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An Adaptive Social Network-Aware Collaborative Filtering Algorithm for Improved Rating Prediction Accuracy

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ABSTRACT When information from traditional recommender systems is augmented with information about user relationships that social networks store, more successful recommendations can be produced. However, this information regarding user relationships may not always be available, since some users may not consent to the use of their social network information for recommendations or may not have social network accounts at all. Moreover, the rating data (categories and characteristics of products) may be unavailable for a recommender system. In this paper, we present an algorithm that can be applied in any social network-aware recommender system that utilizes the users' ratings on items and users' social relations. The proposed algorithm addresses the issues of limited social network information or limited collaborative filtering information for some users by adapting its behavior, taking into account the density and utility of each user's social network and collaborative filtering neighborhoods. Through this adaptation, the proposed algorithm achieves considerable improvement in rating prediction accuracy. Furthermore, the proposed algorithm can be easily implemented in recommender systems.

INDEX TERMS Social computing, recommender systems, performance evaluation.

I. INTRODUCTION

Recommender systems (RSs) continuously augment their information repositories with data from diverse sources, ranging from smartphones and wearable devices to websites and social networks (SNs), to promote the formulation of successful personalized recommendations in a wide range of domains, from consumer products, such as books, office supplies and CDs, to travel and leisure as well as from restaurants and movies to smartphone apps [1]. Collaborative filtering (CF) is a widely used approach for making recommendations, stemming from user behavior and actions. CF synthesizes the informed (implicit or explicit) opinions of humans, in order to make personalized and accurate predictions and recommendations [2]. Since traditional CF RSs rely only on opinions expressed by users on items, either implicitly (e.g. purchasing an item, or clicking an advertisement banner, hence indicating a positive assessment) or explicitly (entering a rating for an item), their most significant advantage is that explicit content description is not required (contrary to content-based systems).

In the context of CF, personalization is achieved by formulating recommendations for any user U based on the opinions of other users that have rated items similar to U: this approach is underpinned by the CF fundamental assumption that if users U_1 and U_2 have similar behavior on some items (e.g. watching, listening, buying, rating assignment), they will act similarly on others [2].

Traditional CF-based RSs do not consider the social interactions among users, assuming that they are independent from each other. However, this approach results in failure to incorporate important aspects that may substantially enhance recommendation quality, such as influence, interaction and tie strength among users [3].

SN-aware RSs take into account static data from the user profile, such as age, gender or location, complemented with dynamic aspects and contextual information stemming from user behavior and/or SN state, such as user mood, time, item

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general acceptance, and social influence [4] to supplement the traditional CF data (such as item static characteristics and user ratings). By taking this information into consideration in the recommendation process, the SN RSs manage to achieve better user-targeted recommendations.

However, in some cases the CF-based and SN-based information that a recommender system has at its disposal may be limited: some users may not consent to the use of their SN information for recommendations or may not have SN accounts at all, or the rating data (categories and characteristics of products) may be unavailable for a recommender system service. And, conversely, in some cases, the CF-based near neighbors (NNs) of a user U may be limited in number or have low similarity, or have little utility, in the sense that they have rated very few items that U has not already rated. More generally, the successful combination of CF-based and SN-based information effectively depends on discovering which rating prediction information source, the CF NNs or the SN relations, is considered as the most reliable predictor for each individual user in a dataset.

Previous work has addressed the aforementioned problem, by proposing a simple yet effective algorithm, which successfully combines limited CF information, concerning users' ratings on items, with limited SN information, concerning users' social relations, in order to improve rating prediction accuracy in SN-Aware CF systems [5].

In this paper, we extend the work presented in [5] by proposing an algorithm which can be applied in any SN-aware RS that utilizes user ratings on items and user social relations. The proposed algorithm addresses the issues of limited SN information or limited CF information for some users by adapting its behavior, taking into account the density and utility of each user's SN and CF neighborhoods. Through this adaptation, which optimizes the system for individual users [6], the proposed algorithm achieves considerable improvement in rating prediction accuracy. This is attested by the results of our experiments, in which the performance of the proposed algorithm is evaluated against five contemporary and widely used SN CF datasets. In the same experiments, the performance of the proposed algorithm is compared against the performance of the algorithm presented in [5], which also tackles the same problem, however it assumes that all users of the dataset share the same prediction significance between CF and SN prediction information in RSs.

Notably, in our experiments we use:

1) both dense and sparse CF datasets (a CF dataset's density refers to the number of ratings when compared to the number of users and items in it [2]),
2) both dense and sparse SN datasets (a SN dataset's density refers to the number of relations when compared to the number of users in it [3]), and
3) both undirected edge (friendships) and directed edge (trusts) SN datasets.

The experimental results show that the proposed algorithm introduces considerable prediction accuracy gains under all conditions. Since, additionally, the proposed algorithm necessitates only basic SN information (user relationships), as well as basic CF information (a user-item rating matrix), we can conclude that it can be applied to any SN RS dataset. It is also worth noting that the proposed technique can be combined with other algorithms that have been proposed for improving rating recommendation quality, prediction accuracy or prediction coverage in CF-based systems, focusing either on traditional CF-based systems (clustering techniques, concept drift, etc.) [7], [8] or on SN CF-based systems (influence, trust, etc.) [9].

The rest of the paper is structured as follows: Section II overviews related work, while Section III presents the proposed algorithm. Section IV evaluates the proposed algorithm and finally, Section V concludes the paper and outlines future work.

II. RELATED WORK

Recommender systems are increasingly utilizing SN data, in order to leverage the accuracy of recommendations offered to users, alleviate the cold start problem and augment recommendation variety [10].

The necessity for extending recommendation algorithms to take the SNs information into consideration is established in multiple research works. [9] and [11] include comprehensive analyses of the effect of social relationships in advertisement recommendations, also proposing quantifiers for measuring social influence and tie strength of users. Specifically, [9] computes social influence via social cues through an optimized relevance determination, combining user behavior and response average rates. That approach demonstrates the substantiality of the inclusion of minimal social cues in advertising and measures the positive correlation between the buyers' responses and the depth of their relation with affiliated peers. The work from [11] reports on a predictive model that utilizes social media data that are mapped to tie strength. It distinguishes between weak and strong with accepted accuracy and demonstrates how tie strength modeling may enhance social media design elements, including message routing, privacy controls, information prioritization and friend introductions.

The role of SNs in the recommendation procedure is examined in a large-scale field experiment that randomized exposure to friend information signals to ascertain the relative role of weak and strong ties [3], [12]. In addition, the work in [13] develops a way to combine SN information and CF methods for improved recommendation accuracy, through methods for selecting neighbors and boosting data from friends using user preference ratings and user SN relations collected from SN sources. The work in [14] investigates the role of SN relations by developing a track recommendation system based on a common CF item recommendation method that weighs up both SN-derived annotations and inherent friendships among users, items and tags, in the social graph. The work in [15] proposes a RS that utilizes trust in SNs for personalized user recommendations. The main concept is that the algorithm may assist community members to make decisions about the rest of the community members using trust and distrust between users. The work in [16] proposes a query personalization algorithm that exploits the browsing and rating information of items by users as well as the influence information from SNs used for personalized query adaptation. The queries were adapted by (re)writing the specification of the query sorting procedure to allow for re-ordering of data based on the projected user interest.

The algorithms in the above listed works necessitate the availability of additional information, either regarding the user profile (age, location, gender, etc.), or the item description (taxonomical categorization, price, value for money, etc.), or the relationships between users (social influence, tie strength, etc.). In this sense, their applicability is limited when compared to the algorithm proposed in this work that only requires the availability of basic SN-sourced information (i.e. elementary friendship or trust relationships among users).

Notably, the work in [5] proposes an algorithm that also confines its needs for SN-sourced data to elementary friendship or trust relationships among users, and computes SN-aware CF-rating predictions by synthesizing a CF-based prediction with a SN-based one. However, this algorithm uses the same weight coefficients for the CF- and SN-based predictions in the synthesis step, an approach that does not take into account the particular properties of each user's CF- and SN-based neighborhoods.

The present paper extends the work in [5], and hence advances the state-of-the-art, by introducing an algorithm that is able to adapt its behavior to the features of each user's CF- and SN-based neighborhoods. More specifically, the proposed algorithm analyzes the users' already entered ratings, and computes a personalized set of weight coefficients associated to CF- and SN-based predictions for each user. Through this approach, the proposed algorithm significantly leverages prediction accuracy. In this paper we also present our experiments, the findings of which quantify the prediction accuracy improvement and establish that the proposed approach consistently achieves improved accuracy under two correlation metrics and across five contemporary datasets that contain both CF ratings and SN relations.

III. THE PROPOSED ALGORITHM

In CF, predictions for a user U are computed based on U's *NN*s, i.e. a set of users that have rated items similarly to U. The similarity metric between two users U and V is typically based on the Pearson Correlation Coefficient (PCC) [2], denoted as *sim_pcc(U,V)*, which is expressed as:

$$sim\_pcc\,(U,V)=\frac{\sum_k \left(r_{U,k}-\overline{r_U}\right)*\left(r_{V,k}-\overline{r_V}\right)}{\sqrt{\sum_k \left(r_{U,k}-\overline{r_u}\right)^2 * \sum_k \left(r_{V,k}-\overline{r_V}\right)^2}} \quad (1)$$

where k ranges over items that have been rated by both U and V, while $\overline{r_U}$ and $\overline{r_V}$ are the mean values or ratings entered by users U and V, respectively.

Similarly, the Cosine Similarity (CS) metric [2], denoted as *sim_cs(U,V)*, is expressed as:

$$sim\_cs\,(U,V)=\frac{\sum_k r_{U,k} * r_{V,k}}{\sqrt{\sum_k \left(r_{U,k}\right)^2} * \sqrt{\sum_k \left(r_{V,k}\right)^2}} \quad (2)$$

Then, for user U, his NN users, NN_U, are selected from the set of users who have a positive similarity with user U.

Afterwards, the computation of a rating prediction $p_{U,i}$ for the rating of user U on item i, is expressed as:

$$p_{U,i}=\overline{r_u}+\frac{\sum_{V\in NN_u} sim_{CF}\,(U,V)*\left(r_{V,i}-\overline{r_V}\right)}{\sum_{V\in NN_u} sim\,(U,V)} \quad (3)$$

where the $sim_{CF}(U,V)$ denotes either the *sim_pcc(U, V)* or the *sim_cs(U, V)*, depending on the similarity metric adopted in the particular CF system implementation.

The work in [5] introduced the concept of *SN NN*s, of a user U: user V is considered to be a SN NN of a user U in the context of a SNS, if a social relation (such as trust or friendship- has been established between users U and V in the context of S. The set of SN NNs of user U will be denoted as SN_NN_U and is formally expressed as:

$$SN\_NN_U=\{V\in users\,(S):r\,(U,V)\in S_r\} \quad (4)$$

where *users(S)* is the set of users within S, r is a social relationship within S and S_r is the extension of relationship r in the context of S. Similarly, we denote the initial CF NNs of a user U, as CF_NN_U.

Furthermore, the algorithm presented in [5] follows a metasearch score combination algorithm [17], [18] to combine the two partial prediction scores, the first of which is based on the traditional, CF near neighborhood of the user (CF_NN_U), while the second one is based on the SN-based near neighborhood of the user (SN_NN_U). More specifically, the score computed on the basis of the CF near neighborhood score is denoted as $p_{U,i}^{CF}$, computed as:

$$p_{U,i}^{CF}=\frac{\sum_{V\in CF_{NN\,U,i}} sim_{CF}(U,V)*\left(r_{V,i}-\overline{r_V}\right)}{\sum_{V\in CF\_NN_U} sim_{CF}(U,V)} \quad (5)$$

while the score computed on the basis of the SN-based near neighborhood is denoted as $p_{U,i}^{SN}$ and computed as:

$$p_{U,i}^{SN}=\frac{\sum_{V\in SN\_NN_{U,i}} sim_{SN}(U,V)*\left(r_{V,i}-\overline{r_V}\right)}{\sum_{V\in SN\_NN_U} sim_{SN}(U,V)} \quad (6)$$

The notations $CF\_NN_{U,i}$ and $SN\_NN_{U,i}$ denote the CF-based and SN-based NNs of U, respectively, who have rated item i.

Regarding the computation of $sim_{SN}(U,V)$ quantity, which represents the SN-based user similarity, in this work we adopt the following approach:

- If the SN dataset provides values representing the strength/weight of the relationship between users U and V, $sim_{SN}(U,V)$ is set to this value.
- If the SN dataset does not provide relationship strength/weight values, then $sim_{SN}(U,V)$ is fixed to

1.0 for all user pairs *(U,V)* for which a relationship is established within the SN. Under this arrangement, all relationships are deemed of equal strength/weight, while the extent to which these relationships affect the rating prediction outcome is further tuned through an overall weight value associated with the SN dimension, as detailed below.

In a number of research efforts, certain features of SN structure and/or interaction among users have been shown to denote the strength of relationships between users; such features include the tie strength, number of common/mutual relations, intimacy of message content etc. [3], [16]. The exploitation of these features to compute a value for $sim_{SN}(U,V)$ will be addressed in our future work.

Finally, partial predictions $p^{CF}_{U,i}$ and $p^{SN}_{U,i}$ are combined, and the result is adjusted by the mean value of ratings entered by U, $\overline{r}_U$, in order to formulate the rating prediction $p_{U,i}$, as shown in equation (7):

$$p_{u,i} = \begin{cases} \overline{r_U} + p^{CF}_{U,i}, & \text{if } SN\_NN_{U,i} = \theta \\ \overline{r_U} + p^{SN}_{U,i}, & \text{if } CF\_NN_{U,i} = \theta \\ \overline{r_U} + w_{CF} * p^{CF}_{U,i} + w_{SN} * p^{SN}_{U,i}, & \\ & \text{if } SN\_NN_{U,i} \neq \theta \\ & \wedge CF_N N_{U,i} \neq \theta \end{cases} \tag{7}$$

In equation (7), the w_{SN} parameter denotes the weight assigned the prediction computed by considering only the *SN NNs* of U, while the w_{CF} parameter, which is complementary to the w_{SN}parameter ($w_{CF}+w_{SN} = 1.0$), corresponds to the weight assigned to the prediction computed by considering only the *CF NNs*, respectively. If no *SN NNs* of U's who have rated the item *i* exist, then the prediction is based exclusively on the ratings of his *CF NNs*, and vice versa.

When combining the results of the partial predictions, as shown in equation (7), the algorithm presented in [5] uses the same $w_{CF}$and w_{SN}values for all users. Such a strategy, however, may be suboptimal, because the properties of the CF-based and SN-based neighborhoods of the different user may vary significantly, necessitating thus the use of personalized weight assignments. For instance, a user U_1may have a CF-based neighborhood of high cardinality and a SN-based one of low cardinality, indicating that for the particular user the CF neighborhood-based partial prediction should be assigned a higher weight than the SN neighborhood-based one. Conversely, for another user U_2 the inverse condition may hold, e.g. the similarities sim_{CF} between U_2 and his CF-based neighborhood may be close to 0.3, while at the same time the SN-based neighborhood of U_2 is of high cardinality, pointing to the use of a lower weight for the CF neighborhood-based partial prediction.

The algorithm proposed in this paper modifies equation (7) by catering for using personalized weights for the two partial predictions in the combination step. More specifically, the third case of equation (7), corresponding to the condition ($SN\_NN_{U,i} \neq \emptyset \wedge CF\_NN_{U,i} \neq \emptyset$) is modified as shown in equation (8):

$$\overline{r_U} + w^{CF}_U * p^{CF}_{U,i} + w^{SN}_U * p^{SN}_{U,i} \tag{8}$$

Regarding the computation of the personalized weights w^{CF}_U and w^{SN}_U, in this paper, we adopt the following approach: for each user U, we compute the values of w^{CF}_U and w^{SN}_Uthat minimize the rating prediction error for the ratings already entered for the particular user. More specifically, for each user U we iteratively hide each rating $r_{U,i}$ that U has entered in the database, and subsequently we compute the partial predictions $p^{CF}_{U,i}$ and $p^{SN}_{U,i}$ for the particular item, considering only the non-hidden ratings. Then, the rating prediction error for the particular prediction is:

$$err_{U,i} = r_{U,i} - (\overline{r_U} + w^{CF}_U * p^{CF}_{U,i} + w^{SN}_U * p^{SN}_{U,i}) \tag{9}$$

Finally, we try to find the values of w^{CF}_U and w^{SN}_U which minimize the overall rating prediction error for the predictions concerning user U. The overall rating prediction error may be expressed by any error metric, such as the Mean absolute error (MAE), the root mean squared error (RMSE), the mean absolute percent error (MAPE) [19], and so forth.

In the context of the present paper, we have targeted the minimization of the MAE metric. In order to compute the values of $w^{CF}_U$and w^{SN}_Uthat minimized the MAE, we iteratively explored the w_{CF} values {0.0, 0.1, 0.2, …, 1.0} and their respective complementary w^{SN}_Uvalues {1.0, 0.9, 0.8, …, 0.0}, under the constraint $w^{CF}_U + w^{SN}_U = 1.0$. The setting that achieved the lowest overall prediction error was then extracted, stored in the user's profile, and used for formulating predictions for the particular user.

The overall concept of the proposed approach is depicted in Fig. 1.

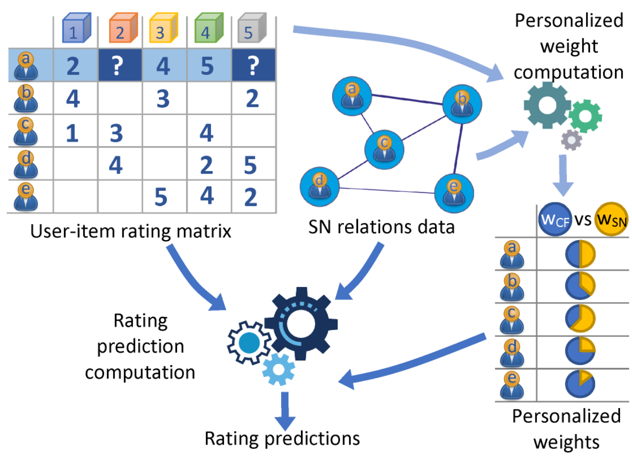

FIGURE 1. Overall concept of the proposed approach.

In the next section, we assess the performance of the proposed algorithm, in terms of prediction accuracy and overhead.

TABLE 1. Datasets summary.

Dataset name	#Users	#Items	#Ratings	Avg. #Ratings / User	Density	#Social Relations	Avg. #Social Relations / User	Type of Items	Type of Relations
Ciao [20]	30K	73K	1.6M	53.4	0.07%	40K	1.3	General	Trust
FilmTrust [21]	1.5K	2.1K	35K	23.5	1.13%	1.8K	1.2	Movies	Trust
Epinions [22]	49K	134K	665K	13.5	0.009%	487K	9.9	General	Trust
LibraryThings [23]	83K	506K	1.7M	20.5	0.004%	130K	1.6	Books	Trust
Dianping SocialRec 2015 [24]	148K	11K	2.1M	14.5	0.13%	2.5M	17	Restaurants	Friendship

IV. EXPERIMENTAL EVALUATION

In this section, we report on the experiments that were carried out to measure the prediction improvement both in terms of prediction accuracy and coverage, as well as the prediction process performance overhead, due to inclusion of the *SN NNs* in the rating prediction computation process. We note here that while the prediction computation is an online process (computing rating predictions for items, in order to make timely recommendations to users), the computation of the w_U^{CF} and w_U^{SN} coefficients, which incurs an additional processing cost, can be performed in an offline fashion or be offloaded to a different machine. While, theoretically, the values of w_U^{CF} and $w_U^{SN}$for any user U may change whenever a new rating is entered into the database, the magnitude of such change is small (or even zero, when the rating is entered by a user not belonging to $U's$ CF- or SN-neighborhood). Hence, the recalculation of these coefficients can be performed periodically, or whenever a significant number of new ratings have been entered in the database.

For our experiments we used a machine equipped with six Intel Xeon E7 - 4830 @ 2.13GHz CPUs, with 256GB of RAM and a 900GB HDD with a transfer rate of 200MBps, which hosted the datasets and ran the rating prediction algorithms.

In the remainder of this section, we present and discuss the results obtained from applying the algorithm presented above on five datasets [20]–[24]. The five datasets used in our experiments have the following properties:

- They contain both user-item ratings and social relations between SN users.
- They vary with respect to the type of dataset item domain (restaurants, movies, books music, etc.), size, CF-density and SN-density.
- They are up to date (published in the last 10 years) and are widely used for benchmarking in SN CF research.

Table 1 summarizes the basic properties of the considered datasets.

A. PREDICTION ACCURACY EXPERIMENTS

This subsection presents the experiments that focus on the measurements of the rating prediction improvement achieved by the proposed algorithm, due to the inclusion of the limited SN information, and compare it against (i) the SN RS algorithm presented in [5], which utilizes the same w_U^{CF} and w_U^{SN}weights for every user in each dataset, and (ii) the plain CF algorithm [2], which does not take into account the SN relations. The plain CF algorithm is used as a baseline. To quantify the rating prediction accuracy of the contending algorithms, we used two well-established and widely used in CF error metrics, namely the mean absolute error (MAE), which handles all errors uniformly, and the Root Mean Squared Error (RMSE) that amplifies the importance of high deviations between predictions and the ground truth (hidden ratings).

To compute the MAE and the RMSE prediction error metrics, we employed the standard ''hide one'' technique [2]: each time, we hide one rating in the database and then predict its value based on the ratings of other non-hidden items. Furthermore, both the Pearson Correlation Coefficient (PCC) and the Cosine Similarity (CS) similarity metrics are used in our experiments.

In our first experiment, random ratings of each user are hidden (5 rating selections per user) and then their values are predicted. To further validate our results, we conduct an additional experiment in every dataset containing the ratings' timestamps, where the last rating of each user in the database is hidden and then its value is predicted. The results of these two experiments were in close agreement (less than 3% difference in results) and therefore we report only on the results of the first experiment, for conciseness purposes.

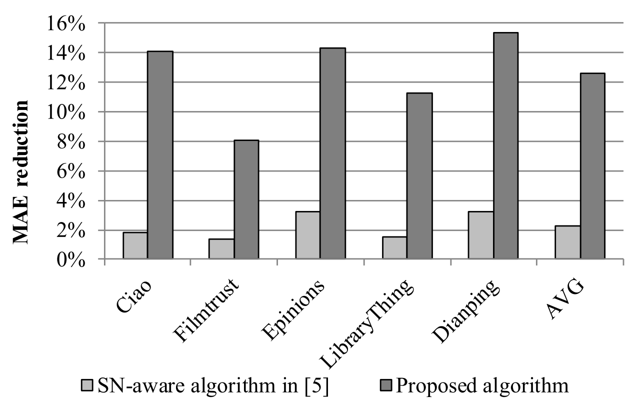

FIGURE 2. Reduction of the MAE for all datasets, using the PCC as the similarity metric.

1) EXPERIMENTS USING THE PEARSON CORRELATION COEFFICIENT

Fig. 2 illustrates the performance metrics regarding the MAE reduction when similarity between users is measured using the PCC. In Fig. 2 we can observe that the proposed algorithm achieves an average MAE reduction over all datasets equal to 12.6%, surpassing the corresponding improvement achieved by the algorithm presented in [5] (2.2%) by approximately 5.6 times. On the individual dataset level, the performance edge of the proposed algorithm against the algorithm presented in [5] ranges from 4.4 times higher for the "Epinions" dataset to 7.8 times higher, observed for the "Ciao" dataset. The lowest MAE improvement for the proposed algorithm is observed for the "Filmtrust" datasets (8.1%), which has the lowest $\frac{\#\text{Social Relations}}{\#\text{Users}}$ ratio among the five datasets (1.2). On the contrary, the highest MAE improvement for the proposed algorithm is observed for the "Dianping SocialRec 2015" dataset (15.3%), which has the highest $\frac{\#\text{Social Relations}}{\#\text{Users}}$ ratio among the five datasets (17.0). This fact demonstrates the capacity of the proposed algorithm to exploit the available SN information, in order to improve the prediction accuracy of the RS. Furthermore, we can observe that accuracy improvement achieved by the proposed algorithm is positively correlated to the density of available SN relations.

Fig. 3 demonstrates the performance metrics regarding the RMSE reduction when similarity between users is measured using the PCC.

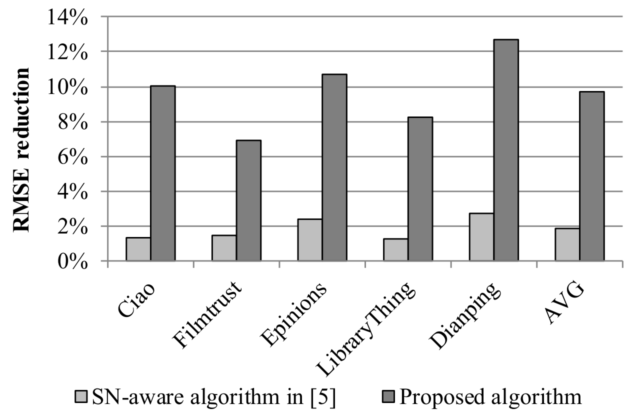

FIGURE 3. Reduction of the RMSE for all datasets, using the PCC as the similarity metric.

We can observe that the proposed algorithm achieves an average RMSE reduction over all datasets equal to 9.7%, surpassing the corresponding improvement achieved by the algorithm presented in [5] (1.8%) by approximately 5.3 times. On the individual dataset level, the performance edge of the proposed algorithm against the algorithm presented in [5] ranges from 4.4 times higher for the "Epinions" dataset to 7.5 times higher, observed for the "Ciao" dataset. The lowest and highest RMSE improvement, achieved by the proposed algorithm, are again observed for the "Filmtrust" and "Dianping SocialRec 2015" datasets (6.9% and 12.7%, respectively). As noted above, these datasets have the lowest and highest $\frac{\#\text{Social Relations}}{\#\text{Users}}$ ratios, respectively, among the five datasets used in the experiment. This fact reasserts that the proposed algorithm can successfully exploit the SN information available, in order to improve the RS's prediction accuracy, and the magnitude of the improvement is positively correlated to the density of available SN relations.

2) EXPERIMENTS USING THE COSINE SIMILARITY METRIC

Fig. 4 illustrates the performance metrics regarding the MAE reduction when similarity between users is measured using the CS metric.

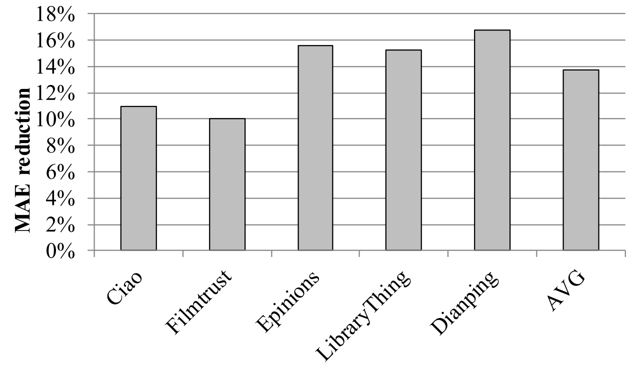

FIGURE 4. Reduction of the MAE for all datasets, using the CS as the similarity metric.

This graph does not include measurements regarding the accuracy improvements achieved by the algorithm presented in [5], since that publication does not report on the algorithm accuracy improvement under the CS metric.

We can observe that the proposed algorithm achieves an average MAE reduction of 13.7% over all datasets. The lowest MAE improvement for the proposed algorithm is again observed for the "Filmtrust" datasets (10%), while the highest MAE improvement for the proposed algorithm is again observed for the "Dianping SocialRec 2015" dataset (16.8%). Again, that accuracy improvement achieved by the proposed algorithm is positively correlated to the density of available SN relations.

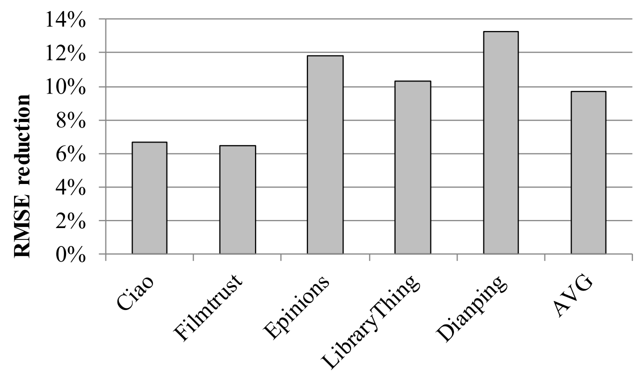

FIGURE 5. Reduction of the RMSE for all datasets, using the CS as the similarity metric.

Finally, Fig. 5 illustrates the performance metrics regarding the RMSE reduction when similarity between users is measured using the CS metric. We can observe that the proposed algorithm achieves an average RMSE reduction of 9.7%

over all datasets. The lowest and highest RMSE improvement, for the proposed algorithm, are again observed for the "Filmtrust" and the "Dianping SocialRec 2015" datasets (6.5% and 13.3%, respectively).

B. COVERAGE INCREASE ASSESSMENT

This subsection presents the experiments that focus on the quantification of rating prediction coverage improvement achieved by the proposed algorithm. Fig. 6 depicts the coverage increase achieved by the proposed algorithm, using the coverage of the plain CF algorithm as a baseline. We can observe that the coverage increase attained by the proposed algorithm ranges from 3.8% (for the case of the LibraryThing dataset) to 32.3% (for the case of the Epinions dataset), with an average of 10.13%.

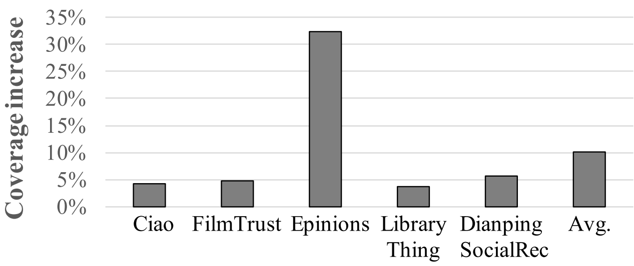

FIGURE 6. Coverage increase achieved by the proposed algorithm, compared to the one presented in [5] using the plain CF algorithm as a baseline.

These improvements are identical to the ones achieved by the algorithm proposed in [5]. This is expected, since both algorithms exploit the social relationship data to enhance the information from the user-item rating database in a structurally similar fashion. Nevertheless, the algorithm proposed in this paper uses a more elaborate method to calculate the weights assigned to the CF and SN dimensions, thus achieving higher rating prediction accuracy while maintaining the coverage increase.

C. PERFORMANCE EVALUATION

This subsection discusses the experiments that aimed to measure the overhead introduced to the prediction computation process, due to inclusion of the SN NNs. As noted above, this measurement does not include the computation of the per-user w_U^{CF} and w_U^{SN} coefficients, which will be performed in an offline fashion.

Fig. 7 depicts the total time needed by the plain CF algorithm and the proposed algorithm to compute varying numbers of predictions. The measurements depicted in Fig. 7 correspond to the findings from the "Dianping SocialRec 2015" dataset, which is the "densest" SN dataset among the 5 datasets tested (avg. #Social Relations / User = 17), and consequently the performance overhead introduced by the proposed algorithm is larger. Hence, the performance metrics in Fig. 7 correspond to a "worst case scenario" (among the used datasets) for the proposed algorithm.

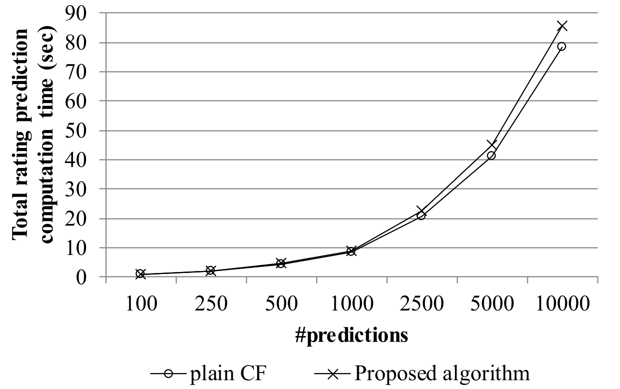

FIGURE 7. Recommendation formulation overhead due to the inclusion of the SN NNs.

In Fig. 7 we can observe that the performance overhead sustained due to the consideration of the SN-based neighborhood ranges from 7% to 9%. Considering the improvement in rating prediction accuracy, this overhead is deemed small to tolerable. In absolute numbers, the proposed algorithm formulates rating predictions in less than 9msec for all cases, which indicates that the proposed algorithm can be effectively used for the formulation of timely recommendations in the context of interactive SNs.

Fig. 8 illustrates the algorithm scalability when hardware parallelism is exploited. The measurements presented in Fig. 8 are averaged over all five datasets.

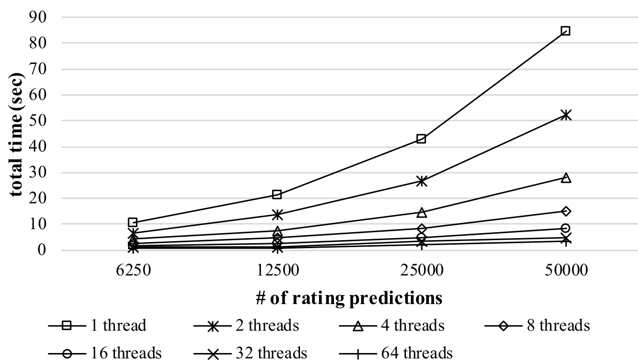

FIGURE 8. Algorithm scalability considering hardware parallelism.

According to the results shown in this figure, we can observe that the time required to compute a number of predictions is reduced by 40% approximately when the number of threads is doubled, provided that an adequate number of underlying hardware cores exist. The reduction is lower than the theoretical value of 50%, owing primarily to memory bus contention. Through the exploitation of the 64 cores of the hardware on which the experiments were run, a throughput of approximately 15,000 predictions/sec was achieved, which is deemed satisfactory. For large-scale SNs, such as Facebook or Twitter, multiple machines may be employed to accommodate higher throughputs.

D. STATISTICAL DISTRIBUTION OF OPTIMAL WEIGHTS

In this subsection we report on our findings regarding the statistical distribution of the per-user optimal weights (w_U^{CF} and w_U^{SN}) computed by the algorithm.

Fig. 9 illustrates the statistical distribution of the w_U^{CF}weight (recall from section III, that, for each user U, $w_U^{CF} + w_U^{SN} = 1.0$, therefore the inverse observations hold for w_U^{SN}).

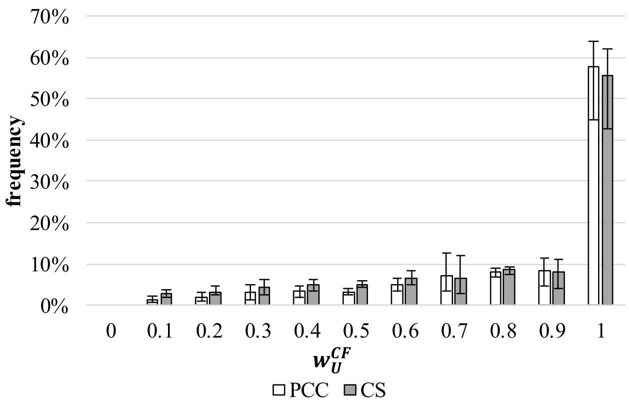

FIGURE 9. Optimal weights frequency, in both similarity metrics.

In Fig. 9, we can observe that under both similarity metrics, in 42%-64% of the cases (55%-58% on average), the optimal $w_U^{CF}$is found to be close to its largest value, 1.0. This is true for the cases where the user's social neighborhood is limited in size or it cannot contribute to the calculation of recommendations for the user, due to the lack of common ratings. This is affirmed by the fact that the w_U^{CF} has been found to obtain higher values in datasets with a small average number of social relations per user, such as the Ciao and the FilmTrust datasets. On the contrary, in datasets where the average number of social relations per user is higher (e.g. Epinions and Dianping SocialRec 2015), the values assigned to w_U^{CF} decrease, in favor of the corresponding w_U^{SN}values. The error bars in Fig. 9 indicate the minimum and maximum values of the respective measures across all datasets. A more thorough investigation of this phenomenon is part of our future work.

V. CONCLUSION AND FUTURE WORK

In this paper, we presented an effective algorithm which combines CF information, concerning users' ratings on items, with SN information, concerning users' social relations. As a result, the proposed algorithm has the ability to adapt its behavior to the density and utility of each individual user's CF- and SN-based neighborhood. To achieve this, the algorithm formulates two partial prediction scores, from the CF and the SN neighborhood, and then combines these two partial predictions using a weighted average metascore combination technique, where the weights are personalized for each individual user. The computation of the personalized weights is done by finding the weight values that achieve the smallest prediction error when tried to predict all the user's available-past ratings in the database. The algorithm refines the approach employed in the algorithm presented in [5], which employs the same weights for all users in the dataset. The presented refinement has been shown to lead to increased rating prediction accuracy.

The presented algorithm was validated through a set of experiments, that aimed to quantify the improvement obtained in prediction accuracy, and measure the overhead introduced in the rating prediction computation process, due to the consideration of the *SN NNs* in the recommendation process. In these experiments, five datasets containing both CF information (user-item-rating) and SN information (user-user-relation) were used, and measurements were taken under two similarity metrics widely used in RSs, namely the PCC and the CS. Additionally, two types of social relations, trust (directed) and friendship (undirected), were considered to examine the behavior of the proposed algorithm in a multitude of parameters. The algorithm has proven to successfully adapt to the characteristics of the dataset, yielding promising results in all cases.

The evaluation results have shown that the presented algorithm provides substantial improvement in rating prediction quality, across all datasets. More specifically, the presented algorithm achieves a MAE reduction of 12.6% and a RMSE reduction of 9.7% on average, as far as the PCC metric is concerned, and by 13.7% and 9.7%, respectively, as far as the CS metric is concerned. In both cases, the performance of the plain CF algorithm is considered as a baseline. Furthermore, the proposed algorithm outperforms the algorithm proposed in [5] in all cases, by 5.5 times on average.

In regard to the rating prediction computation overhead due to the inclusion of the *SN NNs*, this has been quantified to be less than 9% in all cases, when compared to the plain CF algorithm, even when applied to a relatively "dense" SN dataset. The above results clearly indicate that the presented algorithm achieves considerable rating prediction accuracy gains, while the incurred performance penalty is low.

The presented algorithm requires the availability of typical CF information (i.e. a user-rating matrix), as well as typical social relation information (bidirectional friendships or unidirectional trusts), necessitating no additional information, such as user demographic information (age, gender, nationality, location, etc.), item characteristics (price, category, reliability, etc.) or SN contextual information (tie strength, influence, etc.).

Furthermore, the proposed algorithm:

1) can be bootstrapped in an offline fashion, to compute the users' CF and SN weights,
2) exhibits high performance and rating prediction throughput regarding its online phase, within which rating predictions are computed based on the CF and the SN neighborhood of the users,
3) requires limited extra storage space (only the CF-based weight value per user, while the SN-based weight can

be directly computed from the CF-based weight, since their sum equals to 1.0),

4) it is relatively easy to implement, through the modification of an already existed CF-SN RSs and
5) it can be easily combined with other RSs algorithms, which have been proposed in the literature, for either improving rating prediction accuracy or coverage.

Our future work will focus on investigating the computation-tuning of the $sim(U,V)_{SN}$ parameter value, considering additional information derived by the *SNs* domain (such as users' influence, tie strength, common-mutual relations, demographic data, contextual information, etc.). Furthermore, we are planning to evaluate the presented algorithm under additional user similarity metrics, such as Hamming Distance, Spearman Coefficient, Cosine Similarity and Euclidean Distance [2], where those are proposed by the literature as more suitable for the additional information.

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