A Multidimensional Collaborative Filtering Fusion Approach with Dimensionality Reduction

Xiaoyu Tang, Yue Xu, Ahmad Abdel-Hafez, Shlomo Geva
Science and Engineering Faculty,
Queensland University of Technology,
Brisbane, Australia

xiaoyu.tang@connect.qut.edu.au, {yue.xu, a.abdelhafez, s.geva}@qut.edu.au

Abstract

Multidimensional data are getting increasing attention from researchers for creating better recommender systems in recent years. Additional metadata provides algorithms with more details for better understanding the interaction between users and items. While neighbourhood-based Collaborative Filtering (CF) approaches and latent factor models tackle this task in various ways effectively, they only utilize different partial structures of data. In this paper, we seek to delve into different types of relations in data and to understand the interaction between users and items more holistically. We propose a generic multidimensional CF fusion approach for top-N item recommendations. The proposed approach is capable of incorporating not only localized relations of user-user and item-item but also latent interaction between all dimensions of the data. Experimental results show significant improvements by the proposed approach in terms of recommendation accuracy.

Keywords: multidimensional data, neighbourhood, dimensionality reduction, collaborative filtering, recommender systems.

1 Introduction

In recent years, the development of Web 2.0 techniques and various smart devices have created new opportunities for recommender systems, by revealing more information additional to user-item transactions. For example, Social Tagging Systems (STS) encourage users to employ user-defined keywords to help manage content in a personalized way. Recommender systems built upon STS (Tso-Sutter et al. 2008) utilize social tagging to improve recommendation mechanisms. Context-Aware Recommender Systems (CARS) (Adomavicius and Tuzhilin 2011, Karatzoglou et al. 2010) incorporate context information (e.g. time, location, weather, etc.) into recommendation models to predict new relations more accurately. Tags and contextual information can be treated as additional dimensions to user-item matrix. Thus, the data used by these recommender systems share the property that each user-item transaction involves multiple entities other than merely a user and an item.

The top-N item recommendation task for multidimensional data has been tackled in many different ways. For the neighbourhood-based Collaborative Filtering (CF) approaches, researchers have presented various ways to utilize multidimensional data in user/item profiling and in neighbourhood formation through explicit conversion of dimensions (Marinho et al. 2012, Tso-Sutter et al. 2008, Liang et al. 2010). For example, Liang proposed to construct user profiles by using tags so as to utilize the multiple relationships among users, items and tags for extracting the semantic meaning of each tag for users (Liang et al. 2010). However, these approaches mostly work in ad hoc ways which leads to that they cannot be directly applied to data with more dimensions. Moreover, they cannot take into account the latent relations in data through merely explicit relations from neighbourhood. Differently, some recent Tensor Factorization (TF) based models (Symeonidis et al. 2010, Karatzoglou et al. 2010, Rendle et al. 2009) model multidimensional data as tensors (i.e. multidimensional arrays) and are able to discover holistic latent relationships in data. However, pure TF-based recommendation models lack the ability to utilize localized relationships which are often the privilege of neighbourhood-based CF approaches. Furthermore, the increase of the dimensionality of data can cause serious efficiency problem for the factorization process, which largely restrict the application in practice.

Despite various recommendation models have been proposed in the categories of neighbourhood-based approaches and factorization models, they essentially only deal with parts of relations existing in data. Neighbourhood-based approaches work with user-user or item-item neighbourhood relations, while TF utilizes the global latent interaction between different dimensions. There has not been any research which simultaneously incorporates all these different types of relations in multidimensional data for making recommendations. This is the objective of this paper.

In this paper, we propose to profile users and items through conducting dimensionality reduction on multidimensional data, and we present a novel generic Multidimensional Collaborative Filtering Fusion (MCFF) approach for top-N item recommendation using multidimensional data. Three different levels of structures of data can be captured and utilized simultaneously by the proposed recommendation model. Our approach first transforms data to model user and item profiles by means of observing data from the user and item dimensions respectively. Then, dimensionality reduction is conducted on transformed data for removing noises and revealing implicit relations between all dimensions. Finally, the proposed approach captures the refined localized user-user and item-item relations and also global latent relations between all dimensions, to generate item recommendations.

The contributions of our work are as follows:

- Our profiling method models users and items based on holistic relations in the entire data, and it is directly generalizable to profiling for other entities or dimensions, and extendable to *N*-dimensional data. Compared to existing neighbourhood-based approaches for multidimensional data, our profiling approach can incorporate the multidimensional interaction between different dimensions into the profiles of users/items, and is able to remove noise and keep sound efficiency.
- The proposed multidimensional CF fusion recommendation approach takes advantages of not only the localized neighbourhood relations of users and items, but also holistic latent relations between all dimensions. This enables the recommendation algorithm to understand data more completely than pure TF-based CF models.

We have conducted extensive experiments to validate the effectiveness of the proposed multidimensional profiling method and to evaluate the performance of the proposed recommendation approach MCFF against some state-of-the-art multidimensional CF recommendation algorithms. The experimental results show that our approaches substantially improve the performance of top-N item recommendation in terms of precisions/recalls/F1 scores.

The rest of this paper is organized as follows: Section 2 summarizes the related work. In Section 3 we propose a multidimensional profiling approach for representing users and items. Based on that, we integrate the profiling method into neighbourhood-based CF approaches and propose a novel multidimensional CF recommendation model which fuses user and item neighbourhoods with implicit holistic interaction assimilated. Experimental results are given in Section 4, which shows superior performance of the proposed recommendation model. Finally, Section 5 concludes this paper.

2 Related Work

Traditionally, most of the CF recommender systems are categorized into two families: neighbourhood-based approaches and latent factor models (Adomavicius and Tuzhilin 2005). The neighborhood-based CF recommender systems are usually based on nearest neighborhood relations. Examples include user-based and item-based CF (Desrosiers and Karypis 2011). The latent factor models (Koren et al. 2009, Symeonidis et al. 2010) have received much attention due to its competitive performance in Netflix competition. The entities of data in these traditional CF recommender systems often include only users and items. This kind of data and the recommender systems are 2-dimensional, since each user-item transaction is only associated with two entities: user and item.

The development of information systems working with multidimensional data, such as social tagging systems and context-aware systems, have promoted the recommendation systems to incorporate data with more dimensions. Different categories of recommendation approaches have been proposed for multidimensional data scenario in recent years. Marinho et al. discussed how conventional CF can be applied for computing recommendations in multidimensional data environments through dimension projection (Marinho et al. 2012). They referred to this type of recommendation approaches as projection-based CF. The approaches which fall into this type usually project data between different dimensions in order to reduce the data spaces and predict new user-item relations. Tso-Sutter et al. proposed to extend the typical user-item matrix with tags which are taken as pseudo users and pseudo items (Tso-Sutter et al. 2008). Liang et al. proposed to construct tag-based user profiles using the multiple relationships among users, items and tags to find the semantic meaning of each tag for each user individually (Liang et al. 2010). Tagommenders (Sen et al. 2009) predicts users' preferences for items based on their inferred preferences for tags. They proposed to combine tag preference inference algorithms with tag-aware recommenders and showed empirically that their approach outperforms classic CF algorithms. Although at least three dimensions of data are considered in these approaches, they are not directly generalizable to more dimensions of information. Besides, most of these approaches do not have the ability to incorporate latent multidimensional relations in data for recommendation making. These disadvantages limit their recommendation capacity.

Differently, latent factor models enjoy the ability to discover latent relationships from a holistic perspective. For this category of CF models, a newly emerging stream of methods focusing on multidimensional data is tensor factorization. TF-based recommendation models formulate users, items and additional dimensions such as tags, as multidimensional matrices which are called tensors. Multiverse Recommendation (Karatzoglou et al. 2010) is a TF-based model for context-aware item recommendation which utilizes Tucker Decomposition (TD) for rating prediction task with the user-item-context N-dimensional tensor data. Time is used as the context in this method. Rendle et al. proposed a different approach for creating the initial tensor which expresses user-item-tag relations (Rendle et al. 2009). Instead of using the 0/1 interpretation scheme, they used a so-called Post-Based Ranking Interpretation (PBRI). Symeonidis et al. introduced a unified framework which provides three types of recommendations in STS, using a 3-order tensor to model the relations of users, items, and tags (Symeonidis et al. 2010). Multi-way latent semantic analysis is conducted using Higher-Order Singular Value Decomposition (HOSVD). They reported superior recommendation performance of their model for item recommendation compared to other approaches. To sum up, the TF-based CF models enjoy similar advantages of 2-dimensional latent factor models and are able to use more information from additional dimensions. However, although these approaches hold the holistic perspective of data with latent relationships discovered, they neglect the localized relations which usually are extracted by nearest neighbourhood approaches. Additionally, in real-world implementations, some other drawbacks like low computing efficiency, curse of dimensionality or lengthy training time may become severe problems as the size and dimensions of the data increase, while neighbourhood-based CF usually performs much better when these concerns matter a lot.

As aforementioned, the extraction and utilization of global latent relations and explicit user's/item's localized relations are the core of most CF approaches to provide quality recommendations. However, no research has been done to incorporate all these three layers of relations for making item recommendations. Furthermore, no previous work has proposed a generalizable multidimensional method for user/item profiling and neighbourhood formation. We believe that a novel CF approach effectively utilizing multidimensional latent relations and localized explicit relations possesses an all-sided view of data relations and thus has the ability to provide recommendation of high accuracy, while still enjoy the desirable efficiency in practice. This is the focus of this paper.

3 Multidimensional Collaborative Filtering Fusion

In this paper, for the sake of simplicity, we will describe the proposed approaches with three dimensions: users, items and tags, as in the context of STS. In fact, tags can be replaced with other entities such as item features or categories. The profiling and recommendation approaches proposed in this section can be generalized to data with more dimensions. We define U, I and T as disjoint non-empty finite sets, whose elements are users, items and tags, respectively. In this way, the data is 3-dimensional.

3.1 Multidimensional User/Item Profiling

In this section, we propose a multidimensional profiling approach for users and items. In our approach, the 3-dimensional user-item-tag data is represented as a 3-order tensor $\mathcal{A} \in \mathbb{R}^{|U|\times|I|\times|T|}$, in which a tensor element is represented by a 3-tuple (u, i, t). In the simplest case, the value of (u, i, t) is defined as:

$$e_{u,i,t} = \begin{cases} 1, & \text{if the transaction } (u,i,t) \text{ exists} \\ 0, & \text{otherwise} \end{cases}$$

For social tagging, a transaction or tag assignment (u, i, t) exists if user u collected item i with tag t.

Generally, users' item preferences are represented by users' explicit ratings or implicit ratings. In the context of this paper, the item preference of a user u to an item i, denoted as $r_{u,i}$, is defined as $r_{u,i} = 1$ if u collected i with at least one tag, otherwise $r_{u,i} = 0$ indicating that the user's preference to this item is unknown.

Matricization, also known as unfolding or flattening, is the process of reordering the elements of an N-order tensor into a matrix (Kolda and Bader 2009, Acar and Yener 2009). Some decomposition techniques apply matricization to tensors for extracting and explaining data properties in order to understand the data structure. Illustration of a matricization operation for a 3-order tensor $\mathcal{A} \in \mathbb{R}^{|U|\times|I|\times|T|}$ is given in Figure 1. The three modes/dimensions of the tensor $\mathcal{A}$ are users (U), items (I) and tags (T). Figure 1 shows the U-mode unfolding of the tensor $\mathcal{A}$, denoted as $\mathcal{A}_{(U)} \in \mathbb{R}^{|U|\times|I||T|}$.

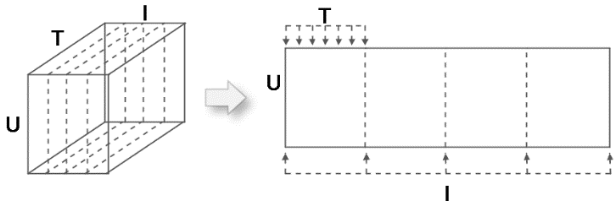

Figure 1: Matricization of a 3-order tensor

Formally, in the mode-n matricization of a 3-order tensor $\mathcal{A} \in \mathbb{R}^{I_1\times I_2\times I_3}$, a tensor element (i_1, i_2, i_3) maps to a matrix element (i_n, j) (Kolda and Bader 2009), where

$$j = 1 + \sum_{\substack{k=1 \\ k\neq n}}^{3} (i_k - 1) J_k \tag{1}$$

and $J_k = \prod_{\substack{m=1 \\ m\neq n}}^{k-1} I_m$.

Inspired by the tensor matricization, we propose to represent users and items by matricizing the tensor $\mathcal{A} \in \mathbb{R}^{|U|\times|I|\times|T|}$ by U-mode and by I-mode. In this way, users are represented by vectors instead of matrices in which each user u is represented by a binary vector $\overrightarrow{u^e}$. Each element u_k^e in $\overrightarrow{u^e}$ corresponds to an item-tag pair (i, t), and $u_k^e = 1$ if $e_{u,i,t} = 1$, otherwise $u_k^e = 0$. Items' representations are similarly formed. The outcomes of the two matricization operations are two matrices: a matrix $\mathcal{A}_{(U)} \in \mathbb{R}^{|U|\times|I||T|}$ with U mapped to row vectors and a matrix $\mathcal{A}_{(I)} \in \mathbb{R}^{|I|\times|U||T|}$ with I mapped to row vectors. Hence, $\mathcal{A}_{(U)}$ can be represented as a vector $< \overrightarrow{u_1^e}, \overrightarrow{u_2^e}, \dots, \overrightarrow{u_{|U|}^e} >^{\mathsf{T}}$ and $\mathcal{A}_{(I)}$ can be represented as a vector $< \overrightarrow{\iota_1^e}, \overrightarrow{\iota_2^e}, \dots, \overrightarrow{\iota_{|I|}^e} >^{\mathsf{T}}$, where $\overrightarrow{u^e}$ and $\overrightarrow{\iota^e}$, which represent a user and an item respectively, are the following vectors:

$$\overrightarrow{u^e} = < e_{u,i_1,t_1}, e_{u,i_2,t_1}, \dots, e_{u,i_{|I|},t_{|T|}} >$$

$$\overrightarrow{\iota^e} = < e_{u_1,i,t_1}, e_{u_2,i,t_1}, \dots, e_{u_{|U|},i,t_{|T|}} >$$

Compared to the tag-aware CF fusion model (Tso-Sutter et al. 2008), the user and item profiles created by the matricization of tensors can essentially preserve the multidimensional semantic relations in the data. However, this also brings up new problems. First, matricization of tensors may lead to misinterpretation if the data are noisy (Acar and Yener 2009). Also, since usually the number of items and tags are quite large, tensor matricization could deteriorate the efficiency of neighborhood formation using the U-mode and I-mode unfolding matrices $\mathcal{A}_{(U)}$ and $\mathcal{A}_{(I)}$ as the profiles of users and items, respectively. In order to solve these problems, we propose to conduct SVD on $\mathcal{A}_{(U)}$ and $\mathcal{A}_{(I)}$ to discover the latent factors and to reduce the representation spaces.

We apply SVD on the matrix $\mathcal{A}_{(U)}$ and matrix $\mathcal{A}_{(I)}$ separately in the same way. Taking $\mathcal{A}_{(U)}$ as an example, through factorizing the matrix $\mathcal{A}_{(U)}$ via the SVD process, latent factors can be extracted and $\mathcal{A}_{(U)}$ can be represented as:

$$\mathcal{A}_{(U)} = \mathcal{U}_{|U|\times|U|} \cdot \mathcal{S}_{|U|\times|I||T|} \cdot \mathcal{V}^{T}_{|I||T|\times|I||T|} \tag{2}$$

By preserving a certain amount of information in the data, i.e., specifying the number of factors to be retained as $k_u \leq |U|$, we can project the representations of users from the vector space $\mathbb{R}^{|I||T|}$ onto the latent factor space $\mathbb{R}^{k_u}$, so as to reduce the dimensions of user profile representations. The space projection operation is fulfilled by the following equation:

$$\mathcal{UF}_{|U|\times k_u} = \mathcal{U}_{|U|\times k_u} \cdot \mathcal{S}_{k_u \times k_u} \quad (3)$$

where $\mathcal{U}_{|U|\times k_u} \in \mathbb{R}^{|U|\times k_u}$ and $\mathcal{S}_{k_u\times k_u} \in \mathbb{R}^{k_u\times k_u}$ represent the truncated matrices of $\mathcal{U}_{|U|\times|U|}$ and $\mathcal{S}_{|U|\times|I||T|}$ respectively, given the number of factors k_u. $\mathcal{UF}_{|U|\times k_u}$ is a matrix where each row vector represents a user's preference measurement in the new latent factor space.

With the reduced user representations, neighbourhood formation can proceed efficiently and accurately. We will discuss this in the next section.

Similar procedure can be defined to reduce item representations by applying SVD on the I-mode unfolding matrix $\mathcal{A}_{(I)}$ to generate a truncated matrix $\mathcal{IF}_{|I|\times k_i}$ with a given factor number k_i for the item space. The profiles of a user u and an item i in latent factor spaces are represented as follows:

$$\overrightarrow{u^f} = < f_1^u, f_2^u, \dots, f_{k_u}^u >$$

$$\overrightarrow{\iota^f} = < f_1^i, f_2^i, \dots, f_{k_i}^i >$$

where $\overrightarrow{u^f}$ and $\overrightarrow{\iota^f}$ are row vectors in $\mathcal{UF}_{|U|\times k_u}$ and $\mathcal{IF}_{|I|\times k_i}$, respectively, $1 \leq k_u \leq |U|$, $1 \leq k_i \leq |I|$. k_u and k_i are the given numbers of factors for decomposing $\mathcal{A}_{(U)}$ and $\mathcal{A}_{(I)}$ respectively.

The extension of the multidimensional profiling approaches proposed in this section to N-dimensional data is straightforward. For the mode-n matricization of an N-order tensor $\mathcal{A} \in \mathbb{R}^{I_1\times I_2\times\cdots\times I_N}$, a tensor element $(i_1, i_2, \cdots, i_N)$ maps to a matrix element (i_n, j), where $j = 1 + \sum_{\substack{k=1\\k\neq n}}^{N} (i_k - 1)J_k$ with $J_k = \prod_{\substack{m=1\\m\neq n}}^{k-1} I_m$ (Kolda and Bader 2009).

In Section 3.2 and Section 3.3, we propose to integrate the multidimensional profiling methods into two neighbourhood-based CF approaches and further propose the MCFF approach based on this profiling method.

3.2 Multidimensional Neighbourhood-based Collaborative Filtering

In this section, we present a user-based CF algorithm integrated with the multidimensional user profiling approach proposed in Section 3.1. The item-based CF algorithm can be similarly integrated with the proposed multidimensional item profiling approach.

The standard user-based CF algorithm (Su and Khoshgoftaar 2009) works with the following procedure:

First, formulate user interests into user profiles for each user. For example, Tso-Sutter et al. proposed to extend the typical user-item matrix with tags which are taken as pseudo users and pseudo items (Tso-Sutter et al. 2008). Differently, user profiles in our approach are created by the multidimensional profiling method presented in Section 3.1.

Secondly, generate user neighbourhoods based on a predefined similarity measurement between any two users, such as Jaccard similarity or Cosine similarity. In our approach, since the user profiles are vectors consisting of real numbers, Cosine similarity is used and it is given in Equation (4):

$$sim(u_i, u_j) = Cosine(u_i, u_j) = \frac{\overrightarrow{u_i^f} \cdot \overrightarrow{u_j^f}}{\left\|\overrightarrow{u_i^f}\right\| \cdot \left\|\overrightarrow{u_j^f}\right\|} \quad (4)$$

Finally, for each target user, based on the item preferences of this user's neighbour users, compute a preference prediction for each new item and then produce a ranked list of top-N item recommendation. The preference prediction $P_{u,i}^{UCF}$ to a new item i for a target user u is given as:

$$P_{u,i}^{MUCF} = \sum_{v\in N_u, i\in I_v} \left(r_{v,i} \cdot sim(u, v)\right) \quad (5)$$

where N_u are the neighbour users of target user u. I_v is the set of items collected by user v. $r_{v,i}$ which is user v's item preference for item i is defined in Section 3.1.

Likewise, item-based CF with multidimensional item profiling can be formulated similarly:

$$P_{u,i}^{MICF} = \sum_{j\in I_u, i\in N_j} \left(r_{u,j} \cdot sim(i, j)\right) \quad (6)$$

where N_j are the neighbour items of a collected item j which are new to user u. I_u is the set of items collected by user u, and $sim(i, j)$ is the similarity between item i and item j.

Thereby, the two multidimensional neighbourhood-based CF approaches are proposed. They are able to use 3-dimensional user-item-tag data to profile users and items more accurately as stated in Section 3.1. In Section 4, we will empirically demonstrate the multidimensional neighbourhood-based CF approaches can show better recommendation performance than their standard counterparts.

3.3 Fusing User-based and Item-based CF for Multidimensional Item Recommendation

As an additional dimension of transaction data beyond users and items, tags can be seen as features specific to individual transactions, i.e., they are usually related to users and items at the same time. That is, tags (or additional features of other types) are local information for transactions. In this way, the relations in the multidimensional data seen from the aspects of users or items can be different. For example, a user collects the movie *Titanic* with the tag "*love*"; a different user collects the same movie with the tag "*disaster*". This indicates a recommendation model which can appropriately utilize localized neighbourhood relations from both user and item perspectives may lead to improvement of recommendation quality, which forms the basis of some previous works (Wang et al. 2006, Tso-Sutter et al. 2008, Bar et al. 2013, Lee and Olafsson 2009).

In Section 3.2, two neighborhood-based CF approaches with multidimensional user and item profiling have been proposed. A CF fusion approach can be used to unify the power of user neighborhoods and item neighborhoods together for recommendation. In this section, we propose a Multidimensional CF Fusion

(MCFF) approach which fuses the two neighbourhood relations in a way similar to the tag-aware CF fusion model (Tso-Sutter et al. 2008).

CF fusion for the top-N item recommendation task is done by combining the predictions of user-based and item-based CF approaches. In order to compare our MCFF approach with the tag-aware CF fusion model, following the tag-aware CF fusion model, the predictions of user-based CF part and item-based CF part in our fusion approach are computed differently. For the predicting item problem in user-based CF part, recommendations are a list of items that is ranked by decreasing frequency of occurrence in the ratings of his/her neighbours. The following equation gives the preference prediction of user u for an unused item i by the user-based CF part in the fusion model:

$$P_{u,i}^{MUCF2} = \frac{|\{v|v \in N_u, i \in I_v\}|}{|N_u|} \quad (7)$$

where N_u are the neighbour users of target user u, and I_v is the set of items used by a neighbour user v.

For the item-based CF part, the top-N item recommendation is to compute a list of items that is ranked by the decreasing sum of the similarities of neighbouring items, which have been used by user u. This preference prediction of the item-based CF part is given by Equation (6).

Since the preference predictions computed by user-based CF and item-based CF come from different computation methods, they have different scales of values. A normalization process of the preference predictions is needed to unify the recommendations from the two neighborhood-based CF parts, which produces the final preference prediction used for top-N item recommendation ranking:

$$P_{u,i}^{MCFF} = \lambda \cdot \frac{P_{u,i}^{MUCF2}}{\sum_{j \in \widetilde{I_u}} P_{u,j}^{MUCF2}} + (1-\lambda) \cdot \frac{P_{u,i}^{MICF}}{\sum_{j \in \widetilde{I_u}} P_{u,j}^{MICF}} \quad (8)$$

where $0 \leq \lambda \leq 1$, $\widetilde{I_u}$ is the set of new items to be recommended to target user u. Note the neighbourhood sizes of users and items are defined by the same parameter k.

The proposed MCFF approach for multidimensional data can reasonably enhance the recommendation performance, since this approach is able to not only efficiently utilize the multidimensional semantic relations, but also bring out the recommendation power of the localized neighbourhood relations of both users and items. In addition, the application of dimensionality reduction to the unfolded matrices can dramatically reduce the dimension problem while preserving the multidimensional interaction. In fact, our empirical analysis has shown that the proposed MCFF approach provides very promising performance.

4 Evaluation

In this section, we present empirical analysis based on real data collected from Bibsonomy and Delicious. Experimental results show the high effectiveness of the proposed multidimensional user/item profiling approach for making recommendations. The evaluation results of MCFF approach show significantly superior performances compared to other state-of-the-art CF approaches for multidimensional data.

4.1 Datasets

We conducted experiments using datasets from Bibsonomy (Knowledge and Data Engineering Group 2007) and Delicious (Wetzker et al. 2008). The Bibsonomy dataset was collected on 30 April 2007. The Delicious dataset was collected on January 2004. Following the evaluation of TF approach (Symeonidis et al. 2010) to make the datasets less sparse, the notion of *p*-core (Jäschke et al. 2007) was applied to the datasets. The *p*-core of level k means that each user, tag and item has/occurs in at least k posts. Following the evaluation of the TF approach, we use $k = 5$ for both of the two datasets. The original Delicious dataset contains 2419 users, 30838 items and 10926 tags. With $k = 5$, the Delicious dataset contains 216 users, 337 items, and 247 tags. The Bibsonomy dataset we obtained is already applied with $k = 5$ by the dataset provider, Knowledge and Data Engineering Group (Knowledge and Data Engineering Group 2007), and it contains 116 users, 361 items and 412 tags.

4.2 Evaluation Settings

4.2.1 Recommendation Models

Following are the proposed approaches to be examined:

- **Multidimensional Item-based CF (MiCF)**. This is the item-based CF approach integrated with the multidimensional item profiling proposed in Section 3.2.
- **Multidimensional User-based CF (MuCF)**. This is the user-based CF approach integrated with the multidimensional user profiling proposed in Section 3.2.
- **Multidimensional CF Fusion (MCFF)**. This is the multidimensional CF fusion approach proposed in Section 3.3.

In order to compare our proposed approaches against state-of-the-art recommendation algorithms as well as conventional neighborhood-based CF approaches, we have adopted the following models as the baseline models:

- **Item-based CF (iCF)**. This is the item-based CF approach (Deshpande and Karypis 2004). It is actually a 2-dimensional recommendation method with the implicit rating data as input.
- **User-based CF (uCF)**. This is the user-based CF approach (Adomavicius and Tuzhilin 2005). Similar to iCF, it is also a 2-dimensional recommendation method with the implicit rating data as input.
- **Tag-aware CF Fusion (tCFF)**. This CF fusion model uses tags as pseudo users in item-based CF and as pseudo items in user-based CF to extend the profiling ability of the two approaches (Tso-Sutter et al. 2008).
- **Tensor Factorization based CF (TF)**. Symeonidis et al. proposed a tensor factorization based recommender framework which uses HOSVD for factorizing 3-order user-item-tag tensors (Symeonidis et al. 2010). They use kernel-SVD in the process to further improve the recommendation accuracy of the