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Neighbourhood Aging Factors for Limited Information Social Network Collaborative Filtering

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***Abstract*— Businesses benefit by recommender systems since the latter analyse reviews and ratings of products and services, providing useful insight of the buyer perception of them. One of the most popular, successful and easy-to-build recommender system techniques is collaborative filtering. Recommender systems take into account social network information, to achieve more accurate predictions. Unfortunately, however, many applications do not have full access to such "rich" information, so they have to properly manage the limited information, which, in the worst case, is comprised of just the user relationships in the social network. A social network collaborative filtering system combines the two sources of information, in order to formulate rating predictions which will lead to recommendations. However, the vast majority of users change their tastes, as time goes by, a phenomenon termed as concept drift, and in order for a recommender system to be successful, it must effectively face this problem. In this paper, we present a social network collaborative filtering rating prediction algorithm that tunes the weight-importance of each source of information based on the age of the information. The proposed algorithm considerably improves rating prediction accuracy, while it can be easily integrated in social network collaborative filtering recommender systems.**

Keywords—Social Networks, Personalization, Recommender Systems, Collaborative Filtering, Concept Drift, Business, Prediction Accuracy

I. Introduction

The success of a business is based, to a large extent, on how easily it can retain its existing customers, as well as attract new customers online. However, the information available on the internet is chaotic, so the business itself must ensure that the intended message "reaches" its potential customers. In this direction, businesses can adopt and make use of the extensive research that has been done in the field of personalization, since, the more personalization techniques they adopt and use, the more appealing to their clients they seem to be [1-4]. One of the most popular, successful and easy-to-build personalization techniques is collaborative filtering (CF).

In CF, in order to generate a recommendation, a positive rating prediction must be formulated for an item. In order to do so, the opinion of users that are close to the original user (users with similar tastes, concerning their past experienced items) must be taken into account. These users, termed as *near neighbour users (NN)*, formulate the set of the *user's CF neighbourhood* [5-8].

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Nowadays, in order to gather data concerning their potential clients, some recommender systems (RSs) may use social network (SN) information, concerning users, items, locations and activities [9-12]. While in many cases the aforementioned SN information may be extremely "rich" in information, in some cases it is proven to be relatively poor, consisting only of the users' relationships within the social network (formulating each user's *SN neighbourhood*) [13,14].

In a limited information SN CF recommender system, each of the two aforementioned neighbourhoods formulate a (partial) prediction and then these are combined in order to produce the final one [13,14].

Another problem that all RSs face, is that users tend to change their likings and tastes, as time goes by, a phenomenon termed as "concept drift" [15-18]. This phenomenon does not only lead to change of interests but also to change of neighbours for each user, the same way that, in real life, a person rarely trusts at present the same people who used to trust 5 or 10 years ago. As a result, a RS must handle two near neighbour users of a user U, V1 and V2, differently, where the V1 is considered as U's NN based on items that he has rated 5 years ago and V2 on items that he has rated 1 week ago. While many research works that address either the limited SN CF information [13,14] or the concept drift phenomenon [19-22], individually, exist, research concerning concept drift in limited information SN CF is extremely poor.

In this paper, we (1) present a limited information SN collaborative CF rating prediction algorithm that tunes the weight-importance of each partial prediction based on how aged, on average, the ratings used for formulating this partial prediction actually are and (2) evaluate the aforementioned algorithm, in terms of prediction accuracy, using widely used limited information SN CF datasets.

Notably, in our experiments we use two datasets where:

- the one contains many SN relations (i.e. edges in the SN graph), while the other contains few SN relations [23];
- the one contains user ratings on movies, while the other contains user ratings on restaurants [24];
- the one contains undirected SN edges (friendship), while the other contains directed edges (trust) [25].

The rest of the paper is structured as follows: section 2 overviews the related work, while section 3 reports on the algorithm prerequisites that are used in our work. Section 4 presents the proposed prediction algorithm, while Section 5 evaluates it, in terms of prediction accuracy. Finally, section 6 concludes the paper and outlines future work.

II. Related Work

Nowadays, the most successful recommender systems take advantage of information derived from social networks [26-29]. The more social network information available, the more successful suggestions are formulated to the users [62,63]. This information includes many features for both users and items to be recommended, information that may have been given explicitly or implicitly.

However, when combining two sources of personalized information, such as the CF neighbourhood and the SN neighbourhood of a SN CF recommender system, appropriate algorithms are needed that can successfully support this combination, in order to produce successful recommendations [64].

Towards this direction, Capdevila et al. [30] introduce a hybrid RS for location-based SNs, termed as GeoSRS, where SN users can write short text reviews about places of interest that have visited in the past. The presented RS uses both geographical location and text mining information in order to recommend locations.

Margaris et al. [31] present a query personalization algorithm, which reorders the data (query results) projected to the user by (1) integrating SN influence information in the query adaptation process and (2) taking into account the browsing and rating information of items by users.

Yan et al. [32] present an approach for the complexity management from adding social relation networks to RSs. The aforementioned method, with the use of a fitting algorithm of relationship networks, generates an individual relationship network for each item and user, in order to control the relationship propagation and contracting. Subsequently, individual relationship networks are regularized by taking into account the taste diversity between relationship members, in order to capture the time-evolving nature of tastes and emphasize the aspect of homophily. Finally, in order to generate recommendations, the regularized individual relationship networks are fused into a matrix factorization (MF) algorithm.

Pham et al. [33] analyse the correlations between SN relations and user interest similarities, to build a SN RS using memory-based CF models with user-oriented methods. They also employ sentiment analysis techniques in order to identify, for each user, the top-K favourite products, which is exploited by the social RS in the rating prediction computation process.

Chamoso et al. [34] present a business and employment-oriented SN RS. This RS extracts the information needed from the SN and utilises it for new job offers and contracts recommendation to its users. The presented RS utilizes information mined from job offer descriptions, user profiles and user activities and then, new ties, which are likely to become relationships, are discovered by the application of relative metrics integrated in the RS.

Amato et al. [35] introduce a user-centred RS algorithm for recommendations for big data applications. The algorithm processes interactions between the users and the multimedia content, generated in a single or more than one SN.

Ma et al. [36] propose a SN relationship- and geographic information-based CF algorithm which addresses low accuracy/efficiency and raw data sparsity. The proposed algorithm manages to reduce sparsity, firstly by storing complementary social relation data into the user-item rating matrix and, secondly, by filtering it using user geographic information. The aforementioned process improves the data complementation accuracy, as well as manages to reduce the data complementation error.

Margaris et al. [14] introduces an algorithm which is able to combine limited CF information, comprising only of users' ratings on items, with limited SN information, comprising only of users' social relations, for formulating SN CF rating predictions. The presented algorithm effectively achieves to improve both prediction accuracy and prediction coverage in CF RSs.

Another major problem that recommender systems face is concept drift, which was mentioned in the previous section, where important research work has been done to address it.

Ang et al. [37] develop an approach, termed as PINE, which is able to combines reactive adaptation, via drift detection, and handling of future changes via early warning, in order to address the adaptation problem in the case of asynchronous external changes. Additionally, the presented approach is parameter-insensitive, achieves higher accuracy and reduces communication cost.

Lo et al. [38] present a Temporal Matrix Factorization approach in order to address concept drift in each individual user preferences. In order to do so, they construct a time series of rating matrices from the ratings database and use the time series in order to capture the concept drift dynamics for each individual user and finally, they use the captured dynamics in the rating prediction computation phase.

Margaris and Vassilakis [39] propose an algorithm which computes dynamic averages concerning users' ratings, in order to follow the users' marking practices shifts, for overcoming the concept drift phenomenon. Furthermore, a comparative evaluation, concerning dynamic average-based CF algorithms, is performed and the results show that these types of algorithms exhibit better performance than the plain CF algorithm in terms of rating prediction accuracy, albeit with a small drop in rating prediction coverage.

Gama et al. [40] add incremental concept drift, which consists of intermediate concepts in between, and reoccurring concepts (i.e. new concepts that, either have been previously seen and may reoccur after some time, or have not been seen at all in the past), in order to extend the patterns of changes in RSs.

Liu et al. [41] present an Anomaly Analysis Drift Detection (AADD) method which, based on anomaly analysis of learner's accuracy, associated with the similarity between learners' training domain and test data, (1) manages to achieve concept drift detection and (2) improves the performance of non-stationary environment machine learning algorithms.

Ning et al. [42] introduce a method for detecting concept drift in a case-based reasoning system. They present a competence model that is able to detect differences through changes in competence. The presented detection method provides statistical guarantees on the reliability of the changes detected, as well as requires no prior knowledge of case distribution.

Liu and Aberer [43] present a context-aware RS, termed as SoCo, which incorporates elaborately processed information derived by SNs. SoCo groups the ratings with similar contexts, by handling contextual information with the use of random decision trees to partition the user-item rating matrix.

However, none of the aforementioned works can effectively support limited SN information combined with limited CF information, for a rating prediction formulation, and at the same time copy with concept drift phenomena.

This paper extends the work in [14], by introducing a limited information SN CF rating prediction algorithm which tunes the weight-importance of each partial prediction based on how aged, on average, the ratings used for formulating this partial prediction actually are, in order to effectively overcome concept drift phenomena within SN CF recommender systems neighbourhoods.

III. SN CF Prediction Formulation Foundations

In CF, in order to formulate a rating prediction, the opinion of close users, to the user whose rating is being formulated, must be taken into account [44,45]. This set of users, which formulates the user's CF neighbourhood, is termed as NN users.

In order to measure the closeness between two users U1 and U2, in CF systems, a similarity metric must be used (sim_{CF}), where in most of the cases, this metric is the Pearson Correlation Coefficient (PCC), defined as:

$$sim_{CF}(U1,U2) = PCC(U1,U2) = \frac{\sum_k (r_{U1,k}-\overline{r_{U1}})*(r_{U2,k}-\overline{r_{U2}})}{\sqrt{\sum_k (r_{U1,k}-\overline{r_{U1}})^2 * \sum_k (r_{U2,k}-\overline{r_{U2}})^2}} \quad (1)$$

where k is the set of the commonly rated items by both users *U1* and *U2*, while $\overline{r_{U1}}$ and $\overline{r_{U2}}$ are the average values of all the ratings belong to users *U1* and *U2,* respectively, in the rating database.

Having the active user's *U*'s NNs in hand, the final CF step is to formulate the prediction, using the following prediction formula:

$$p^{CF}_{U,i} = \overline{r_u} + \frac{\sum_{V \in NN_u} sim_{CF}(U,V)*(r_{V,i}-\overline{r_V})}{\sum_{V \in NN_u} sim_{CF}(U,V)} \quad (2)$$

where the $p^{CF}_{U,i}$ is the CF prediction to be formulated, for the rating of user *U* on item *i*,

Similarly, to the SN prediction formulation, following the work in [14], which presented the *SN NN*s concept of a user (based on the existence of a social relation, such as friendship or trust, between two SN users), the following formula produces the SN partial prediction:

$$p^{SN}_{U,i} = \frac{\sum_{V \in SN\_NN_{U,i}} sim_{SN}(U,V)*(r_{V,i}-\overline{r_V})}{\sum_{V \in SN\_NN_U} sim_{SN}(U,V)} \quad (3)$$

where the $p^{SN}_{U,i}$ is the SN prediction to be formulated, for the rating of user *U* on item *i*.

In contrary to the computation of the $sim_{CF}(U1, U2)$, which is based on the PCC metric, in order to quantify the similarity between two SN users, $sim_{SN}(U1, U2)$, we follow the approach presented in [14], where in the absence of a specific weight/strength of the relationship between two SN users *U1* and *U2*, the $sim_{SN}(U1, U2) = 1.0$. Obviously, if the SN dataset provides a specific $sim_{SN}(U, V)$ value, this one is used.

The last step of producing a SN CF prediction is to combine the aforementioned partial predictions (i.e. the $p^{CF}_{U,i}$ and the $p^{SN}_{U,i}$). Following the work in [14] we use a metasearch score combination algorithm in order to combine the two partial prediction scores, $p^{CF}_{U,i}$ and $p^{SN}_{U,i}$, shown in the following equation:

$$p_{U,i} = \begin{cases} \overline{r_U} + p^{CF}_{U,i}, & if SN\_NN_{U,i} = \emptyset \\ \overline{r_U} + p^{SN}_{U,i}, & if CF\_NN_{U,i} = \emptyset \\ \overline{r_U} + w_{CF} * p^{CF}_{U,i} + w_{SN} * p^{SN}_{U,i}, & if SN\_NN_{U,i} \neq \emptyset \wedge \\ & CF\_NN_{U,i} \neq \emptyset \end{cases} \quad (4)$$

where the w_{CF} and the w_{SN} parameter (complementary values, i.e. $w_{SN} + w_{CF} = 1.0$) indicate the weight assigned to the $p^{CF}_{U,i}$ and the $p^{SN}_{U,i}$ (partial) predictions, respectively.

As expected, if the item for which a prediction is being formulated has not been rated by any CF NN, then the final prediction is equal to the $p^{SN}_{U,i}$ partial prediction and vice versa.

TABLE I. DATASETS SUMMARY

Dataset name	#Users	Relations Types	#Social Relations	#Items	Items types	#Ratings
Ciao [50]	30,000	Trust	40,000	73,000	Movies	1,600,000
DianpingSocialRec 2015 [51,52]	148,000	Friendship	2,500,000	11,000	Restaurants	2,100,000

As can be seen by equation (4), the algorithm introduced in [14] uses the exact same weights for the two partial (CF and SN) predictions, in order to formulate the final one, for all the users in the dataset, ignoring the oldness of the relationships between the user and his CF neighbourhood and SN neighbourhood actually are (i.e. how old the ratings, of the commonly rated items by the user's NNs, are).

In the following section, an algorithm that tackles the aforementioned problem is proposed. The proposed algorithm is able to adapt its behavior by taking into account how old each user's neighborhoods' ratings are and effectively tuning the weights of the partial predictions, assigning a higher value to the "fresher" ones.

IV. THE PROPOSED ALGORITHM

The algorithm introduced in this paper modifies formula (4) presented in the previous section, by catering for the use of personalized aging weights (*aging factors*) for the two partial predictions, $p_{U,i}^{CF}$ and $p_{U,i}^{SN}$, for the combination step, based on the oldness of the ratings set to item *i* by each partial neighbourhood.

More specifically, in the first step of the algorithm, the two aging factors (AFs) are computed, following the approach presented in [46], using the min-max normalization formula:

$$AF_{X,i} = \frac{\underset{u \in X\ NNs}{\text{avg}}\,(\text{t}(r_{u,i})) - \min\,(t(r_{any_{user},i}))}{\max\,(t(r_{any_{user},i})) - \min\,(t(r_{any_{user},i}))} \qquad (5)$$

where X = {CF, SN}, $t(r_{u,i})$ is the timestamp of rating $r_{u,i}$, $\underset{U \in X\ NNs}{\text{avg}}(\text{t}(r_{u,i}))$ is the average timestamp value among all ratings concerning users who belong in the specific NN set (either CF or SN) to item *i*, $\min(t(r_{any_{user},i}))$ and $\max(t(r_{any_{user},i}))$ the minimum and maximum timestamp in the database among ratings entered concerning the item *i*, respectively (simulating item's *i* lifetime, as proposed in [48]).

Since the two AFs (the AF_{CF} and the AF_{SN}) must be complementary with one another (i.e. $\text{AF}_{\text{SN}} + \text{AF}_{\text{CF}} = 1.0$), the two AFs are again normalized, using the following standard normalization formula:

$$AF_{CF,i} = \frac{AF_{CF,i}}{AF_{CF,i} + AF_{SN,i}}$$
$$AF_{SN,i} = \frac{AF_{SN,i}}{AF_{CF,i} + AF_{SN,i}} \qquad (6)$$

In the next section, the performance of the presented algorithm will be quantified, in terms of rating prediction accuracy, in limited information SN CF datasets.

V. PERFORMANCE EVALUATION

In this section we report on the experiments that are designed in order to assess the rating prediction improvement achieved by the presented algorithm, in terms of the Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE) metrics.

In order to compute the MAE and the RMSE, we employed the standard "hide one" technique [47,53], where one rating of one user is hidden and is predicted, each time, based on the ratings of other non-hidden items.

The results are compared against the results from:

1. The limited information SN CF algorithm introduced in [14], which is able to cope with limited CF and SN information, however, it sets the exact same weights to the partial (CF and SN) predictions for all the users in each dataset (this algorithm will be denoted as *same_weights*);
2. The plain CF algorithm [5,48], which does not take into account the SN relations the two datasets contain and hence is used as a yardstick.

For hosting the datasets and running the rating prediction algorithms, we used a PC equipped with a quad core Intel N5000@1.1GHz CPU, 8GB of RAM and one 256GB SSD with a transfer rate of 560MBps.

In the experiments we have used two datasets which exhibit the following properties:

1. They contain user ratings on items, including their timestamps, as well as SN user relations;
2. They vary with respect to the type of dataset item domain (movies and restaurants), and number of social relations;
3. They are widely used for benchmarking in SN CF research and they are up to date; published in the last 10 years.

The basic attributes of the considered datasets are summarized in Table 1.

In order to validate our results, two experiments were conducted:

1. In the first one, the value of each user's last rating was hidden and tried to be predicted;

2. In the second one, the last rating of each user was dropped, and then the new last (the rating initially ranked as second to last) was hidden and predicted, as well, following the work in [49].

Due to the close agreement of the aforementioned two experiments' results (less than 1% result difference) and for conciseness, the results of the first experiment only are reported.

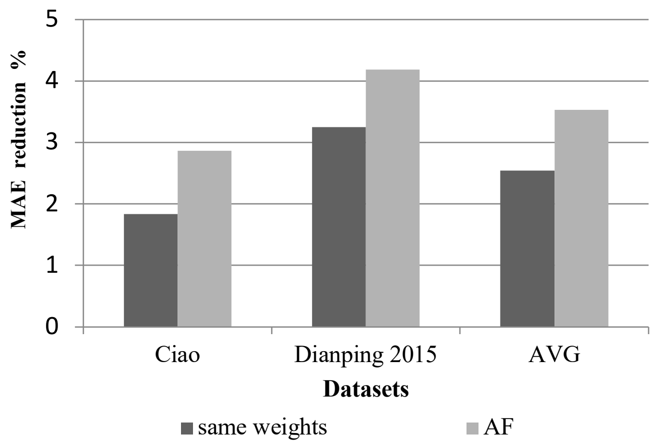

Fig. 1. MAE reduction achieved by the proposed algorithm for the two datasets tested.

The performance measured by the MAE reduction is demonstrated in Fig. 1. We can observe that the proposed algorithm (termed as AF in Fig. 1 and Fig. 2) is the one achieving the best results for both the datasets tested. More specifically, the average MAE reduction achieved over the two datasets equals to 3.53%, approximately 39% bigger than the corresponding improvement achieved by the *same_weights* algorithm (2.54%) presented in [14].

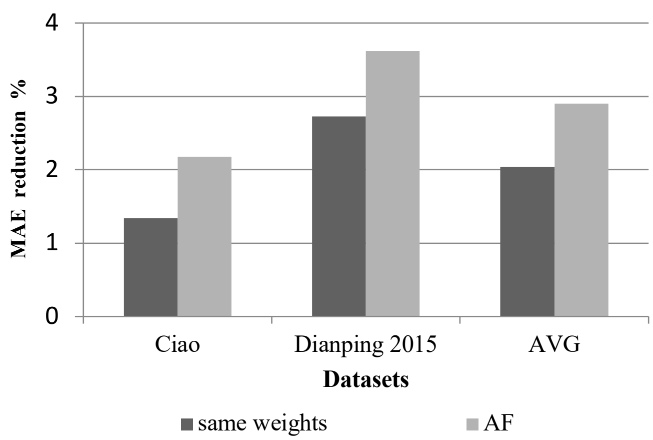

Fig. 2. RMSE reduction achieved by the proposed algorithm for the two datasets tested.

The performance measured by the RMSE reduction is demonstrated Fig. 2. We can observe that the proposed algorithm, again, achieves the best results for both the datasets tested. More specifically, the average RMSE reduction achieved over the two datasets equals to 2.9%, approximately 43% bigger than the corresponding improvement achieved by the *same_weights* algorithm (2%) presented in [14].

VI. Conclusion And Future Work

In this paper, we proposed a simple, yet effective algorithm that effectively combines limited CF information, concerning users' ratings on items, with limited SN information, concerning users' social relations. It takes into account the relative oldness of each user's neighbourhood (CF and SN) that takes part in the prediction, in order to improve prediction accuracy in SN CF RSs. The presented algorithm uses a weighted average metascore combination approach that combines the two partial prediction rating scores, formulated separately by the SN and the CF neighbourhoods. It sets the aging factors in these two scores, based on the relative time of the ratings concerning the item for which the user prediction is formulated, of each neighbourhood.

The proposed algorithm has been validated through a set of experiments, aiming to quantify the obtained gains in prediction accuracy, gain insight on the effect that this combination has in the rating prediction quality.

In these experiments, two datasets containing both CF information (user-item-rating-timestamps), and SN information (user-user-relation) and using two types of social relations, directed (trust) and undirected (friendship), were used to examine the behaviour of the proposed algorithm in this category of datasets. The evaluation results have shown that the proposed algorithm may provide substantial improvement on rating prediction quality, across all datasets. The MAE decreases by 3.5% and the RMSE declines by 2.9%, on average, surpassing by approximately 40% the corresponding improvements achieved by the *same_weights* algorithm presented in [14]. In both cases, the performance of the plain CF algorithm is taken as a baseline.

The proposed algorithm requires no additional information derived either from the CF or the SN data information sources, such as items' characteristics (e.g., category, colour, price and size), users' demographics (e.g. gender, age and location) or SN's contextual information (e.g. influence, tie strength and group membership) and, hence, can be easily applied to almost every SN CF system [54,55].

Our future work will focus on investigating more aging factors concerning the oldness of the ratings in the database, Furthermore, we are planning to tune the $sim(U1, U2)_{\mathrm{SN}}$ similarity parameter value, considering additional information derived from the SNs domain, such as social circles [56-58] and textual reviews [59-61]. Last, we are planning to evaluate the presented algorithm under additional user similarity metrics, such as the Euclidean Distance, the Hamming Distance, and the Spearman Coefficient [65,66] for the cases which those metrics are proposed by the literature as more suitable for the additional information.

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