorithms are much better for this datsaet when compared to their performances on the other datasets mentioned above.

5.8 Discussions

Overall, DISCHIST and RECW perform the best according to the experimental results. We consider CNT as the baseline for our experiments. Average Hit Rates of CNT, DISCHIST and RECKW for the test transactions over all the four datasets are .148, .288 and .287 respectively. Hence, DISCHIST and RECKW achieve close to 100% improvement in Hit Rate over the baseline. Similarly, average MRR for the three algorithms are .044, .121 and .142 respectively. So, for MRR, RECW and DISCHIST achieve close to 230% and 175% improvements respectively over the baseline. Both DISCHIST and RECKW give importance to the recent purchases of the target user as well as the experts, and hence attempt to address the issues of both user dynamics and the item dynamics.

Looking at the individual datasets, we see that for the Amazon Music and DVD datasets and the Netflix dataset, DISCHIST performs the best according to Hit Rate. RECKW and RECK come next in terms of performance. According to MRR, algorithms RECKW and DISCHIST perform the best. The trend is little different for the Amazon Book dataset where RECKW and RECK are better than DISCHIST. It means that for this dataset, the algorithms should only consider the most recent purchases of the test user and use that for expert selection. This may be due to the fact that users have very focused interest in a very limited set of categories or sub-categories for book items. It appears that the size of that *interest set* is much smaller for book data, when compared with the same for Music, DVD or Movie data. Hence giving importance to purchases made long back, even if the importance weights for those items are low, act as distraction for the recommendation algorithms. In this work, we have used the same parameters to specify the decay function for all the datasets. However, depending on the domain of the items or the selling trend of the individual items, different parameters can be used for the decay function for different datasets or even for individual items.

6 CONCLUSIONS

In this work, we have explored a few time-aware user based collaborative filtering algorithms for the recommendation problem. We have analyzed the benefits of using the time-of-purchase information in both the phases of *expert selection* and *recommendation generation*. Giving importance to time factor in the expert selection phase tries to address the problem of the target user's interest shift. Giving importance to the most recent items purchased by the experts attempts to capture the item dynamics. Experimental results indicate that recommendation performance can be improved by giving more importance to the recent purchases of both the user and the experts.

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