Improving Collaborative Filtering's Rating Prediction Quality by Exploiting the Item Adoption Eagerness Information

Dionisis Margaris
Department of Informatics and Telecommunications,
University of Athens
Athens, Greece
margaris@di.uoa.gr

Dimitris Spiliotopoulos
Department of Informatics and Telecommunications,
University of the Peloponnese
Tripoli, Greece
dspiliot@uop.gr

Costas Vassilakis
Department of Informatics and Telecommunications,
University of the Peloponnese
Tripoli, Greece
costas@uop.gr

ABSTRACT

Collaborative filtering generates recommendations tailored to the users' preferences by exploiting item ratings registered by users. Collaborative filtering algorithms firstly find people that have rated items in a similar fashion; these people are coined as "near neighbors" and their ratings on items are combined in the recommendation generation phase to predict ratings and generate recommendations. On the other hand, people exhibit different levels of eagerness to adopt new products: according to this characteristic, there is a set of users, termed as "Early Adopters", who are prone to start using a product or technology as soon as it becomes available, in contrast to the majority of users, who prefer to start using items once they reach maturity; this important aspect of user behavior is not taken into account by existing algorithms. In this work, we propose an algorithm that considers the eagerness shown by users to adopt products, so as to leverage the accuracy of rating prediction. The proposed algorithm is evaluated using seven popular datasets.

CCS CONCEPTS

• Information → Collaborative filtering

KEYWORDS

collaborative filtering, item adoption eagerness, rating prediction quality, evaluation, Pearson correlation coefficient, cosine similarity

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1 INTRODUCTION

Collaborative filtering (CF) generates recommendations tailored to the users' preferences by exploiting item ratings registered by users.

These ratings reflect the users' preferences and likings. For each user u, CF algorithms firstly find people that have rated items in a fashion similar to u; these people are coined as "u's near neighbors" (NNs) and their ratings on items are combined in the recommendation generation phase to predict ratings that u would assign to items s/he has not reviewed yet [8], and ultimately generate recommendations for u. CF is based on the premise that people that have rated items similarly in the past are bound to continue doing so in the future as well [14, 20].

Many extensions of the basic CF algorithm have emerged, taking into account various features of the user profile [17, 46, 49, 60, 63], temporal behavior [15, 21, 25, 30, 31, 33, 35–37, 43] or inter-user relationships [6, 7, 22, 38]. Research has identified that people exhibit different levels of eagerness to adopt new products: according to this characteristic, there is a set of users, termed as "Early Adopters" (EA) [51], who are prone to adopting items eagerly, i.e. they start using a product or technology as soon as it becomes available, providing useful feedback, for other users and vendors. On the contrary, other users prefer to wait to use items, until they reach maturity. This behavioral aspect of users has been shown to be associated with different mentalities and psychological factors [26, 54], which in turn affect rating criteria. Nevertheless, this aspect is not taken into account by existing CF algorithms, while this is also true for individual elements of CF algorithms, most notably similarity measures [9, 45]

In this work, we introduce an algorithm that moderates the weight that each individual rating r on an item i is taken into account when formulating a rating prediction p on that specific item, by considering the item adoption eagerness information; this aspect is reflected on the particular item's adoption phases that the registered rating r and the prediction to be formulated p fall in. Effectively, the algorithm boosts the weight of r when both r and p fall into the early adoption phase, while it attenuates the weight of r when r and p fall into different adoption phases of i. We also evaluate the performance of the proposed algorithm, under different user similarity metrics and across seven datasets. Furthermore, we have conducted and present an detailed comparative evaluation between (i) the proposed algorithm, (ii) the algorithm presented in [36] which is based on rating abstention intervals and (iii) the user variability-based algorithm presented in [37]. The algorithms in [36, 37] are state-of-the-art (both of them have been published in 2018) and utilize temporal information for increasing rating prediction accuracy. Furthermore, the algorithm in [37] does not necessitate additional information on users or items and maintains rating prediction accuracy levels, while the algorithm in [36] requires information about user social ties and exhibits coverage drops.

Finally, it is noteworthy that the algorithm proposed in this paper can be used in conjunction with other algorithms which aim to improve performance, reduce rating prediction errors and leverage recommendation quality in systems based on CF. Algorithms that can be used in conjunction with the proposed one include clustering based techniques [16, 28], utilization of data sourced from social networks (SNs) [7, 38] or abrupt/gradual forgetting of old user ratings [30, 31].

The remaining of the paper is organized as follows: in Section 2 related work is overviewed, while the proposed algorithm is detailed in Section 3. Section 4 presents experiments conducted to tune and evaluate the proposed algorithm, as well as their results, while Section 5 concludes the paper and outlines future work.

2 RELATED WORK

Considerable research efforts have targeted the issue of CF-based systems accuracy. In this context, algorithms utilizing numerous characteristics of the ratings database and/or information from linked databases have been proposed [12, 20, 32, 40].

Rating timestamps is a feature utilized in numerous algorithms aiming to improve rating prediction accuracy. The algorithms presented in [30, 31] examine different methods for tacking the fact that old-aged ratings may not be aligned with the current user preferences. Towards this direction, old-aged ratings are either removed from the database (a method termed as abrupt forgetting), or their importance is attenuated (gradual forgetting). The abrupt forgetting methods have been shown to achieve higher benefits in terms of rating prediction accuracy, while additionally reducing the size of the ratings database. On the other hand, abrupt forgetting increases the sparsity of the ratings database, leading thus to some decrements in the rating prediction coverage, i.e. the capability to generate personalized rating predictions for users.

Knowledge-based recommender systems (KB-RSs) utilize higher-level knowledge regarding CF entities (i.e. items and users) to determine the items which meet the requirements of individual users and generate thus successful recommendations. Margaris et al. [39] present a KB-RS targeted to leisure time recommendations in the context of social media. This algorithm identifies influencing relationships among the users of the social network, while it additionally exploits (i) qualitative attributes associated with venues (e.g. atmosphere, price and service levels), (ii) the actual distance between the locations where venues are located and (iii) the individual users' profile and venue selection patterns.

With the proliferation of SN, many algorithms have emerged targeting the formulation of recommendations in the context of SN. Margaris et al. [38] consider the aspect of information diffusion in SNs in the context of recommendation generation, asserting that users' receptiveness to recommendations is not uniform across different item categories. Consequently, identifying and utilizing item category-specific sets of influencers for each user can lead to the formulation of more reliable recommendations, as compared to a model that employs a single set of influencers for each user. Trust propagation mechanisms within SN are considered in [41], which embeds this aspect in a matrix factorization-based RS.

Recently, the variability of user ratings has been recognized as a feature that can be exploited to improve rating prediction accuracy [37]. Additionally, the work in [36] exploits temporal information from the user rating database to identify periods that users have not submitted new ratings, which are termed as rating abstention intervals; the presence of rating abstention intervals is shown to be positively associated with a shift of interest, and therefore can provide the basis for amplifying or attenuating the weight assigned to user ratings in the recommendation generation process. The algorithm presented in [36] also calculates and utilizes influence levels between users, by considering the interaction that have taken place among users in social networks.

However, none of the aforementioned works considers the aspect of item adoption eagerness in the rating prediction computation. The present paper fills this gap by presenting an algorithm that leverages the similarity score of users whose ratings both belong to a particular item's EA phase, or both do not, and evaluates its performance using different user similarity metrics and datasets.

3 THE PROPOSED ALGORITHM

The basic CF formula for calculating a rating prediction $p_{U,i}$ for the rating of user U on item i is depicted in formula (1) [8]:

$$p_{U,i} = \overline{r_u} + \frac{\sum_{V \in NN_u} sim(U,V) * (r_{V,i} - \overline{r_V})}{\sum_{V \in NN_u} sim(U,V)} \quad (1)$$

where $\overline{r_U}$ and $\overline{r_V}$ are the mean value or ratings entered by users U and V, $sim(U,V)$ is a quantification of the similarity between users U and V, while NN_u denotes U's NNs.

The algorithm proposed in this paper adapts the prediction computation formula, by introducing terms that correspond to items' adoption eagerness (IAE). More specifically, formula (1) is modified as follows:

$$p_{U,i} = \overline{r_u} + \frac{\sum_{V \in NN_u} sim(U,V) * IAE\_factor(U,V,i) * (r_{V,i} - \overline{r_V})}{\sum_{V \in NN_u} sim(U,V) * IAE\_factor(U,V,i)} \quad (4)$$

where the $IAE\_factor(U,V,I)$ is a factor moderating the importance of rating $r_{V,i}$ in the context of the computation of prediction $p_{U,i}$, taking into account whether users U and V have adopted item i eagerly ("early adopters") or not ("late adopters"). The rationale behind the usage of the $IAE\_factor(U,V,i)$ is that users exhibiting different degrees of eagerness to adopt items assess and rate items with different mentalities and criteria: hence ratings entered within an item's early adoption phase convey an eager adopter's view and will thus be more useful for other eager adopters, but of less value for late adopters. A similar remark holds for the ratings of late adopters.

More specifically, the computation of the *IAE_factor(U,V,i)*quantity takes into account whether the (factual) rating of user *V* for item *i* and the (predicted) rating of user *U* on item *i* both belong to the early adoption phase of item *i* (denoted as EA_i), or not (i.e. they both belong to the late adoption phase or they belong to different phases). Formula (3) illustrates the computation method for the *IAE_factor(U,V,i)* quantity.

$$IAE\_factor(U,V,i) = \begin{cases} \text{EA}, & if\ \ U_i\ and\ V_i \in \text{EA}_i \\ \text{LA}, & if\ \ U_i\ and\ V_i \notin \text{EA}_i \\ \text{DIFF}, & \text{otherwise} \end{cases} \quad (3)$$

In formula (3) *EA* is a constant that is used when both users' ratings on item *i*, belong to the item's *EA* lifetime phase; and similarly *LA*is a constant employed when both users ratings on item *i*, belong to its *Late Adoption*lifetime phase. The *DIFF* constant is employed when the two ratings belong to different lifetime phases of item *i* (Early and Late).

According to [51], the *early adoption* phase for an item corresponds to the initial 16% of the item lifespan in the market.In some cases, the lifetime of the product is available through the official vendor pages (e.g. [35]). In the absence of official information, the lifetime of the product is approximated as follows:

1) the beginning of the product lifespan is set to the timestamp of the earliest rating on the product within the ratings database,
2) if the category of the product has a nominal lifespan (e.g. [26] reports that the lifetime of mobile phones is 3 years while that of cars is 10 years), then the end the product lifespan is computed by adding the nominal product category lifespan to the beginning of the product lifespan. Otherwise, the end of the product lifespan is set equal to the timestamp of the most recent rating on the product within the ratings database.

Taking the above into account, a rating $r_{U,i}$ belongs to the *early adoption* phase of item *i* if the timestamp of $r_{U,i}$belongsto the first 16% of the lifespan of item *i*in the market; otherwise $r_{U,i}$belongs to the product's *late adoption* phase.

In the next section, we explore the optimal setting for parameters *EA, LA* and *DIFF*, while we also evaluate the proposed algorithm's performance.

4 ALGORITHM TUNING AND PERFORMANCE EVALUATION

In this section, we report on the experiments conducted to:

1. Calculate the optimal values for parameters *EA, LA* and *DIFF*, which are used in the *IAE_factor* function of the presented algorithm.
2. Compute the prediction improvement, introduced by the presented algorithm, due to the consideration of the *item adoption eagerness* information in the CF rating prediction computation process.

Due to space limitations, detailed information on the experiments and their results is listed in [29].

In order to compute the optimal values for parameters EA, LA and DIFF, we experimentally searched the parameter value assignment solution space, by iteratively selecting parameter value assignments and assessing the impact that each particular parameter value assignment had on the accuracy of rating prediction. Rating prediction accuracy was quantified using two popular error metrics, namely the Mean Absolute Error (MAE), and the Root Mean Squared Error (RMSE). We opted to use two metrics, because each one of them highlights different aspects of the quality of the results: more specifically, the MAE metric treats all error magnitudes uniformly since it averages the absolute values of errors; on the other hand the RMSE metric squares error magnitudes before summing them up, therefore larger errors are emphasized. The error between an individual prediction and the corresponding actual rating was computed using the standard "hide one" technique [13, 14, 27, 36, 37]: the rating was hidden, and its value was subsequently predicted by combining non-hidden ratings. In our first experiment, only the last rating of each user was hidden and then its value was predicted; we also executed a second experiment, where -for each user- a random rating was hidden and then its value was predicted. The rating prediction quality metrics obtained from these two experiments were in close agreement (the absolute magnitude of their differences had an upper bound of 1.8% in all cases), and thus we confine ourselves to presenting only the results of the first experiment. All reported experiments were run on seven datasets, five which have been sourced from Amazon [2, 42], while the remaining two are sourced from MovieLens [18, 44]. The datasets sourced from Amazon are relatively sparse, while the ones sourced from MovieLens are relatively dense; a dataset's density is computed as $d(DS) = \frac{\#ratings}{\#users*\#items}$ [52]). We choose to test both sparse and dense datasets, in order to establish that the proposed algorithm can be used in every dataset.

In the next two subsections, we outline and discuss the results obtained from the conducted experiments.

4.1 Tuning of algorithm parameters

The first experiment aimed to determine the optimal values for the parameters EA, LA and DIFF. Since only the ratios *EA/LA* and *LA/DIFF* (and not the actual parameter values) affect the algorithm performance, we fix *LA* to 1 and vary the values of *EA* and *DIFF*. We explored both the Pearson and cosine similarity measures (PCC and CF, respectively) and under both metrics, the setting attaining the highest reduction in the MAE and the RMSE is when the DIFF parameter is set to 0.5 and the EA parameter is set to 2.0. More specifically, this setting achieves an average MAE reduction of 3.7% and an average RMSE reduction of 3.18%, when the PCC metric is used. The respective reductions concerning the CS metric are 3.55% and 3.02%. Figure 1 depicts MAE reduction under different *EA* and *DIFF* parameter value combinations, using the PCC measure.

4.2 Performance evaluation

In this subsection, we present the results produced by the presented algorithm and contrast them with the ones produced by the algorithm proposed in [37], i.e. the CF variability algorithm.We selected the CF variability algorithm for the comparison because (i) it has been published in 2018, and thus is a state-of-the-art algorithm, (ii) it targets the improvement of prediction accuracy in the context of CF, (iii) it does not require any additional information about users or items (e.g. item taxonomical information or social ties between users) and (iv) it maintains prediction coverage levels. We note here that no other algorithm addresses the particular aspect of user behavior considered by the proposed algorithm; thus, in the absence of such an algorithm, the comparison is made with an algorithm that exploits similar features of ratings (i.e. temporal features). Taking into account the results of subsection 4.1, we set parameters *EA* and *DIFF* to 2.0 and 0.5, respectively.

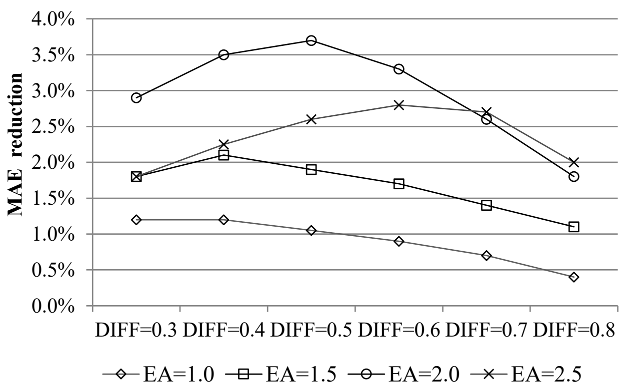

Figure 1: MAE reduction under different EA and DIFF parameter value combinations, using the PCC similarity metric

Figure 2 depicts the reduction in the MAE attained by the proposed algorithm, along with the respective attainment of the CF variability algorithm, proposed in [37]. In both cases, MAE reduction percentages are calculated against the performance of the plain CF algorithm.

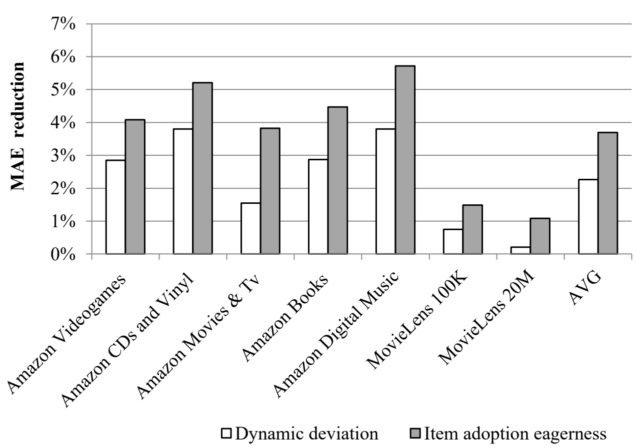

Figure 2: MAE reduction achieved by the proposed algorithm, in comparison to the CF variability algorithm [37]

In Fig. 2 we can notice that the proposed algorithm outperforms CF variability algorithm, in all tested datasets. More specifically, the proposed algorithm reduces the MAE by 3.7%, which is 63.4% higher than the reduction attained by the CF variability algorithm (2.26%). The widest performance margin is observed for the MovieLens 20M dataset (414%), while the narrowest one for the Amazon CDs and Vinyl dataset (37%). As far as the RMSE is concerned, the reduction achieved by the proposed algorithm is equal to 3.18%, while the reduction attained by the CF variability algorithm is 1.48%, therefore the performance edge is 114.6%. The experiment and its results is described in more detail in [29]. Finally, we give a performance comparison between the proposed algorithm and the rating abstention-based algorithm presented in [36]; the algorithm in [36] is a state-of-the-art algorithm utilizing temporal, within-user history information to reduce prediction errors, while it has been demonstrated to achieve higher error reductions than other state-of-the art algorithms. As noted above, the MAE reduction attained by the proposed algorithm averages to 3.7% over all tested datasets, surpassing the corresponding improvements of the rating abstention-based algorithm reported in [36], which average to 2.99%. While the absolute difference is limited to 0.7% and the relative difference is 23.7%, we emphasize that the rating abstention-based algorithm [36]:

- necessitates the existence of information about user social ties, which is not always available.
- exhibits a drop in coverage, which is substantial in the context of sparse datasets.

On the contrary, the algorithm presented in this paper fully maintains coverage levels and does not necessitate any additional information. It is also noteworthy that the rating abstention-based algorithm presented in [36] has been demonstrated to outperform other state-of-the-art algorithms, e.g. the pruning-based algorithms in [31, 34] and the temporal dynamics-based algorithm reported in [23].

5 Conclusion and Future Work

In this paper, we proposed an algorithm that incorporates, in the rating prediction computation process, the aspect of the users' eagerness to adopt new items and technologies, aiming to increase prediction accuracy. We also reported on a set of experiments conducted to validate the performance of the proposed algorithm: in these experiments we used two user similarity metrics and seven datasets, both sparse and dense. These experiments showed that the consideration of the item adoption eagerness aspect entails considerable prediction accuracy gains.

We have also compared the proposed algorithm against (i) the user rating variability algorithm [37] and (ii) the rating abstention based algorithm presented in [36]. The proposed algorithm outperformed both these algorithms. The proposed algorithm can be straightforwardly incorporated in a CF-based RS, since (1) it does not require any extra information on users or items, (2) it introduces only minimal processing overhead for rating prediction formulation, which has been quantified to be less than 3%, indicating the feasibility of this approach, (3) it needs minimal additional storage space, for computing and storing only each item's EA phase, (4) it can be directly implemented as a modification of existing CF-based systems and (5) it can be used in conjunction with other algorithms that aim to leverage rating prediction accuracy, performance and/or coverage. In our future work we plan to study additional methods to improve rating prediction quality in CF. Furthermore, we will study the algorithm's performance under more similarity metrics, such as the Euclidean distance and the Spearman coefficient [19]. We will also work on a suitable integration of the proposed method into matrix factorization techniques [24]. Finally, this work may be used with other algorithms to improve accuracy in language analysis [1, 3, 55, 58, 59, 61, 62], semantics [11, 48, 50, 56] and analysis of social media content [4, 5, 47, 53, 57].

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