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.

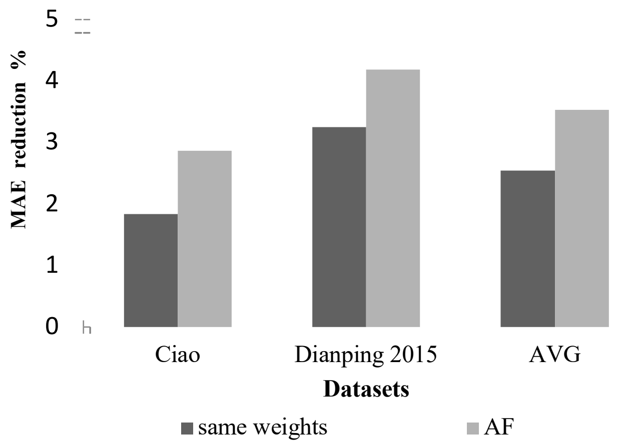

Fig. 1. MAE reduction achieved by the proposed algorithm for the two datasets tested.

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].

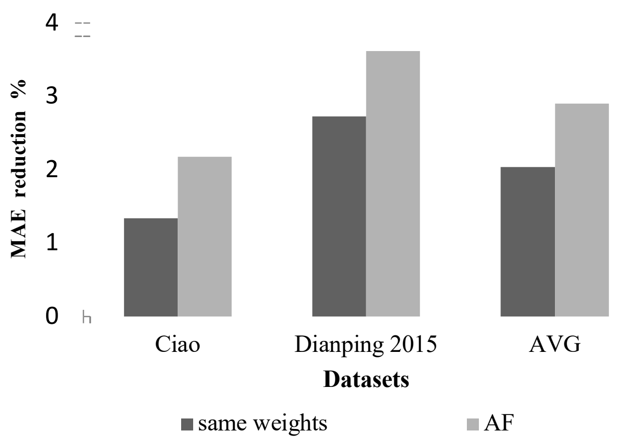

Fig. 2. RMSE reduction achieved by the proposed algorithm for the two datasets tested.

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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