Time and Local Popularity in top-N Recommendation

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ABSTRACT

Items popularity is a strong signal in recommendation algorithms. It affects collaborative filtering algorithms and it has been proven to be a very good baseline in terms of results accuracy. Even though we miss an actual personalization, global popularity of items in a catalogue can be used effectively to recommend items to users. In this paper we introduce the idea of a form of personalized popularity also considering how its changes over time affect the accuracy of recommendation results. Although the proposed approach results quite light in terms of computational effort, its accuracy results highly competitive compared to state of the art model-based collaborative approaches.

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1 INTRODUCTION

Collaborative-Filtering (CF) [15, 20] algorithms more than others have gained a key-role among various approaches to recommendation, in helping people to face the information overload problem when looking for the most relevant and personalized items in a catalogue. Some of them use additional information to build a more precise user profile in order to serve a much more personalized list of items[5, 11]. However it is well known [14] that all the algorithms based on a CF approach (either in their pure version or in a hybrid one) are affected by the so called “popularity bias” where popular items tend to be recommended more frequently than the ones in the long tail. Nevertheless, a recommendation algorithm purely based on most popular items, although it relies on a global and general property of the dataset, without any actual personalization, has been proven to be a strong baseline [9]. It is noteworthy that a popularity-based recommendation algorithm does not require a heavy computational effort as it just considers the occurrence of an item within the profiles of all the users in a system. In the approach we present here, we change the “global” perspective of a “most popular” algorithm and we introduce a more fine-grained personalized version of popularity by assuming that it is conditioned by the items that a user already experienced in the past. To this extent, we look at a specific class of neighbors, that we name Precursors, defined as the users who already rated the same items of u in the past. This leads us to the introduction of a time-aware analysis while computing a recommendation list for u. Actually, it has been proven that exploiting temporal aspects in the rating process may improve the recommendation performance [6, 8] and, in the last years, we are witnessing a growing interest in time-aware RS.

As time is considered a contextual feature, most of the works that make use of it are classified as constituting a specialized family of Contextual-Aware RS (CARS) [2, 3]: the Time-Aware RS (TARS) [1, 16, 26]. Dealing with TARS we know that in neighborhood-based models, the freshness of the different ratings is often considered a discriminative factor between different candidate items. This can be implemented using a time window [17, 19] that filters out all the ratings that stand before (and/or after) a certain time relative to the user or the item. Recently, an interesting work that makes use of time windows has been proposed in [7] where the authors focused on the last common interaction between the target user and her neighbors (last common rated item) to populate the candidate items list. For a time-aware algorithms, also the splitting strategy plays a key-role. In [7] a single timestamp is used as a splitting condition for all the users, so that they retain 80% of ratings for training and the remainder for testing. A pioneer work was proposed more than a decade ago in [10] which used an exponential decay function $e^{-\lambda t}$ to penalize old ratings. After that, an exponential decay function [16] was used to integrate time in a latent factors model. In the last years, several Item-kNN [10, 18] with a temporal decay function have been deployed. Similarly a User-kNN model could be enhanced with a temporal decay function, this variant is also used in [7]. Another interesting work was proposed in [25] that incorporates time in Item-Item similarity where a more general perspective over the time decay functions was assumed proposing three different kinds of time decay: exploiting concave, convex and linear functions.

In this paper we present $\text{TimePop}$, an algorithm that combines the notion of personalized popularity conditioned to the behavior of users’ neighbors with the introduction of the notion of Precursors thus taking into account the temporal dimension. These contributions are weighted with an exponential decay function, with a few modifications (see Section 2.1) to make the approach more flexible and precise independently of the adopted dataset. Differently from some of the approaches previously described, in $\text{TimePop}$ we avoided both the time window approach that could severely restrict the selection of candidates and the fixed number of candidate items that could heavily affects the algorithm results. We evaluated our approach on three different datasets and compared with state of the
art collaborative approaches, and we show that TimePop outperforms significantly the competing algorithms in terms of Precision and nDCG.

The reminder of the paper is structured as follows: in the next section, we detail the ideas behind TimePop and we expose the lightweight process needed to compute recommendations. Section 3 is devoted to the description of the experimental setting. Conclusion and future work close the paper.

2 TIME-AWARE LOCAL POPULARITY

The leading intuition behind TimePop is the that the popularity of an item has not to be considered as a global property but it can be personalized if we consider the neighbors of a user. As a matter of fact, a recommendation list based on a global popularity is exactly the same for all the users with no personalization. We started from this observation to formulate a form of personalized popularity and then we realized that considering the temporal dimension may strengthen this idea.

Given an item, the first step towards the introduction of this time-aware local popularity is the identification of subsets of users sharing the same degree of popularity and refer to them as neighbors when computing a recommendation list. In general, we may say that users are supposed to process and exploit information (such as popularity) analogously to people that share with them tastes or way of thinking. Still, in each of these subgroups we have that the same item is enjoyed by users in different time frames. In our model, among these people, for a single user we consider those who already enjoyed the same items of him but before she did it. We name these users Precursors. This leads us to the second ingredient behind TimePop: personalized popularity is a function of time. The more the ratings about an item are recent, the more its popularity is relevant for the specific user. In order to exploit the temporal aspect of these rating the contributions of Precursors can be weighted, e.g., by using a temporal decay function.

We now introduce some basic notation that will be used in the following. We use \( u \in U \) and \( i \in I \) to denote users and items respectively. Since we are not just interested in the items a user rated but also at when the rating happened we have that for a user \( u \) the corresponding user profile is \( P_u = \{ (i_1, t_{u_1}), \ldots, (i_n, t_{u_n}) \} \) with \( P_u \subseteq I \times \mathbb{R} \), being \( t_{ui} \) a timestamp representing when \( u \) rated \( i \). We now can formally define Precursors and show a way to compute them.

**Definition 2.1 (Candidate Precursor).** Given \( (i, t_{ui}) \in P_u \) and \( (i, t_{ui'}) \in P_{u'} \), we say that \( u' \) is a Candidate Precursor of \( u \) if \( t_{ui'} < t_{ui} \). We use the set \( \hat{P}^u \) to denote the set of Candidate Precursors of \( u \).

A user \( u' \) is a Candidate Precursor of \( u \) if \( u' \) rated at least one common item \( i \) before \( u \). Although this definition catches the intuition behind the idea of Precursors, it is a bit weak as it considers also users \( u' \) who have only a few or even just one item in common with \( u \) and rated them before she did so. Hence, we need to introduce a threshold taking somehow into account the number of common items in order to enforce the notion of Precursors: This threshold can be personalized and set manually or it can be computed automatically as we will see in the following.

**Definition 2.2 (Precursor).** Given two users \( u' \) and \( u \) such that \( u' \) is a Candidate Precursor of \( u \) and a value \( \tau_u \) we say that \( u' \) is a Precursor of \( u \) if the following condition holds:

\[
\frac{\left| \{(i | (i, t_{ui}) \in P_u \land (i, t_{ui'}) \in P_{u'} \land t_{ui'} < t_{ui}\} \right|}{|\hat{P}^u|} \geq \tau_u
\]

The threshold value \( \tau_u \) can be computed in different ways that may also depend on the specific dataset and on the user. A general procedure to evaluate \( \tau_u \) can be that of considering the mean of the common items previously rated by the Candidate Precursors of \( u \).

\[
\tau_u = \frac{\sum_{u' \in \hat{P}^u} \left| \{(i | (i, t_{ui}) \in P_u \land (i, t_{ui'}) \in P_{u'} \land t_{ui'} < t_{ui}\} \right|}{|\hat{P}^u|}
\]

To give an intuition on the computation of Precursors and of \( \tau_u \) let us describe the simple example shown in Figure 1. Here, for the sake of simplicity, we suppose that there are only four users and ten items and \( u \) is the user we want to provide recommendations to. Items that users share with \( u \) are highlighted in blue and items with a dashed red square are the ones that have been rated before \( u \). We see that \( \hat{P}^u = \{ u_2, u_4 \} \). Indeed, although \( u_3 \) rated some of the items also rated by \( u \) they have been rated after. By applying equation (1) we have \( \tau_u = \frac{2}{4} = 0.5 \). Then, only \( u_2 \) results to be in \( \hat{P}^u \) because she has 3 > 2 shared items rated before those of \( u \). As for \( u_3 \), it is more likely that \( u \) is a Precursor of \( u_4 \) and not vice versa.

![Figure 1: Example of Precursors computation.](image)

2.1 The temporal dimension

As the definition of Precursor goes through a temporal analysis of user behaviors, we understand how time plays an important role in the overall process. On the one side, we may look at the timestamp of the last rating provided by a Precursor in order to identify how active is her in the system. Intuitively, the contribution to popularity for users who have not contributed recently with a rating is lower than "active" users. On the other side, given an item in the profile of a Precursor we are interested in the freshness of its rating. As a matter of fact, old ratings should affect the popularity of an item less than newer ratings. Summing up, we may classify the two temporal dimensions as old/recent user and old/recent item. In order to quantify these two dimensions for Precursors we introduce the following timestamps:

- \( t_0 \): this is the reference timestamp. It represents the "now" in our system;
- \( t_{ui} \): is the time when \( u' \) rated \( i \);
- \( t_{ui'} \): represents the timestamp associated to the last item \( i \) rated by the user \( u' \).
In order to embed time in a recommendation approach, a temporal decay $e^{-\beta \Delta T}$ is usually adopted where $\Delta T$ is a variable taking into account the age of a rating. Different temporal variables are typically used [10, 16], and they mainly focus on old/recent items. $\Delta T$ may refer to the timestamp of the items with reference to the last rating of $u'$ [10] $\Delta T = t_{u'i} - t_{u'i}$ or to the reference timestamp [16] $\Delta T = t_0 - t_{u'i}$. As we stated before, we really would like to catch the temporal behavior of both old/recent users and old/recent items at the same time. We may analyze the desired ideal behavior of $\Delta T$ depending on the three timestamps previously defined as represented in Table 1. Let us focus on each case. In the upper-left case we want $\Delta T$ to be as small as possible because both $u'$ and the rating for $i$ are "recent" and then highly representative for a popularity dimension. In the upper-right case, the rating is recent but the user is old. The last item has been rated very close to $i$ but a large value of $\Delta T$ should remain because the age of $u'$ penalizes the contribution. The lower-left case denotes a user that is active on the system but rated $i$ a long time ago. In this case the contribution of this item is almost equal to the age of its rating. The lower-right case is related to a scenario in which both the rating and $u'$ are old. In this scenario, the differences between the reference timestamp minus the last interaction and the reference timestamp minus the rating of $i$ are comparable: $(t_0 - t_{u'i}) \approx (t_0 - t_{u'i})$. In this case, we wish the contribution of $\Delta T$ should consider the elapsed time from the last interaction (or the rating) until the reference timestamp. All the above observations lead us to the following formulation:

$$\Delta T = |t_0 - 2t_{u'i} + t_{u'i}|$$

(2)

It is quite straightforward deriving the ideal behavior for each case in Table 1 using Equation (2).

### 2.2 The Recommendation Algorithm

We modeled our algorithm TimePop to solve a top-N recommendation problem. Given a user $u$, TimePop computes the recommendation list by executing the following steps:

1. Compute $P^{u}$;
2. For each item $i$ such that there exists $u' \in P^{u}$ with $(i, t_{u'i}) \in P_{u'}$ compute a score for $i$ by summing the number of times it appears in $P_{u'}$ multiplied by the corresponding decay function;
3. Sort the list in decreasing order with respect to the score of each $i$.

For sake of completeness, in case there were no precursors for a certain user, a recommendation list based on global popularity is returned to $u$. Moreover, if TimePop is able to compute only $m$ scores, with $m < N$, the remaining items are returned based on their value of global popularity $^1$.

### 3 EXPERIMENTAL EVALUATION

In order to evaluate TimePop we used three different datasets: two of them related to the movie domain—the well-known Movielens1M dataset and Amazon3 Movies—and a dataset referring to toys and games—Amazon Toys and Games. "All Unrated Items" [24] protocol has been chosen to compare different algorithms where, for each user, all the items that have not yet been rated by the user all over the platform are considered.

**Dataset splitting.** In order to evaluate time-aware recommender systems in an offline experimental setting, a typical k-folds or hold-out splitting would be ineffective and unrealistic. We wanted the training set to be as close as possible to an on-line real scenario in which the recommender system is deployed. To reach this goal we used the splitting from [12], also used in [7]. Best practices in recommender systems evaluation suggest that it represents a more realistic temporal dynamic in an actual time-aware recommendation scenario. In details, we used a fixed timestamp $t_0$ that has been chosen by finding the one that maximizes the number of users that maintain at least 15 ratings in the training set and 5 ratings in the test set. We exploited such a timestamp thus obtaining a training set that represents the past of our system with reference to $t_0$, and a test set that collects the events that are going to happen, i.e., all those ratings happening after $t_0$. Training set and test set for the three datasets are publicly available$^4$ for research purposes. The resulting datasets characteristics are depicted in Table 2.

In order to evaluate the algorithms we measured two well-known accuracy metrics: Precision ($P@N$) and normalized Discount Cumulative Gain, nDCG (nDCG@N). Each metric was computed per user and then the overall mean was returned using the RankSys$^5$ framework. In order to measure metrics the threshold to consider a test item relevant has been set to the value of 4 w.r.t a 1-5 scale for all the three datasets.

**Baselines.** We evaluated our approach w.r.t CF and time-aware techniques. MostPopular was included as TimePop is a time-aware variant of "Most Popular". From model-based collaborative filtering approaches we selected some of the best performing matrix factorization algorithms WRMF trained with 10 latent factors, a regularization parameter set to 0.015, $\alpha$ set to 1 and 15 iterations, and FM[21], computed with an ad-hoc implementation of a 2 degree factorization machine with 10 latent factors, considering users

| Dataset        | # users | # items | # ratings | spars.% |
|----------------|---------|---------|-----------|---------|
| movielens      | 859     | 3,375   | 185,035   | 93.61756|
| AmazonMovies   | 3619    | 68,514  | 288,339   | 99.88371|
| AmazonToys     | 1108    | 24,158  | 38,317    | 99.85685|

Table 2: Datasets statistics after splitting.

$^1$We wish to highlight that in the experimental evaluation presented in this work, the former conditions never occur. Hence, the results only refer to recommendations provided by TimePop.

$^2$https://grouplens.org/datasets/movielens/1m/

$^3$http://jmcauley.ucsd.edu/data/amazon/

$^4$https://github.com/sisin/f_lab/DatasetsSplits

$^5$http://ranksys.org/
and items as features, trained using Bayesian Personalized Ranking Criterion[22]. Moreover, we compared our approach against the most popular memory-based kNN algorithms, Item-kNN and User-kNN [23], together with their time-aware variants (Item-kNN-TD, User-kNN-TD)[10]. We included TimeSVD++ [16] in our comparison even though this latter has been explicitly designed for the rating prediction task while TimePop computes a top-N recommendation list. We included TimeSVD++ as it is one of the most important advances in time-aware RS. Finally BFwCF [7] is an algorithm that takes into account interaction sequences between users and it uses the last common interaction to populate the candidate item list. In this evaluation we included the BFwCF variant that takes advantage of similarity weights per user and two time windows, left-sided and right-sided (Backward-Forward). BFwCF was trained using parameters from [7]: 100 neighbors, indexBackWards and indexForwards set to 5, normalization and combination realized respectively via DummyNormalizer and SumCombiner. Recommendations were computed with the implementation publicly provided by authors. For all user-based and item-based scheme algorithms 80 neighbors were considered. Recommendations for MostPopular, WRMF, TimeSVD++ and FM were computed with an ad-hoc implementation based on MyMediaLite implementation. Item-kNN, User-kNN, Item-kNN-TD and Item-kNN-TD were computed with the implementation publicly provided by MyMediaLite and [10]. In particular, in order to guarantee a fair evaluation, for all the time-based variants the $\beta$ coefficient was set to $\frac{1}{200}$ [16]. TimeSVD++ was trained using parameters used in [16].

3.1 Results Discussion

Results of experimental evaluation are shown in Figure 2 which illustrate Precision (2a, 2b, 2c) and nDCG (2e, 2f, 2g) curves for increasing number of top ranked items returned to the user. Significance tests have been performed for accuracy metrics using Student’s t-test and p-values and they result consistently lower than 0.05. By looking at Figure 2a and Figure 2d we see that TimePop outperforms comparing algorithms in terms of accuracy on AmazonMovies dataset. We also see that algorithms exploiting a Temporal decay function perform well w.r.t. their time-unaware variants (User-kNN and Item-kNN) while matrix factorization algorithms (WRMF, TimeSVD++ and FM) perform quite bad. We assume this is mainly due to the high sparsity of the User-Item matrix (99.88%, Table 2). Results for Amazon Toys and Games dataset are analogous to those computed for Amazon Movies. The evaluation on the Movielens dataset shows some differences with reference to the previous two datasets. TimePop is still the most accurate approach, however WRMF, Time SVD++ and FM provide results which are more accurate than those computed for the two Amazon datasets. If we look at the sparsity values of the User-Item matrix (see Table 2) we observe Movielens dataset is less sparse than the other datasets. For this dataset it is worth to notice that taking into account time is not a key element (User-kNN-TD and Item-kNN-TD perform worse than the time-unaware variants), and MostPopular shows very high performance, even better than Matrix Factorization techniques. This is probably due to the strong popularity bias of MovieLens dataset. As for the lower influence of time in the accuracy of results we took a look at the distribution of timestamps in the various datasets with reference to the users. It is well known that timestamps in Movielens are related to the time ratings are inserted on the platform and they do not reflect the exact time of fruition for the item [4, 7, 13]. Moreover, in Movielens there are several users that rated a lot of movies the same day, with a user who reached the maximum of 1,080 movies rated the same day and another one with an average number of ratings per single day of 884. In Amazon Movies (maximum of 216 and a maximum average of 37) and Amazon Toys (maximum of 42 and a maximum average of 22.3) the trends are much different and this could heavily affect the results of time-aware algorithms. Nonetheless, it is important to notice that, despite that, TimePop always outperforms competing algorithms also in a dataset with low sparsity and high popularity bias such as Movielens.

http://www.mymedialite.net/
4 CONCLUSION AND FUTURE WORK

In this paper we presented TimePop, a framework that exploits local popularity of items combined with temporal information to compute top-N recommendations. The approach relies on the computation of a set of time-aware neighbors named Precursors that are considered the referring population for a user we want to serve recommendations. The contribution of each Precursor is eventually weighted by exploiting the freshness of both users and ratings. We compared TimePop against state-of-art algorithms showing its effectiveness in terms of accuracy despite its lower computational cost in computing personalized recommendations.

We are currently working on the adoption of the ideas behind TimePop to the identification and computation of time-aware communities in recommender systems. Another aspect we want to explore is the possibility to adapt the local popularity of the Precursors to matrix factorization techniques, to improve the quality of the data on which the factorization is performed on and then speed up the recommendation process.

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