Decentralized Recommender Systems

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Abstract

This paper proposes a decentralized recommender system by formulating the popular collaborative filtering (CF) model into a decentralized matrix completion form over a set of users. In such a way, data storages and computations are fully distributed. Each user could exchange limited information with its local neighborhood, and thus it avoids the centralized fusion. Advantages of the proposed system include a protection on user privacy, as well as better scalability and robustness. We compare our proposed algorithm with several state-of-the-art algorithms on the FlickerUser Favor dataset, and demonstrate that the decentralized algorithm can gain a competitive performance to others.

1 Introduction

The paper discusses decentralized recommender systems, which is in contrast to the typical recommender systems built on centralized infrastructures (the “cloud”, etc.). The decentralized network [1] had been thoroughly investigated in control and communication fields, defined as a set of distributed but connected agents, who are generally not strongly connected in a graph theoretic sense. Each agent collects data by itself, and executes computation via limited communication within only local neighborhoods. Fig. 1 shows a comparison of a centralized network (left) and a decentralized network (right).

2 Model and Algorithm

As a most popular tool in recommender systems, Collaborative Filtering (CF) is usually formulated as matrix factorizations problem [7, 11]. It predicts user rating \( R_{i,j} \) (of \( i \)-th user on \( j \)-th item) as a dot product of the user profile of the \( i \)-th user, denoted as a row vector \( U_i \), and the item profile of the \( j \)-th item denoted as a column vector \( V_j \), i.e., \( R_{i,j} = U_i^T V_j \). The recommendation problem can be formulated as solving the following matrix factorization problem:

\[
\begin{align*}
\min_{U, V, Z} & \; \frac{1}{2} ||UV - Z||_2^2 \\
\text{s.t.} & \; P_{\Omega}(Z) = P_{\Omega}(R)
\end{align*}
\]

Here \( P_{\Omega} \) denotes the projection over the set of available ratings, and \( Z \) is an auxiliary matrix.

It is assumed that CF is performed by \( L \) users jointly in a decentralized manner, and \( R \) is segmented into \( L \) non-overlapped parts, denoted as \( R_i, \; i = 1, 2, ..., L \). For example, the easiest case to segment \( R \) is to divide by columns. The \( i \)-th user \( (i = 1, 2, ..., L) \) observes \( R_i \). Note some level of synchronization is still required to collaboratively utilize information from all users. The trade-off strategy is to share partial data only among users in the local neighborhood. After observing the problem structure, authors in [2] suggested an variant of nonlinear Gauss-Seidel (GS) iterations, named decentralized matrix completion (DMC) algorithm. The \( i \)-th user will hold \( R_i, \) as well as \( U_i, V_i, \) and \( Z_i \) based on its own computations. Note \( U_i \) here is of the same size as \( U, \) and \( Z_i \) of the same dimension as \( R_i \), so in other words,
Algorithm 1 Decentralized matrix completion (DMC) algorithm for solving (2.1)

Require: \( P_{ij}(R_{ij}), (i = 1, 2, ..., L) \); initializations of \( U_i, V_i, \) and \( Z_i \) for each \( i \)-th user \((i = 1, 2, ..., L)\); step size \( \beta \);
ITER
1: FOR \( t=1 \) to ITER DO
2: Each \( i \)-th user updates \( V_i \): \( V_i = (U_i^T U_i)^{-1} U_i^T Z_i \)
3: Each \( i \)-th user updates \( Z_i \): \( Z_i = U_i V_i + P_{ij}(R_{ij} - U_i V_i) \)
4: Each \( i \)-th user propagates \( U_i \) to its one-hop neighborhood \( N_i \).
5: Each \( i \)-th user updates \( U_i \):
   \[
   U_i = \frac{Z_i V_i^T - a_i + \beta \sum_{j \in N_i} U_j}{1 + 2 \beta |N_i|} \]
   \[
   a_i = a_i + \beta (|N_i| U_i - \sum_{j \in N_i} U_j)
   \]
6: END
Ensure: \( U_i, V_i, \) and \( Z_i \), \( i = 1, 2, ..., L \)

\( Z_i = U_i V_i \). In each iteration, the \( i \)-th user first updates \( V_i \) and \( Z_i \) independently, then exchanging \( U_i \) with its one-hop connected neighborhood users, and finally update \( U_i \) via the average consensus algorithm. The algorithm is summarized in Algorithm 1. It obtains similar reconstruction errors, compared to centralized solutions .

3 Experiments
We compare our proposed algorithm with state-of-the-arts in this section, including Probabilistic Matrix Factorization (PMF) [8], and Collaborative Topic Modeling (CTR) [9], on a collected image recommendation dataset from Flickr.

FlickrUserFavor dataset: The dataset contains 350,000 images collected from Flickr, from 140 user groups and uploaded by 20,298 users. We use the “like” feedback provided by users as binary ratings. 75% of the rating matrix is used as training, and 25% as testing.

Evaluation Measurement: We use the averaged ranked order of all the rated images in the testing dataset for a specific user to evaluate performances. Among these ranked images, we determine those for which a user has exhibited a “like” preference in the test data, and report the average percentile score (APS) of the ranked images which are indeed preferred by the user. The lower the APS, the better the algorithm is, which means the user preferred images are ranked in top positions. Finally, the mAPS is reported with the mean of the APS scores for all target users.

Performance Comparison: PMF [8] is the most classical collaborative filtering algorithm for recommender system. Wang et.al. also proposed the Collaborative Topic Model [9] which involves both content and user ratings, where we use the Hierarchical Gaussianization (HG) [10] as the image features. For the proposed decentralized algorithm, we set the rank as 64, and using 8 agents.

mAPS comparisons are shown in Table 1. It is shown that DMC is capable to achieve competitive performance as CTR, while is far better than PMF. Moreover, we do not use any content information in our algorithm, while CTR uses content to indicates similarities between items. That suggests a further direction improve our algorithm too.

Table 1: Performances of the proposed approaches compared with other baseline methods. The second column indicates whether or not the algorithm uses content information. Without using content information and the fusion center, the proposed algorithm achieves a competitive performance.

| method   | Content | mAPS |
|----------|---------|------|
| PMF      | N       | 61.99|
| CTR      | Y       | 52.76|
| DMC      | N       | 53.46|

4 Conclusion
This paper discusses a decentralized recommender system. We formulate the popular collaborative filtering model into a decentralized matrix completion problem. Each user, with only partial rating data, can exchange user profile factors with its local neighborhood, while keep item profile factors private. We compare our proposed algorithm with several state-of-the-arts on the FlickrUserFavor dataset, and illustrate comparable results to the conventional ones.

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