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Consensual Recommender Systems

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Abstract: Recommender systems (RS) have proven their effectiveness in supporting personalised purchasing decisions. Collaborative filtering (CF) is the most widely used operational basis of RSs. Leading to lower accuracy of recommendations, CF suffers, however, from the scalability and the sparsity problems. As a remedy, the concept of consensual recommender systems (C-InCF) is proposed. To deal with on-line data, C-InCFs create models incrementally applying incrementally learning CF. Then, C-InCFs take the social connections of group members expressed by rating-weighted networks into consideration. To this end, either points of agreement between the group members are determined by the average consensus protocol. Real-world decision problems usually depend on multiple criteria, and not just a single one. Hence, C-InCFs take multi-criteria ratings into account in contrast to most recommender systems considering only ratings of one criterion. Multi-criteria ratings possibly raise, however, conflicts in the recommendation phase, which are dealt with by seeking Pareto-optimal solutions. Finally, the C-InCF concept is empirically evaluated with an artificial dataset indicating better performance than existing CF methods.

1 Introduction

Recommender systems were proposed several decades ago to provide personalised recommendations out of many possible choices, which are based on records of the previous behaviour of persons (called users) [1, 18]. The technique most successfully applied as operational basis of recommender systems is collaborative filtering (CF) [18]. Nevertheless, CF still suffers from two major problems, which are scalability and sparsity.

Scalability problem: when a search is conducted following the inclusion of new users and new items in all the user-item rating matrices, the corresponding computational overhead results in poor scalability [20].

Sparsity problem: when the number of user ratings is very small compared to the number of user ratings that need to be predicted [20], prediction accuracy fails and predictions are insignificant.

To deal with the scalability problem, designing and developing models can allow systems to learn in order to capture the complexity of user-item matrices and, then, make intelligent predictions based on the models learnt. We orientate ourselves at the advantages of model-based CF with a learning algorithm for model creation, which leads to higher prediction accuracy, but without a need to search whole user-item rating matrices when grouping users into models [6]. Design and creation of models are based on statistical and machine learning techniques. An example for the former is probabilistic latent semantic analysis [6], and clustering [14, 17] is one for the latter. Models constructed by these techniques are used to predict interested users' ratings of particular items.

For setting up models in model-based collaborative filtering, clustering is an intermediate step. The clusters generated by clustering algorithms are used for further analyses and prediction purposes [20]. There are several clustering algorithms employed for model-based collaborative filtering such as K-nearest neighbours (K-NN), hierarchical, density-based and K-Means clustering [20]. In our experimental comparison presented below, K-Means and K-NN are used as part of model creations, as they are the simplest methods for pattern classification based on similarity measurement (e.g. using the Euclidean distance) to compute distances between users. Furthermore, incremental collaborative filtering based on the Mahalanobis distance [9] and fuzzy membership, as proposed in [7], is also used for comparative study.

To deal with the sparsity problem, social relationships among users are a promising aspect, which was considered by many researchers in order to improve accuracy and efficiency of CF techniques. In daily life, as part of their communication members of human communities typically recommend items to each other. Items could be things for living, such as pieces of cloths. To capture this, we consider the characteristics of social networks as follows [3, 21]. Users and their relationships are represented by unidirectional graphs, in which users give rise to nodes and connection links between users and their neighbours to edges. User preferences are taken into account in form of similarity matrices.

Since social connections among users are created based on rating values which are, in turn, derived from a model generated by an incremental model-based CF technique, we consider the agreement in each group of the model. In [12], network-based distributed decision making systems were discussed. To find an agreement between the members of a group, they need to interact with each other on a certain quantity of interest. They reach agreement by finally adjusting their mutual decision states. A consensus protocol is an interaction rule that specifies the information exchange between group members and their neighbours in order to reach group agreement.

Concerning local information exchange, the information available to group members consists of the initial decision stage and the degree of connection. To apply the consensus concept to recommender systems, we draw on the following analogy to multi-agent systems: (i) members or users are identified with agents, (ii) multi-criteria ratings of users are identified with the initial stage values of agents, and (iii) the degree of connection is identified with preferential attachment concept of scale-free networks. Note that only static social networks are considered in this paper.

Based on applying the consensus concept in recommender systems, we utilise consensus protocols to find agreements between group members. Furthermore, to improve efficiency and prediction accuracy of recommender systems, we do not only consider social connections but also complex rating values and preferences, resp., of members. Generally, recommender systems condense composite ratings over many criteria into single numerical values to represent user preferences for items [1]. For recommendation purposes, multi-criteria optimisation is being employed for many decades in the multi-criteria decision making (MCDM) area to find optimal solutions in decision processes.

Multi-criteria decision analysis aims to assist a decision maker in selecting the best alternatives (attributes/items) in the presence of multiple and conflicting criteria [1, 22]. It is very difficult to decide which solution suits the criteria best, because the criteria may conflict with each other. The concept of Pareto optimality [13] constitutes an alternative in finding a set of optimal solutions for multiple-criteria optimisation problems [5].

Definition 1 *Pareto Optimality [10]: An element $x \in X$ is called Pareto-optimal iff there is no other $y \in X$ such that for a set of objective functions $\{f_i \mid i \geq 1\}$ holds $f_i(y) \leq f_i(x)$ for all i and $f_i(y) < f_i(x)$ for at least one i .*

Multi-criteria optimisation finds sets of solutions which do not take users' preferences [1] into account. Recommender systems do that, but there is no explicit communication between users on their preferences. Therefore, employing implicit sharing of preferences and experiences between users, and allowing each user to influence recommendations provided to others can be expected to cope better with decision problems to be simultaneously solved for several users.

In this paper, we propose an approach called Consensual Recommender Systems (C-InCF) which improves the performance of recommender systems by drawing on consensus achieved in social networks. A C-InCF is defined as to recommend items to individual users based on multi-criteria ratings given by users who share similar preferences in a group; recommendations of items are derived from agreements which users in similarity groups reach by sharing and/or exchanging information and using consensus protocols.

Before a C-InCF can provide recommendations, it needs to be established in two phases. The first, the learning phase comprises clustering, establishing social connections and forming consensus. To form a behavioural model, groups of users are created by clustering based on their rating matrix. Then, the users in each cluster create their social connections by considering preferential attachments. Finally, it is tried to find group agreements in order to represent the reference point of each group in the model. Once a model is established, interested parties can ask for recommendations in the second, the recommendation phase of the C-InCF. Such a query has the form of a multi-criteria rating vector to be compared with the reference points in the model in order to determine the most similar cluster. This processing step is usually called prediction. It needs to be followed by a step to resolve the conflicts immanent to multi-criteria decision problems. This is achieved by seeking Pareto-optimal solutions finally offered as recommendations to the enquirer.

2 Consensus Problem

The consensus problem has a long history in computer science, particularly in distributed computing [4, 8]. In the context of networked multi-agent systems, however, the consensus problem is related to group coordination, i.e. to make a decision for a group of agents or to reach an agreement regarding a certain quantity of interest that depends on the states of all agents. The consensus problem is also related to the cooperative control problem, where all agents try to reach a global consensus asymptotically [12]. Under a certain topology of multi-agent

systems, the consensus problem is to design a consensus protocol, i.e. a communication rule to exchange state information between users and their neighbours to reach consensus via distributed decision making, because each user has only local information of its neighbours [15]. Taking the analogy of multi-agent systems, and identifying user preferences with agent states, the average consensus will be employed here to find agreement points.

To employ an implicit sharing of preferences and experiences between users in a recommender system, social connections and the corresponding information exchange between users may be considered to capture the behaviour of users in a real-world network.

An interaction topology of a network of $n \in \mathbb{N}$ agents is described by a directed graph $G_n = (V_n, E_n)$ where V_n is a set of vertices v_i , $i = 1, \dots, n$, and E_n a set of edges $\eta_{ij} = (v_i, v_j)$, $i, j = 1, \dots, n$. Herein, the edge η_{ij} from v_i to v_j denotes that agent v_j receives information from agent v_i . The adjacency matrix $A = [a_{ij}] \in \mathbb{R}^{n \times n}$ associated with G_n is defined as

$$a_{ij} = \begin{cases} 1, & \text{if } v_i, v_j \in E_n, \\ 0, & \text{otherwise.} \end{cases}$$

For an agent v_i , $i = 1, \dots, n$, its neighbourhood is defined as $N_i = \{v_j \mid a_{ij} \neq 0, i \neq j, j = 1, \dots, n\}$ and its degree as $\deg(v_i) = \sum_{j \neq i} a_{ij}$.

Definition 2 A discrete-time consensus protocol [11] reads:

$$x_i[t+1] = x_i[t] + \epsilon \sum_{j \in N_i} a_{ij}(x_j[t] - x_i[t]), \quad i = 1, \dots, n, \quad (1)$$

where $x_i[t]$ denotes the information state of agent v_i at time step t , and $0 < \epsilon < \frac{1}{\Delta}$ is a parameter of the sampling period, in which Δ is the agents' V_n maximum degree.

A group of agents is said to reach a global consensus if $x_i[t] = x_j[t]$ for each pair (v_i, v_j) , $i \neq j$ in this group. The common agreement value of a group's agents is called the collective decision [12], denoted by α . For the case that the graph G_n is undirected, i.e. $a_{ij} = a_{ji}$, $i, j = 1, \dots, n$, it was shown [11] that a consensus is asymptotically reached:

$$\alpha_i = \lim_{t \rightarrow \infty} x_i[t] = \frac{x_i[0] + \sum_{j \in N_i} x_j[0]}{1 + |N_i|} \quad (2)$$

Based on this important result, averaging the initial information states of an agent and the ones in its neighbourhood appears to be an appropriate algorithm to establish consensus.

3 Consensual Recommender Systems

In this section, the notion of Consensual Recommender Systems (C-InCF) is proposed with the aim to recommend a set of optimally agreeing solutions to interested users by applying a consensus protocol. Our work starts with creating models of users with the same interest, involving techniques from data mining and machine learning. Then, we focus on relations between users, represented by the topology of scale-free networks, to find group agreements in order to improve the quality of recommendations to communities. In the corresponding decision processes, Pareto-optimal solutions are sought. A C-InCF works in two phases, the learning and the recommendation phase.

3.1 Learning Algorithm

First, we state the learning algorithm and then provide further details on its steps.

Input: Take input vectors from the repository database.

Clustering: Group users employing user-item rating matrices and any feasible clustering algorithm (e.g. K-means or K-NN).

Social connection: Create social connections among users in each group.

Consensus: Derive the group agreement points of each group employing an average consensus protocol.

Output: The model \mathbf{W} of user behaviour built.

Clustering When running a clustering algorithm such as K-Means or K-NN, usually the number of clusters to be formed needs to be prescribed. This approach may be replaced by another one determining an appropriate number of clusters itself. Accordingly, here we employ our previous work, the incremental approach of InCF, as described in [7] giving rise to an algorithm C-InCF. Thus, the clustering step is initialised by randomly selecting an input vector f_1 from the repository database \mathbf{F} . Initially, the model \mathbf{W} is formed by the cluster $\{f_1\}$. For all further feature vectors $f \in \mathbf{F}$ the following loop is executed:

1. Calculate the membership of f in all clusters of \mathbf{W} .
2. Determine the winning cluster as the one in which f assumes the highest membership value.

3. **If** the value of f 's membership in the winning cluster does not exceed a given threshold, **then** merge f with the winning cluster and exit the loop. Otherwise, extend the model by a new cluster consisting just of f ($\mathbf{W} := \mathbf{W} \cup \{f\}$).

Social connection For later consensus building, we create connections between the members of each cluster in form of a *rating-weighted network* based on the Barabási-Albert (BA) model [2] according to the following mechanism:

1. *Growth* starts from an initial network with m_0 users, and adds in its course step by step new users with $m(\leq m_0)$ connections linking each new user to m former ones.

For instance, we have $m_0 = 3$ and $m = 2$.

2. *Preferential attachment*: Let k_i be the degree of a user i , i.e. its number of connections identifying its popularity, and r_i be the number of items rated by user i . Then, the ratings-weighted probability for a new user joining the network to be connected with user i is

$$P_i = \frac{k_i r_i}{\sum_j k_j r_j} \quad (3)$$

where j ranges over all users present so far.

For example, Given $k_1 = 2$ and $k_2 = k_3 = 1$. Assuming now $r_1 = 4$ and $r_2 = r_3 = 3$, we obtain $P_1 = (2 \cdot 4) / (1 \cdot 3 + 1 \cdot 3) = 1.33$, $P_2 = (1 \cdot 3) / (2 \cdot 4 + 1 \cdot 3) = 0.27$ and $P_3 = (1 \cdot 3) / (2 \cdot 4 + 1 \cdot 3) = 0.27$. Thus, the new user is connected to user 1.

Consensus An average consensus protocol according to Definition 1 is employed to determine agreement point of the group members, which is represented by the reference points of each cluster:

3.2 Recommendation Algorithm

The recommendation phase aims to classify the characteristics of a consulting user r by associating with him or her the closest agreement point in the model resulting from the learning mode. In the algorithm's first part (steps 2 and 3) prediction is carried out as in other recommender systems. The conflicts contained in the set of recommendations elaborated are resolved (step 4) before the results are delivered.

1. **Input:** Take a vector r expressing a query.
2. **Find similar group:**
 - Calculate the membership of user r in all clusters of \mathbf{W} generated in the learning mode.
 - Determine the winning agreement point as the one in which r assumes the highest membership value.
 - If the value of r 's membership in the winning agreement point does not exceed a given threshold, **then** associate r with the winning cluster.
3. **Prediction:** Derive recommendations for r from the the winning cluster and its characteristics.
4. **Decision support:** Derive from the recommendations Pareto-optimal ones.
5. **Output:** Offer the set of Pareto-optimal recommendations to enquirer r .

4 Experimental Analysis

To foster comparability it is customary to carry out empirical analyses on the basis of publically available benchmark datasets. Since datasets with multi-criteria ratings could not be found, however, in this section we use an artificial one to evaluate the effectiveness of the proposed C-InCF method in comparison with existing techniques. We consider as an example 11 users and 4 movies (items). As shown in Table 1, the users have rated the criteria "Actor" and "Story" with values between 1 (low) and 5 (high). Here, the users were grouped into a model by incremental clustering. The five groups of users determined, namely {User1, User10}, {User2, User6, User7, User9}, {User3}, {User4, User8, User11} and {User5} as well as their connections. The initial parameters used in creating the connections among users in each group are each user's degree of connections and number of items rated. For this, the concept of preferential attachment in a scale-free network, which is here a undirected graph, with the preferential probability as given by Eq. (3) is applied.

4.1 Evaluation Criteria

The evaluation results in values for the prediction accuracy calculated from Normalised Mean Absolute Errors (NMAE) which, in turn, are determined from Mean Absolute Errors (MAE), i.e. averages of the absolute differences between actual and predicted ratings [20]:

Table 1: Artificial user-item rating matrix with multi-criteria ratings [Actor, Story]

	Item1	Item2	Item3	Item4
User1	[2,4]	[3,3]	[5,1]	[0,0]
User2	[0,0]	[2,1]	[4,2]	[3,3]
User3	[4,2]	[0,0]	[3,5]	[2,1]
User4	[5,3]	[2,3]	[5,1]	[4,3]
User5	[3,3]	[2,4]	[0,0]	[4,4]
User6	[0,0]	[2,3]	[3,3]	[2,2]
User7	[2,2]	[3,3]	[4,4]	[3,1]
User8	[4,4]	[5,1]	[4,2]	[3,3]
User9	[0,0]	[2,3]	[3,1]	[4,4]
User10	[3,3]	[1,2]	[4,2]	[0,0]
User11	[3,2]	[0,0]	[0,0]	[1,3]

$$MAE = \frac{1}{n} \cdot \sum_{\{i,j\}} |p_{i,j} - r_{i,j}| \quad (4)$$

where n is the total number of ratings over all users, $p_{i,j}$ is the rating on item j predicted for user i , and $r_{i,j}$ is the actual rating. The lower MAE is, the better is the prediction [20]. Since different recommender systems may use different numerical rating scales, NMAE normalises MAE to express errors as full-scale percentages [6]:

$$NMAE = \frac{MAE}{r_{max} - r_{min}} \quad (5)$$

where r_{max} is the highest and r_{min} is the lowest rating occurring [16].

A further quantity needed for evaluation is the sparsity level SL defined in [18, 19] as

$$SL = 1 - \frac{\text{total number of ratings}}{\text{total number of users} \times \text{total number of items}} \quad (6)$$

5 Experimental Results

In this section, the performance of the proposed C-InCF method employing the average consensus protocol is compared to the one provided by existing techniques, namely K-Means, K-NN and InCF [7]. Then, the effect of applying multiple instead of single criteria in the proposed method is illustrated.

5.1 Effect of C-InCF on the Sparsity Problem

Figure 1 shows that C-InCF outperforms the other three existing algorithms in each of the sparsity levels considered. One of the latter for the artificial dataset (Table 1) is $1 - (35/11 \cdot 4) = 79.54\%$. The best result is attained for 97.72% of sparsity, for which C-InCF yields the average NMAE value 0.075. K-NN gives rise to the worst NMAE (0.215) for 79.54% sparsity.

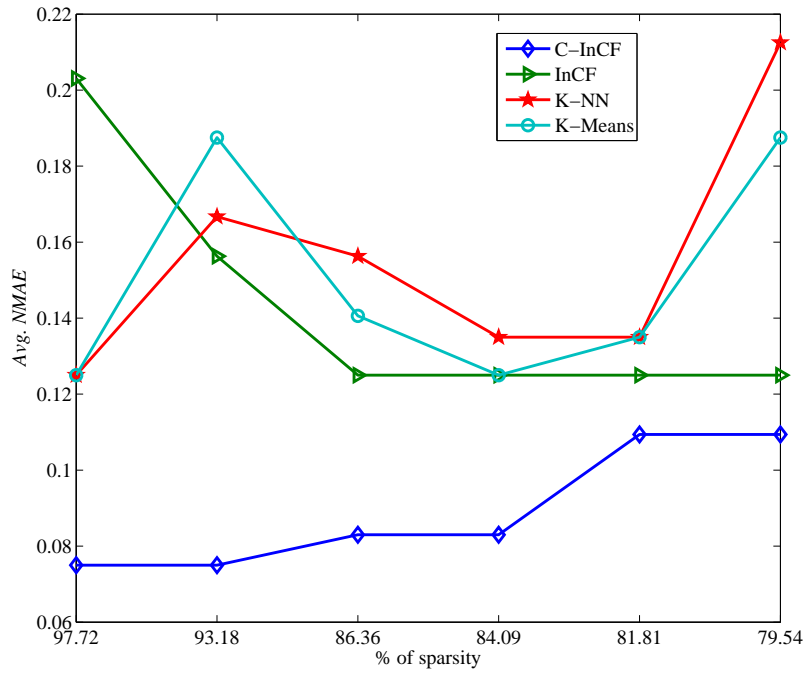


Fig. 1: Average NMAEs for training datasets of different sparsity

The interesting point is that both the here proposed C-InCF and the earlier introduced InCF perform better than recommendation based on K-Means and K-NN clustering at the lowest level of sparsity considered in this experiment, viz. at 79.54%. This effect may be due to the use of different similarity measures. Whereas K-Means and K-NN employ the Euclidean distance, C-InCF and InCF use the Mahalanobis distance allowing for more variety in the shapes of clusters.

5.2 Effect of C-InCF on Multi-criteria Ratings

In Figure 2 we compare the results achieved for two input datasets containing ratings of a single criterion and of multiple criteria. As shown by the average

NMAE values for different sparsity levels, expressing complex user preferences by means of multi-criteria item ratings generally leads to better prediction accuracy than by rating just one criterion.

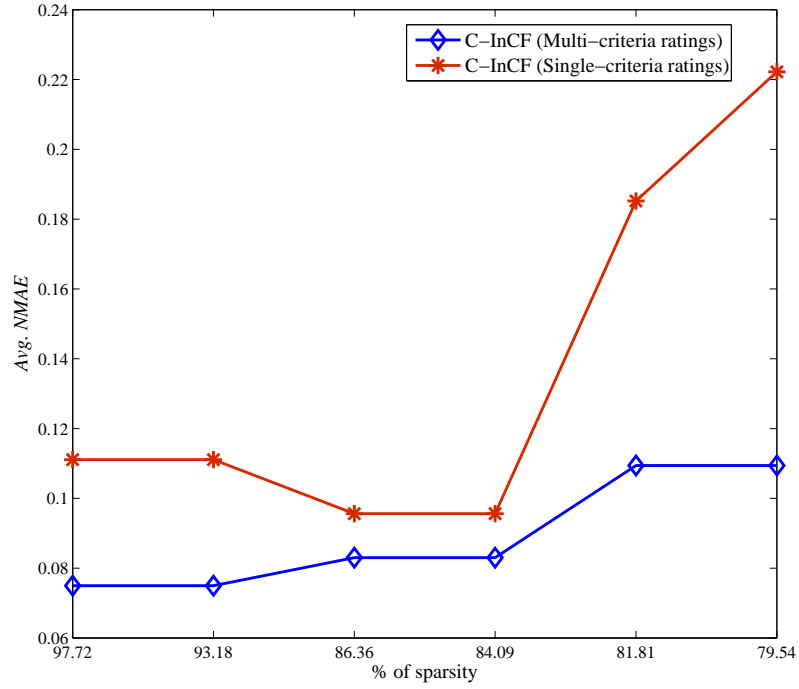


Fig. 2: Average NMAEs for training datasets of different sparsity and single- and multi-criteria C-InCF

6 Conclusion

Consensual recommender systems aim to recommend items to individual users based on implicit ratings of other users and considering a group agreement. This approach addresses two main problems of recommender systems, viz. the scalability problem and the sparsity problem which affecting to the accuracy of prediction.

To deal with the former, C-InCF has an ability to learn new individual users incrementally without losing the previous knowledge. To deal with the latter, a point of agreement among users based on interactions between them in a social connection is sought. If there are conflicting opinions (which are identified here as rating values), a consensus protocol is employed on the network to determine agreement points. Such a protocol is a communication rule to exchange

state information between users and their neighbours as well as to reach consensus by means of distributed decision making. Furthermore, to improve the accuracy of prediction, multi-criteria ratings are utilised as an input to recommender systems, Pareto optimality is applied to find optimal solutions when criteria conflicts need to be resolved.

In summary, consensual recommender systems were shown to yield more accurate recommendations for datasets with various sparsity levels than the existing model-based collaborative filtering algorithms.

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