Collaborative Filtering beyond the User-Item Matrix: A Survey of the State of the Art and Future Challenges

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Over the past two decades, a large amount of research effort has been devoted to developing algorithms that generate recommendations. The resulting research progress has established the importance of the user-item (U-I) matrix, which encodes the individual preferences of users for items in a collection, for recommender systems. The U-I matrix provides the basis for collaborative filtering (CF) techniques, the dominant framework for recommender systems. Currently, new recommendation scenarios are emerging that offer promising new information that goes beyond the U-I matrix. This information can be divided into two categories related to its source: rich side information concerning users and items, and interaction information associated with the interplay of users and items. In this survey, we summarize and analyze recommendation scenarios involving information sources and the CF algorithms that have been recently developed to address them. We provide a comprehensive introduction to a large body of research, more than 200 key references, with the aim of supporting the further development of recommender systems exploiting information beyond the U-I matrix. On the basis of this material, we identify and discuss what we see as the central challenges lying ahead for recommender system technology, both in terms of extensions of existing techniques as well as of the integration of techniques and technologies drawn from other research areas.

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1. INTRODUCTION

The ability of recommender systems to generate direct connections between users and items that represent matches in interests and preferences makes them an important tool for alleviating information overload for Web users. Recommender systems are now ubiquitous online, where they support media consumption and also sales, such

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as with e-commerce platforms, for example, Amazon[1] and eBay.[2] The most successful and widely used recommendation technique is collaborative filtering (CF), which is based on the core assumption that users who have expressed similar interests in the past will share common interests in the future [Goldberg et al. 1992]. In the past few decades, significant progress has been made in recommender system performance by deploying CF to exploit user-item (U-I) relations, which are typically encoded in a U-I matrix [Adomavicius and Tuzhilin 2005; Burke 2002; Ekstrand et al. 2011; Herlocker et al. 2004]. However, in recent years, a large number of recommendation scenarios have emerged in which various additional information sources are available in addition to the U-I matrix. In such cases, CF can be either enhanced to improve recommendation performance further or else be utilized to pursue different tasks other than product/item recommendation.

The goal of this survey is to provide an overview and analysis of recommender scenarios that involve additional information sources beyond the U-I matrix and the recommender system techniques that support them. Regarding the additional information sources, we refer in particular to the rich side information related to users and items and the information related to the interaction between users and items. We pursue our goal by elucidating the connection between the problem in a given recommender scenario and the algorithms that have been developed to address it. Then, we assess the state of the art and on this basis formulate future challenges and identify the most productive opportunities for further research and development in the field of recommender systems.

Our intention is also to complement and extend the information coverage of previous recommender systems surveys. For instance, Adomavicius and Tuzhilin [2005] reviewed not only the CF-based recommendation methods but also the alternative paradigms, such as the *content-based* and *hybrid* recommendation methods. Their work can be considered to anticipate our survey because they predicted, in their outlook, that the information derived from the context of a recommendation scenario will play a growing role in the future of recommender systems. We follow up on this prediction and investigate how this and other additional information available beyond the U-I matrix can help improve the CF-based recommendation. We do not go in depth into the fundamentals and realization possibilities of the CF-based recommender paradigm, because this paradigm was covered extensively in the works of Ekstrand et al. [2011] and Konstan and Riedl [2012]. These surveys include an analysis of the connection between CF-based recommender algorithms and domain-specific applications, as well as an overview of evaluation frameworks. Another category of surveys includes experimental analysis of different recommendation algorithms, as well as their characteristics and usefulness with respect to different recommendation scenarios [Breese et al. 1998; Cacheda et al. 2011; Cremonesi et al. 2010; Herlocker et al. 2004]. We do not perform an empirical study but instead choose to focus on the following main contributions:

—We survey and analyze the key theoretical and empirical contributions of CF deploying the sources of information beyond the U-I matrix that have been exploited and the types of algorithms that have been developed to integrate them.
—We present and discuss a series of key challenges in the direction of CF that can be anticipated to be valuable for future research.

The remainder of this survey is structured as follows. In the next section, we briefly review the conventional CF. Then, in Section 3, we present the categories of additional information that can be used to expand the CF paradigm beyond the techniques relying

[1]http://www.amazon.com/.
[2]http://www.ebay.com/.

Table I. An Example Movie Recommendation Scenario with Four Users and Six Movies
User preferences are indicated by a 1–5 rating scale.

	Titanic	Inception	Toy Story	Taken	Skyfall	Matrix
Alice	5	?	3	?	?	1
Bob	?	1	?	4	?	?
Jim	2	4	?	?	?	5
Kate	?	2	?	?	3	?

solely on the U-I matrix. We then introduce and analyze in Section 4 the key research contributions proposed so far to take this information into account when developing recommender systems. Based on this analysis, we identify and discuss in Sections 5 through 7 a series of key challenges that we consider to be important for future work. Concluding remarks can be found in Section 8.

2. BACKGROUND ON CONVENTIONAL COLLABORATIVE FILTERING

In this section, we briefly introduce conventional CF—that is, CF that exploits solely the U-I matrix in order to generate recommendations for individual users. We first formally define the problem of CF and then cover the two major categories of traditional CF approaches, the *memory-based* CF and *model-based* CF [Adomavicius and Tuzhilin 2005; Ekstrand et al. 2011].

2.1. Problem Definition

In a standard setting of CF, we have a set of users (e.g., M users) and a set of items (e.g., N items). The preferences of users to individual items can be denoted by a U-I matrix R, in which the value of R_{ij} denotes the preference of user i to item j, if $R_{ij} > 0$. The user preferences can be expressed either directly, such as by ratings, or indirectly using binary values indicating whether the user has clicked, viewed, or purchased the items. Note that the known preferences of users to items are usually very limited, which makes the matrix R typically sparse. Conventionally, we use $R_{ij} =?$ to denote the case that the preference of user i to item j is unknown. Under this setting, the problem of CF can be defined as such: *Given a U-I matrix R that represents a known set of M users' preferences to N items, recommend to each user a list of items that are ranked in a descending order of relevance to the user's interest.* One note is that the items with known preferences from a user are not considered for recommendation, assuming that the user would not like to appreciate a recommended item that she has already consumed before. For example, as shown in Table I, a U-I matrix is presented, consisting of ratings from four users to six items. Then, a CF method is to generate recommendations (in terms of a ranked list of unseen movies) based on the U-I matrix to each user—for example, the movies *Inception*, *Taken*, and *Skyfall* need to be ranked in a descending order of predicted relevance as the recommendations to Alice.

2.2. Memory-Based Collaborative Filtering

Memory-based approaches to CF are categorized as *user based* or *item based*. Given a U-I rating matrix, a typical user-based CF approach predicts a user's rating on a target item by aggregating the ratings that a few similar users have previously given to that item [Resnick et al. 1994]. Similar users are identified using a similarity metric, usually the Pearson correlation or the cosine similarity [Singhal 2001], applied to rating vectors, each containing ratings of items in the collection that have been assigned by one particular user. Usually, the K nearest neighbors—that is, the K users with the highest similarities to the given user—are selected, and their ratings on the target item are aggregated in order to generate a predicted rating for the given user on that item. Following the notations in Section 2.1, we can formulate the predicted rating of user i to item j as follows:

$$\hat{R}_{ij} = \frac{1}{C} \sum_{k \in Z_i} sim(i,k) R_{kj}, \tag{1}$$

where Z_i is the set of K neighboring users of user i, C is a normalizing constant, and $sim(i,k)$ designates the similarity (in terms of a predefined similarity measure) between user i and user k. The computed similarities represent the key characteristic of memory-based CF. They form the "memory" of the system, which is used to produce later recommendation. Note that Eq. (1) is the simplest form of representing user-based CF and that many adjustments can be applied, as reported by Adomavicius and Tuzhilin [2005].

Extending this core mechanism, modifications and enhancements have been proposed to improve user-based CF, such as by introducing fine-grained neighbor-weighting factors [Herlocker et al. 1999], by exploiting a recursive neighbor-seeking scheme [Zhang and Pu 2007], and by using user-user similarity based on a subspectrum of user preferences [Shi et al. 2009].

In contrast to user-based CF, item-based CF approaches recommend items on the basis of information about other items that a user has previously rated [Deshpande and Karypis 2004; Linden et al. 2003; Sarwar et al. 2001]. The recommended items for the given user are ranked by aggregating the similarities between each candidate item and the items that the user has rated. Item similarity is defined by a similarity metric, usually the cosine similarity [Linden et al. 2003] or adjusted cosine similarity [Sarwar et al. 2001], between vectors that represent each item by the scores assigned by users. Similar to Eq. (1), we can also formulate item-based CF in the simplest form as follows:

$$\hat{R}_{ij} = \frac{1}{C} \sum_{k \in Z_j} sim(j,k) R_{ik}, \tag{2}$$

where Z_j is the set of K neighboring items of item j, C is a normalizing constant, and $sim(j,k)$ designates the similarity (in terms of a predefined similarity measure) between item j and item k.

Two drawbacks are typical for memory-based CF approaches. First, the computation of similarities between all pairs of users or items is expensive due to its quadratic time complexity. Second, the recommendation accuracy depends on the adopted similarity measure, which is usually based on a suboptimal relation between users or between items. On the other hand, the paradigm of conventional memory-based CF provides an elegant opportunity for integrating the rich side information of users and items for refining similarities, as will be discussed further in Section 4. This expansion can help compensate for the disadvantages mentioned previously.

2.3. Model-Based Collaborative Filtering

Model-based CF approaches are based on prediction models that have been trained using the U-I matrix, in whole or in part, as input [Adomavicius and Tuzhilin 2005; Ekstrand et al. 2011]. The trained prediction models can then be used to generate recommendations for individual users. In a simple and general form, we can represent model-based CF as follows:

$$f(p_i, q_j) \rightarrow R_{ij}, \quad i = 1, 2, \ldots M, \quad j = 1, 2, \ldots N, \tag{3}$$

in which p_i and q_j denote a set of model parameters for user i and item j, respectively. f is a function that maps the model parameters to the known data (e.g., ratings). Thus, the task of model-based CF is to estimate the model parameters p and q from the known

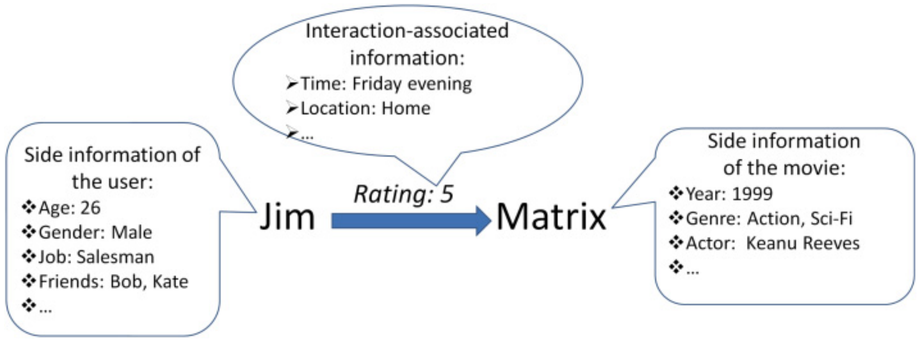


Fig. 1. Example of the side information and the interaction-associated information that can be deployed by a recommender system.

data R under the function f. Examples of conventional model-based CF approaches include the Bayesian network model [Breese et al. 1998], which models the conditional probability between items; the latent semantic model [Hofmann 2004], which clusters users and items around latent classes of U-I interactions; and the mixture model [Si and Jin 2003; Kleinberg and Sandler 2008], which models probability distributions of items within each cluster of like-minded users. Recently, matrix factorization (MF) techniques have attracted considerable attention due to their advantages with respect to scalability and accuracy, as witnessed by the algorithms developed within the Netflix contest [Koren et al. 2009]. Generally, MF models learn low-rank representations (also referred as latent factors) of users and items from the information in the U-I matrix, which are further used to predict new scores between users and items. For the convenience of readability, we include the most common formulation of MF as shown next, with the notations partly defined in Section 2.1:

$$U^*, V^* = \arg\min_{U,V} \left\{ \frac{1}{2} \sum_{i=1}^{M} \sum_{j=1}^{N} I_{ij} \left(R_{ij} - U_i^T V_j\right)^2 + \frac{\lambda_U}{2} \|U\|_F^2 + \frac{\lambda_V}{2} \|V\|_F^2 \right\}, \tag{4}$$

in which U and V are two matrices of latent factors, and U^* and V^* stand for their optimal values obtained from the minimization. Specifically, U_i is a column vector of U, representing the latent factors of user i. Likewise, V_j represents the latent factors of item j. I_{ij} is an indicator function that is equal to 1 if $R_{ij} > 0$, otherwise 0. $\|U\|_F$ denotes the Frobenius norm of the matrix, and λ_U and λ_V are regularization parameters that are usually set to alleviate model overfitting. MF is also formulated from a probabilistic perspective—that is, as a probabilistic matrix factorization (PMF) problem [Salakhutdinov and Mnih 2008a, 2008b]. The PMF framework models the conditional probability of latent factors given the observed ratings and includes priors that handle complexity regularization. Model-based CF, in particular the MF approaches, can be extended to incorporate additional information into recommender systems. In Section 4, we will review these extensions in detail.

3. ALTERNATIVE INFORMATION SOURCES FOR COLLABORATIVE FILTERING

As mentioned in the Introduction, we look beyond the U-I matrix to include two types of additional information that is considered useful for improving the recommendations: rich side information about users and items, and information about the situation in which users interact (e.g., rate, click, or purchase) with items. The two types of information are illustrated by a toy example in Figure 1 and will be discussed in more detail in the remainder of this section.

3.1. Rich Side Information of Users and Items

The range of sources of side information on users and items stretching beyond the U-I matrix is quite broad and varied. One of the most common side information sources is attribute information [Agarwal and Chen 2009; Bao et al. 2009; Gantner et al. 2010a; Koenigstein et al. 2011; Li et al. 2010; Moshfeghi et al. 2011; Shi et al. 2010a]. User attributes may include information such as the user's gender, age, and hobbies. Item attributes reflect properties of the item, such as category or content. However, two sources of information that have recently increased in importance in the recommender system research are social networks and user-contributed information. In the remainder of this subsection, we discuss these information sources in more detail.

3.1.1. Social Networks. The emergence of social networks has impacted a wide range of research disciplines in the past years [Grossman 2006; Lazer et al. 2009; Watts 2007], and recommender systems are no exception. Specifically to the recommender system area, social networks introduce information in the form of user-user relationships, which may be particularly useful for improving the quality of recommendation. In general, the social relationships between users can be either directed or undirected. Social trust and distrust relationships are among the most studied of directed social relationships [Guha et al. 2004; Leskovec et al. 2010c; Ma et al. 2008, 2009a; Massa and Avesani 2007]. The trust/distrust relationship can usually be described as an asymmetric user-user graph/matrix, which indicates whether one user trusts/distrusts another, as exemplified by the *Web of Trust* in Epinions.[3] Another important directed social relationship is *follow*, exemplified by the follow relationship used by Twitter[4] [Kwak et al. 2010]. The follow relationship is similar to the trust relationship in that it reflects the appreciation of one user (the follower) for another (the followee). In the case of Twitter, the follower receives the followee's microblog posts. The canonical example of an undirected social relationship is friendship, as used in Facebook.[5] Friendship can be represented as a symmetric user-user graph/matrix [Konstas et al. 2009], which encodes whether two users are friends of each other. It is also possible to extract more complex relationships, such as tie strength and similarity, between users in a social network by analyzing the link structure and the common patterns of user behavior [Backstrom and Leskovec 2011; Gilbert and Karahalios 2009; Liben-Nowell and Kleinberg 2003]. Recommender system algorithms that attempt to leverage social relationships, both directed and undirected, apply the assumption that users who stand in a positive relationship with each other may also share similar interests, as will be discussed further in Section 4.1.

3.1.2. User-Contributed Information. User-contributed information has become widely available in most recommender systems, and its volume has grown steadily since the introduction of Web 2.0 technology. Strictly speaking, the user ratings contained in the U-I matrix can be considered as one type of user-contributed information as well. Here, we introduce four types of user-contributed information that go beyond the U-I matrix: tags, geotags, multimedia content, and free-text reviews and comments, which are increasingly used in recommender systems:

—*Tags:* Tags are short textual labels that users assign to items [Robu et al. 2009; Sen et al. 2006]. Tags differ from conventional category labels in that users can assign them freely—that is, they are not constrained by a preset list. Users tag items for different reasons. Some tags describe item properties, and others express how

[3]http://www.epinions.com/.
[4]http://twitter.com/.
[5]http://www.facebook.com/.

users feel about an item. Tags are recognized as an information source that can be highly beneficial for improving the performance of recommender systems [Sen et al. 2009; Tso-Sutter et al. 2008; Zhen et al. 2009]. In addition to exploiting tags for recommending items, personalized tag recommendation has also become an active research topic [Hotho et al. 2006; Jäschke et al. 2008], which, however, falls outside the scope of this survey.

—*Geotags:* Since GPS positioning has become a standard functionality of mobile digital devices (e.g., cell phones or digital cameras), location information becomes abundant in social media sites [Luo et al. 2011], such as photo and video sharing sites and microblogging sites. The location information of an item in those sites is usually in the form of geotags—that is, explicit latitude and longitude coordinates. As reflected in its name, geotag can be regarded as a special class of tags that are particularly used for geographical positions. In a photo sharing site, geotags of a photo may indicate that the uploader of the photo has been to that location (or nearby) [Arase et al. 2010; Kurashima et al. 2010; Lu et al. 2010]. Similarly, the geotags of a user's tweets may be used to trace the location of the user [Cheng et al. 2010]. Due to the availability of large quantities of geotags, remarkable progress has been achieved in both the research on exploiting location information for improving recommendation and on facilitating location/travel recommendation.

—*Multimedia Content:* Social media sites, such as Flickr[6] and YouTube[7] [Davidson et al. 2010], have facilitated their users for uploading and sharing multimedia content (e.g., images and videos). The user-contributed multimedia content serves as another type of side information for the online users. For example, the categories of the photos in a user's album may reflect what kinds of items she likes to see. The particular type of videos that a user usually posts may indicate her interest in a particular item. Such information can be exploited for more elaborately modeling the user interests and thus contributing to content recommendation.

—*Reviews and Comments:* Last but not least, moving beyond tags and geotags, free-text reviews and comments that are published by users online are another important source of community contributions. They are valuable not only because of their semantics but also because of the sentiment dimension. For this reason, it is not surprising that reviews and comments have been exploited as a type of side information for improving recommender systems [Aciar et al. 2007; Jakob et al. 2009; Levi et al. 2012; Moshfeghi et al. 2011].

3.2. Interaction-Associated Information

The category of interaction-associated information includes information sources that are directly related to the event of a user interacting (e.g., rating, purchasing) with an item [Adomavicius et al. 2011]. The most common information source in this category is timestamps, which record the time at which a user interacted with an item [Gantner et al. 2010b; Koren 2009, 2010; Xiong et al. 2010]—for example, the time of a day when a user gave a rating to a movie. In addition, other information sources associated with U-I interactions are also exploited for recommender systems, such as the hunger status of a user when she rated a food menu [Ono et al. 2009], or the location where a user downloaded a mobile application [Böhmer et al. 2011]. Note that reviews and comments, as discussed in previous subsection, together with other types of users' feedback to items, can also be categorized as interaction-associated information as long as they provide additional information about the U-I interaction. For example, a

[6]http://www.flickr.com/.
[7]https://www.youtube.com/.

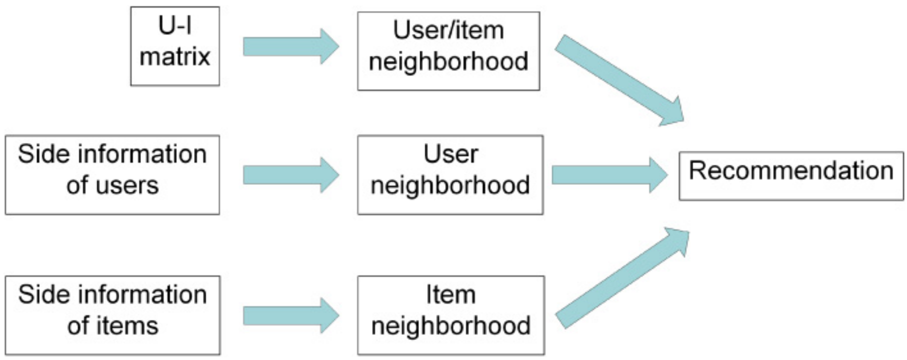


Fig. 2. A conceptual view of the algorithms incorporating the rich side information of users and items to extend memory-based CF.

user's comment on a hotel that explains why she gave a 5-star rating to the hotel may indicate her preference to hotels in a particular situation.

4. STATE-OF-THE-ART ALGORITHMS

For each of the categories of information sources that have just been discussed, a category of algorithms can be identified that have been developed to exploit it. The two categories of algorithms are discussed in this section.

4.1. Collaborative Filtering Using Side Information on Users and Items

4.1.1. Extending Memory-Based Collaborative Filtering. Recall that traditional memory-based CF approaches measure the similarity between users or items based on the U-I matrix. As mentioned earlier, side information can be exploited for calculating or refining the similarities and thereby improving recommendations. Conceptually, we can represent the algorithms that extend memory-based CF for incorporating the rich side information in a diagram, as shown in Figure 2. For instance, in a movie recommendation domain, a user can be represented by the tags that she assigned to movies in the past, whereas a movie can be represented by its genres.

To the best of our knowledge, the first work in this direction was carried out by Melville et al. [2002], who proposed first predicting the missing values in the U-I matrix by using the side information of items (e.g., categories like *title* and *genre*, referred to in this work as "content features") and then deploying user-based CF to generate recommendations. Similar approaches have been studied for different use cases [Burke 2002; Tso-Sutter and Schmidt-Thieme 2006]. Another category of approaches focused on tags as side information [Firan et al. 2007; Shepitsen et al. 2008]. Similar to ratings, tag-derived information also encodes connections between users and items. Tso-Sutter et al. [2008] proposed a similarity fusion strategy that calculates the user-user (or item-item) similarity based on both tags and ratings within a memory-based CF framework. Subsequently, *Tagommenders* [Sen et al. 2009] were proposed as a group of tag-based recommendation algorithms that utilize the inferred preferences for tags to predict the users' preferences for items. In order to address the noisiness of tags, schemes for tag enhancement have been introduced. For example, different weights have been used for different tags, which are then combined with traditional memory-based CF [Liang et al. 2010]. In addition to tags, geotags have also been exploited. Specifically, they have been used to extend memory-based CF for personalized location prediction [Clements et al. 2010b], shop recommendation [Takeuchi and Sugimoto 2006], and restaurant recommendation [Horozov et al. 2006].

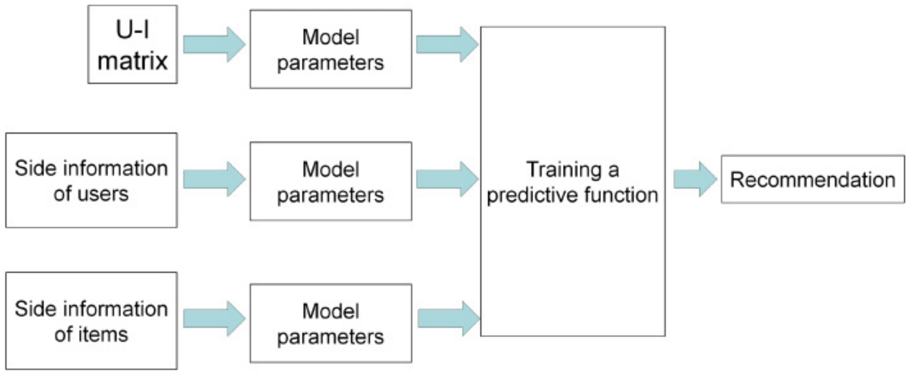


Fig. 3. A conceptual view of the algorithms incorporating the rich side information of users and items to extend model-based CF.

As mentioned in Section 3.1.1, social networks are one of the most important sources of side information. In analogy to nearest neighbors in user-based CF, a social network naturally provides the neighborhood (i.e., similar users) for each user—for example, the trustees of each user in a trust network [Massa and Bhattacharjee 2004]. *TidalTrust* [Golbeck 2005] and *MoleTrust* [Massa and Avesani 2007] are the two most well known models that predict a user's rating on an item by aggregating the ratings from the user's trustees (or connected users in other types of networks). Subsequently, *TrustWalker* [Jamali and Ester 2009a], a random walk model that integrates trust information with traditional item-based CF, has also been proposed. Using both the social network and the user-contributed tags, item recommendations can be generated by taking into account user-user similarities based on the two different information sources, as proposed by Guy et al. [2010].

4.1.2. Extending Model-Based Collaborative Filtering. In addition to memory-based CF, extensive work has also been devoted to extending model-based CF approaches to incorporate rich side information. In general, the algorithms in this direction provide recommendations to individual users by training a predictive function that is based on all of the variables, including the U-I matrix and the side information of users and items, as illustrated in Figure 3.

The earliest work in this direction focused on the classification perspective. For example, each user can be treated as a separate classification problem [Basu et al. 1998; Billsus and Pazzani 1998]. Under this approach, each item is treated as a training instance and is represented by a set of features, such as its ratings from all users and associated side information (e.g., attributes). Then, a classifier is trained for each user and used to predict relevant items for recommendation. Similarly, one can treat each item or each rating as a classification problem [Basilico and Hofmann 2004; Pazzani 1999] by taking all available ratings and/or side information of users and items as features of training instances. The key drawback of these classification models lies in their limited ability to generalize, and specifically, in the danger of overfitting, because these classifiers are usually trained on a limited number of high-dimensional feature vectors.

In addition to classification models, models that are based on topics have also been proposed. Popescul et al. [2001] have extended the aspect/topic model of Hofmann et al. [1999] to incorporate the item side information. Wang et al. [2006] proposed a generalization of latent semantic analysis (LSA) [Hofmann 2004] for this purpose. CF with side information was shown to be an application of this generalized LSA model.

Similar to this work, Wetzker et al. [2009] proposed to extend probabilistic latent semantic analysis (PLSA) [Hofmann 1999] to integrate item-tag relations with the U-I matrix for item recommendation. In step with the increasing amount of location data that has recently become available, such as geotags, geographical topic discovery/modeling has been proposed to extract (latent) topics for locations. Geographical topics have proved themselves to be a particularly useful form of rich side information. One of the earliest contributions on extracting geographical topics from social media was reported by Rattenbury and Naaman [2009], who studied place semantics based on Flickr tags. More extensive and general work was subsequently presented by Yin et al. [2011], who compared different geographical topic modeling strategies (i.e., based on location, text, and the combination of location and text). These authors proposed *latent geographical topic analysis*, which was shown to effectively discover the topics representing a region. Work by Hong et al. [2012] has proposed a new algorithm to discover geographical topics from geotagged Twitter messages and pointed out its usefulness for location recommendation.

Apart from topic models, several other conventional model-based CF approaches have also been adapted to exploit rich side information. One example is the unified relevance models that were first introduced by Wang et al. [2008] using only the U-I matrix. Subsequently, Moshfeghi et al. [2009] showed that those models can be extended to incorporate additional rich side information for improved item recommendation. As another example, Boltzmann machines were applied to CF by Salakhutdinov et al. [2007], first using only the U-I matrix and later extending the approach to incorporate item content features into a unified recommendation model [Gunawardana and Meek 2009]. The work of Salakhutdinov et al. [2007] and Tran et al. [2009] on exploiting Boltzmann machines for CF have first established links between CF and the emerging field of deep learning [Hinton and Salakhutdinov 2006; Hinton et al. 2006], the links we expect to be explored more intensively in the future.

Although most of the conventional model-based CF approaches can be extended to take into account the side information from users and items, a particular family of model-based approaches, MF, has drawn the most attention from the recommender system research community in this respect. Recommender system research that extends MF with rich side information can be considered to have begun with collective matrix factorization (CMF) [Singh and Gordon 2008], which simultaneously factorizes multiple related matrices, including the U-I matrix and matrices containing the side information. Note that CMF is sometimes also referred to as joint matrix factorization (JMF). For example, in a movie recommendation scenario, CMF can jointly factorize both the user–movie rating matrix and a matrix containing movie side information (e.g., a movie-genre matrix). The advantage of CMF lies in that the side information that is incorporated during MF serves to alleviate the sparseness in the U-I matrix, leading to more effective latent factors. Due to the particular importance and wide influence of the CMF framework in the area, we present a conceptual view of CMF in Figure 4. Corresponding to Figure 3, model parameters in CMF are specified as latent factors of users, items, the user side information entity, and the item side information entity (i.e., U, V, P and Q). Note that there could be multiple types of the user/item side information; however, we only keep here one type for the purpose of illustration. The latent factors are derived from the U-I matrix, the relation matrix of the user and its side information entity, and the relation matrix of the item and its side information entity. We also note that the work related to CMF was proposed slightly earlier than Singh and Gordon [2008] and applied to the task, not of recommendation but of document classification [Zhu et al. 2007]. In this work, the authors introduce JMF of both the document-feature matrix and the document-document link matrix. Here, we would also like to emphasize that CMF discovers the latent representations

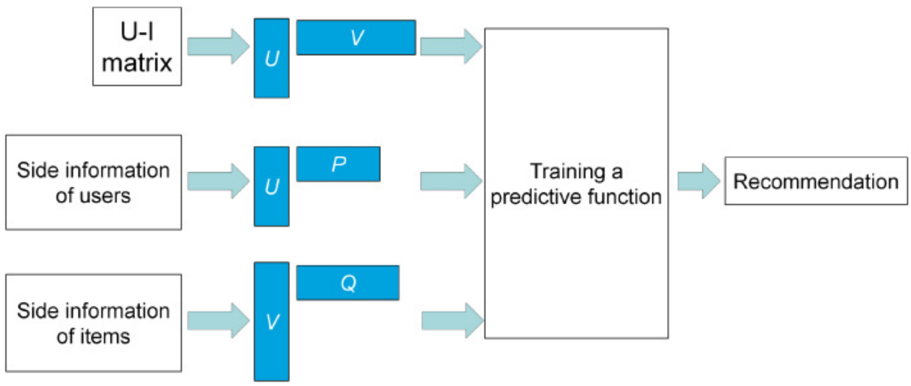


Fig. 4. A conceptual view of the algorithms incorporating the rich side information of users and items by CMF. U: Latent factors of users; V: Latent factors of items; P: Latent factors of the user side information entity; Q: Latent factors of the item side information entity.

of different entities (e.g., users, movies, genres) by decomposing the relations of each paired entities (e.g., relations between users and movies, relations between movies and genres). In contrast, another technique, tensor factorization (TF; to be detailed in Section 4.2.2) discovers the latent representations of different entities by decomposing the relations of all entities simultaneously, which suits to the case of incorporating interaction-associated information.

Various algorithms have been proposed that use CMF as their foundation and introduce various extensions that incorporate different types of side information. In particular, a large amount of work has been devoted to approaches that adapt CMF to integrate the side information derived from social networks. Based on the framework of PMF [Salakhutdinov and Mnih 2008b], approaches have been proposed that improve item recommendations by jointly factorizing a social trust network and the U-I matrix [Ma et al. 2008, 2011b]. Although differences exist between different algorithms, the basic constraint is similar—that is, the latent factors of a user should be similar to the latent factors of her trustees. Other work seeks to exploit distrust relationships. Specifically, Ma et al. [2009a] carries out joint factorization on the social distrust network and the U-I matrix. This approach imposes a penalty when the latent factors of a user are similar to those of her distrustees. Subsequent contributions of Ma et al. [2011, 2011a] extended their previous work from only exploiting social trust relationship to exploiting general (both explicit and implicit) social relationships.

In addition to the large effort devoted to exploiting social networks with MF, other types of side information have also been exploited for improving recommendation performance over MF that solely uses the U-I matrix. Zhen et al. [2009] exploited tags in their algorithm, *TagiCofi*, which jointly factorizes the U-I matrix and the tag-based user-user similarity matrix in order to improve item recommendations. Shi et al. [2010a] proposed joint factorization of the mood-specific movie similarity matrix and the U-I matrix for the purpose of mood-specific movie recommendation. Zheng et al. [2010] proposed joint factorization of the user activity correlation matrix, the location correlation matrix, and the location-activity matrix for the purpose of both location and activity recommendation. Shi et al. [2011c] exploited landmark category information from Wikipedia to build a category-landmark matrix. Joint factorization of the category-landmark matrix and user-landmark matrix leads to an effective landmark recommendation approach for travelers who like to share their geotagged photos online.

We also mention here another category of algorithms [Porteous et al. 2010; Shan and Banerjee 2010], which can be regarded as being related to those mentioned earlier. Shan and Banerjee [2010] present a probabilistic interpretation of CMF that models the conditional probabilities of the latent factors of users and items given not only the U-I matrix but also the additional matrices containing the side information about users and items. However, the work of Porteous et al. [2010] is different from the general CMF framework in an important respect. Porteous et al. [2010] proposed to fit the observed ratings in the U-I matrix with not only the latent factors of users and items but also with user-wise regression against item side information and the item-wise regression against user side information. This model can also be regarded as an ensemble in which pure MF is combined with metadata- or content-based regression predictors.

Several other algorithms that extend MF to incorporate side information have also been proposed beyond the CMF paradigm. In particular, one of the most influential frameworks is *regression-based latent factor models* [Agarwal and Chen 2009], which were proposed to integrate attributes of both users and items with U-I preference data into a generalized linear model for preference prediction. Based on the framework of regression-based latent factor models, social trust relationship of users has been incorporated into MF for improving the learning of latent user factors and, as a result, improving the recommendation performance [Jamali and Ester 2010; Ma et al. 2009]. fLDA [Agarwal and Chen 2010] can be regarded as a specific extension of regression-based latent factor models that targets the recommendation scenarios with rich side information. fLDA makes use of latent Dirichlet allocation (LDA) [Blei et al. 2003] to regularize a factorization model and suits to the cases in which side information can be represented in the form of a “bag of words” (i.e., with statistics of the occurrences of individual words). fLDA fits the relevance scores in the U-I matrix based on the regression predictor against user features and the regression predictor of item features, in combination with the inner product of the user’s interest in the latent topics and the degrees of latent topics estimated from item metadata. fLDA and the work of Porteous et al. [2010] are similar to each other with respect to the use of an ensemble. The key difference lies in their mechanisms of modeling the interaction between latent user factors and latent item factors. In the work of Porteous et al. [2010], this interaction is incorporated directly during MF, whereas fLDA incorporates it through LDA [Agarwal and Chen 2010]. Further work that extends MF to incorporate side information is the localized matrix factorization (LMF) [Agarwal et al. 2011]. This approach employs local latent factors for each entity under different types of side information, referred to as *contexts* [Agarwal et al. 2011]. The local latent factors from different contexts are linked to each other. It should be emphasized that LMF was designed to specifically overcome the drawback of CMF, which uses only global latent factors for each entity, running the danger of introducing severe bias due to unbalanced information sources.

4.1.3. Graph-Based Approaches. Memory-based and model-based approaches to CF represent the largest body of work in this domain. However, there is also another category of approaches, the graph-based approaches, the importance of which has rapidly grown with the increasing availability of additional information that can be of use for recommendation. Graph-based approaches have been well studied and intensively developed in the field of link prediction in social networks [Liben-Nowell and Kleinberg 2003]—a typical example is the random walk and its variants [Tong et al. 2006]. Researchers in the area of recommender systems have exploited random walks in various ways in order to improve CF based on the U-I matrix. Examples include the use of random walks to improve item-item similarity matrix for item-based CF [Gori and Pucci 2007; Yildirim and Krishnamoorthy 2008] to infer social trust relationship for trust-based recommendation [Jamali and Ester 2009a, 2009b].

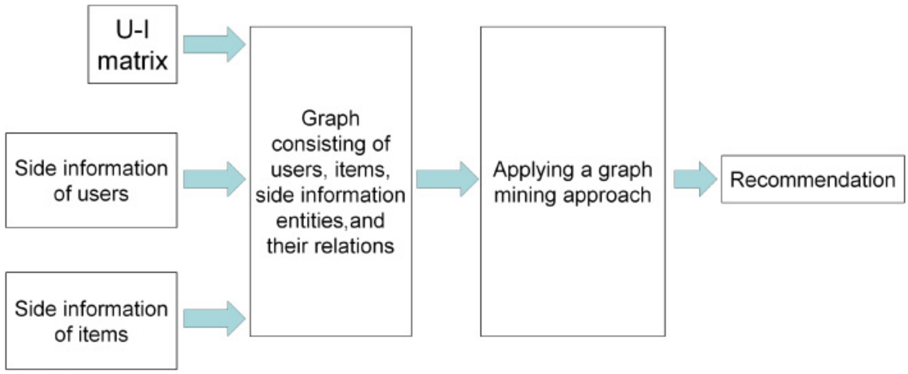


Fig. 5. A conceptual view of graph-based recommendation approaches incorporating the rich side information of users and items.

Graph-based approaches have moved beyond the U-I matrix and have been exploited to incorporate side information into CF algorithms. Figure 5 presents a conceptual view of graph-based algorithms, which consists of two major steps—that is, combining the U-I matrix and all other relations between the user/item and the side information entities into one graph and then applying a graph mining technique. In general, these approaches involve extending the bipartite graph, which consists of user nodes and item nodes, to a *multipartite graph*, which consists of user nodes, item nodes, and nodes representing other entities. Pioneering work in this area was presented by Konstas et al. [2009], who proposed using random walk with restarts to mine relationships in a multipartite graph including users, items, and tags. Along the same line of this work, graph-based approaches have also been exploited for investigating the effect of social tagging on different ranking tasks [Clements et al. 2010a], for providing music recommendation by combining user social relationship and music content features [Bu et al. 2010], and for improving recommendations of new users by inferring users' preferences not only for items but also for item attributes [He et al. 2011]. Although successful examples are presented earlier, one of the key issues in generating recommendations using multipartite graphs is the treatment of different scales that are used for the weights of relationships (edges) between different entities (nodes). For example, the relationship between a user and an item could be weighted by a rating (e.g., a 5-scale number), whereas the relationship between any two users is weighted by the friendship (i.e., a binary indicator). Apart from using heuristic normalizations to attain comparable scales of edge weights [Bu et al. 2010; Clements et al. 2010a], Shi et al. [2011a] have made an attempt to address this issue by adding scalars as additional entities to the graph and introducing the interaction frequency between different entities in the graph so that it serves as the common scale. Although that work focuses on the rater identification problem rather than item recommendation, the idea could still be applied to graph-based recommendations.

Because algorithms based on graphs can be used not only for integrating side information into CF but also for integrating interaction-associated information, we will return to the topic of graph-based recommendation algorithms in Section 4.2.4.

4.1.4. Summary of Properties. In Table II, we summarize and assess the main properties of the algorithms falling in the three discussed categories. The properties are assessed based on the general realizations and evaluations of these algorithms as reported in literature. We analyze five properties, data exploitation, model complexity, space complexity, time complexity, and results explanation, and grade each of them at three

Table II. Properties of the Algorithms for CF Using Side Information on Users and Items

	Extending Memory-Based CF	Extending Model-Based CF	Graph-Based CF
Data exploitation	Low	High	Medium
Model complexity	Medium	High	Low
Space complexity	High	Low	Medium
Time complexity	High	High	High
Results explanation	High	Low	Medium

levels, low, medium, and high. Specifically, *data exploitation* indicates the ability of an algorithm to exploit the known data. *Model complexity* indicates how many parameter settings need to be considered for deploying an algorithm. *Space complexity* indicates how much memory space an algorithm requires. *Time complexity* indicates how many operations an algorithm needs to take for generating recommendations for individual users. Finally, *results explanation* indicates the ability of an algorithm to explain the recommendation results. We explain the grading levels in the table on the example of the algorithms extending the memory-based CF. These algorithms are usually based on the similarities derived from the known data—that is, both the preference data and the side information data. As a result, the ability of these algorithms in exploiting the data usually depends on the adopted similarity measure, which may not always be optimal for deriving useful information from the data. In addition, the time complexity of computing all of the similarities is typically quadratic, and a large space is required for storing the similarities. However, the similarities can naturally serve as a basis for explaining the recommendation results to users—for example, a movie was recommended to a user because the user liked movies of similar genres and with the same actors. In addition, the algorithms in this category usually involve only a limited number of parameters—that is, often only the choice of similarity measure and the size of neighborhood. Thus, those algorithms may not require too much effort for parameter tuning.

In the previous analysis, we did not take into account the potential of exploiting parallel or distributed computing for reducing the time complexity of the algorithms. It is namely so that some of the algorithm categories may be easier to parallelize than the others, which may result in changes in the assessment in Table II. However, the research on parallel and distributed recommender systems is still in its infancy, and it is difficult to draw conclusions in this respect at this time.

4.2. Collaborative Filtering Using Interaction-Associated Information

The early work that exploited interaction-associated information for recommendation integrated this information in a step separated from recommendation generation [Adomavicius et al. 2005, 2011; Baltrunas and Ricci 2009; Panniello et al. 2009]. The separate step is either a prefiltering step that preprocesses the input of the recommendation algorithm or a postfiltering step that processes its output. Subsequent work focused on modeling this information together with the users and items. Generally, these algorithms can be divided into four groups. First, with the availability of timestamps that are associated with U-I interactions, a group of algorithms have been proposed for *time-dependent CF*. These algorithms mainly focus on improving CF performance by modeling the dynamics of user preference over time. Next, the presence of various sources of situational information (also referred to as *contexts* in the literature) that are associated with the U-I interactions gives rise to three additional groups of algorithms that can be distinguished on the basis of the underlying approach they choose: TF, factorization machines (FM), and graph-based approaches. In the following subsections, we cover these four groups in turn.

4.2.1. Time-Dependent CF. Temporal or time-dependent CF refers to CF algorithms that utilize time information for modeling and predicting user preferences on items. For example, in order to recommend movies that fit a user's present-day preferences, a time-dependent CF algorithm usually has more focus on the user's recent ratings on movies rather than the user's ratings from 1 year ago. Note that in this survey, we specifically distinguish time-dependent CF, which generates recommendations that are sensitive to a particular timeline, from *time-aware CF*, which generates recommendations for phases in a temporal cycle. A simple example of a time-aware CF algorithm is an algorithm that recommends movies to a user that are appropriate to watch on *Friday evening*. This subsection focuses not on time-aware CF but rather on time-dependent CF.

Some of the earliest research on time-dependent CF was carried out by Ding and Li [2005], who exploited a decay function for the ratings so that more influence was given by the more recent ratings. The benefit of exploiting the temporal dynamics of U-I interactions was highlighted through the winning solution for the Netflix competition [Koren 2009]. In this work, latent factors of users and items are designed as decay functions of time and also linked to each other based on time. Then, the latent factors of users and items at different time are learned individually and fine grained for improved prediction accuracy. A simplified and incremental version of this work was presented by Liu et al. [2010] for online recommendation over time. Xiong et al. [2010] proposed a time-dependent CF algorithm by exploiting TF, which models each rating as the inner product of the latent factors of users, items, and time slices, with an imposed constraint that the adjacent time slices should share similar latent factors. TF is discussed in more depth in the next subsection.

4.2.2. Tensor Factorization. TF models have been widely studied and have been productively exploited in a wide variety of applications [Kolda and Bader 2009]. A tensor is a multidimensional or multimode array. A matrix is then, in fact, a two-mode tensor. In light of the importance of MF approaches for CF, it is not surprising that TF approaches have also proven to be of significant value, especially in cases in which sources of situational information associated with U-I interactions are available. In other words, in analogy to the use case of MF where the data take the form of [user, item, rating], TF is appropriate for use in scenarios in which the data take the form of [user, item, interaction context, rating]. Among various existing TF models, two are the most often used for CF—that is, the CANDECOMP/PARAFAC (CP) model, which decomposes a tensor as a sum of rank-one tensors, and the Tucker model, which decomposes a tensor into a core tensor multiplied by a factor matrix along with each mode [Kolda and Bader 2009]. A major difference between two TF models can be understood as follows. Although the factor matrices resulting from the CP model have the same rank, they are typically not column/row orthonormal. Compared to this, the factor matrices resulting from the Tucker model are column/row orthonormal but usually have different ranks. A conceptual view at the algorithms based on TF models is depicted in Figure 6, in which the CP TF model is used for illustration.

Inspired by the work on personalized Web search [Sun et al. 2005], where the [user, query, webpage, click (boolean)] data is modeled by Tucker TF, researchers in recommender systems have exploited the Tucker TF model for processing [user, item, tag, usage (boolean)] data for the purpose of either item recommendation [Xu et al. 2006], or tag recommendation [Symeonidis et al. 2008b], or both [Symeonidis et al. 2010]. Rendle et al. [2009a] also exploited the Tucker model for tag recommendation. Their approach imposes a pairwise ranking criterion—that is, the latent factors of users, items, and tags are optimized for ranking. These authors later formalized this ranking criterion with their Bayesian personalized ranking (BPR) [Rendle et al. 2009b] approach. In addition,

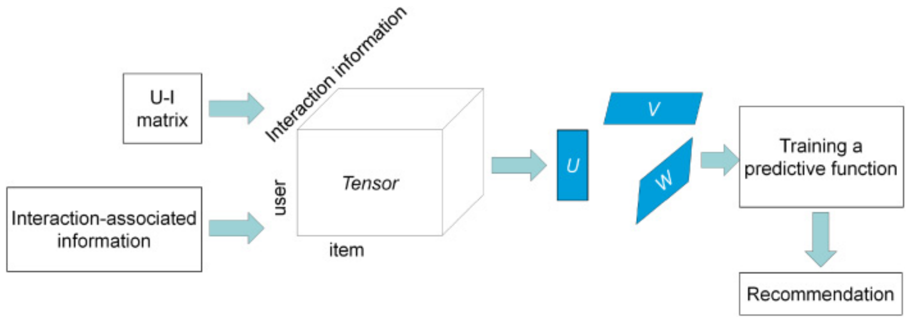


Fig. 6. A conceptual view of the algorithms incorporating the interaction-associated information by tensor factorization (the CP model in this case). U: Latent factors of users; V: Latent factors of items; W: Latent factors of interaction-associated information.

the authors further proposed a pairwise interaction tensor factorization (PITF) model [Rendle and Schmidt-Thieme 2010] to improve the performance of tag recommendation. PITF is substantially different from both the Tucker model and the CP model in that it involves low-order interactions explicitly (i.e., pairwise interactions between all the three modes instead of one ternary interaction). Subsequently, Cai et al. [2011] have proposed low-order tensor decomposition that combines multiple-order TF models to decompose [user, item, tag, usage (boolean)] data. The model achieved further improvement on the task of tag recommendation.

In addition to producing a significant amount of work on TF models that exploit tags, researchers have also studied the use of TF models for exploiting other information sources that are associated with U-I interactions. Karatzoglou et al. [2010] proposed a comprehensive algorithm that exploits the Tucker TF model for incorporating multiple information sources that are associated with U-I interactions. Probabilistic tensor factorization (PTF), an approach that combines PMF and TF, was developed and employed with the CP model for incorporating time information for time-dependent CF [Xiong et al. 2010], and with the Tucker model for the purpose of review recommendation [Moghaddam et al. 2012]. It is also worth mentioning that the work of Chi et al. [2008], who proposed a probabilistic polyadic factorization model developed from the latent semantic/aspect model [Hofmann et al. 1999; Hofmann 2004] to incorporate multiple sources with U-I interactions, was demonstrated to converge with the Tucker TF model. Last but not least, the work by Shi et al. [2012] has proposed to train the CP TF model to directly optimize an evaluation metric—mean average precision—for top-N context-aware recommendation.

4.2.3. Factorization Machines. Factorization machines (FM) [Rendle 2010] is a class of models that combines the advantages of support vector machines (SVM) and factorization models. The key difference between FM and SVM lies in that FM models variable interactions with a factorized parametrization, which allows estimation of reliable parameters for sparse interactions typical in recommender systems. FM has been demonstrated to successfully incorporate various information sources associated with the U-I interactions and enable context-aware recommendation at a low computational cost [Rendle et al. 2011]. The innovative idea of FM is to transform the multidimensional data associated with each U-I interaction into a real-valued feature vector. An SVM-like learning algorithm can then be used for regression against the observed U-I interactions. For example, the three-dimensional data [user, movie, time] associated with a rating is transformed to a $(M + N + K)$-element feature vector, in which M denotes the number of users in the collection, N the number of movies, and K

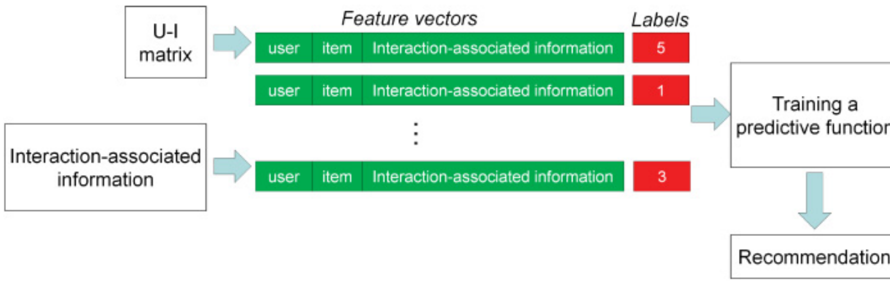


Fig. 7. A conceptual view of incorporating the interaction-associated information by FM.

Table III. Properties of the Algorithms for CF Using Interaction-Associated Information

	Tensor Factorization	Factorization Machines	Graph-Based CF
Data exploitation	High	High	Medium
Model complexity	High	High	Low
Space complexity	Low	Low	Medium
Time complexity	High	High	High
Results explanation	Low	Low	Medium

the number of time slices/bins. We also illustrate in Figure 7 a conceptual view of FM for incorporating interaction-associated information.

FM allows the modeling of higher-order interactions in a way different from TF models and thus provides another promising framework for utilizing multiple information sources with U-I interactions to learn recommendation models [Rendle 2012]. Moreover, it is also shown by Rendle [2012] that FM can recover many other models equivalently under special cases, such as the CP TF model [Kolda and Bader 2009], the PITF model [Rendle and Schmidt-Thieme 2010], and regression-based latent factor models [Agarwal and Chen 2009]. FM models also allow users to include the side information on users and items as additional features into the feature vectors and to address the recommendation scenarios as discussed in Section 4.1.

4.2.4. Graph-Based Approaches. Finally, graph-based approaches, which have been exploited for incorporating side information, as already discussed in Section 4.1.3, have also been exploited for extending CF with interaction-associated information. Conceptually, the process is rather similar to that illustrated in Figure 5, with the only difference in the input information sources—that is, the interaction-associated information instead of the side information. There have been a few contributions in this category. The session-based temporal graph was proposed to capture the U-I interactions over time and simultaneously model users' long-term and short-term preferences. Temporal recommendations are mined from the graph using random walk with restarts [Xiang et al. 2010]. Time intervals associated with user preferences for movies have also been used in the graph in the work of Shi et al. [2011a], as mentioned in Section 4.1.3. This work unifies the relations between different entities. In addition, Lee et al. [2011] have proposed to use random walk with restarts on a graph involving users and items together with interaction-associated information sources, such as location and time.

4.2.5. Summary of Properties. In analogy to the summarization and assessment of the main properties of CF using side information (c.f. Section 4.1.4), we now summarize and assess the same five properties, graded at three levels, for the algorithms of CF using interaction-associated information, as shown in Table III. For example, in the case of TF and FM models, the space complexity refers to the number of latent factors to be stored in the memory. This number can be considered relatively low because it

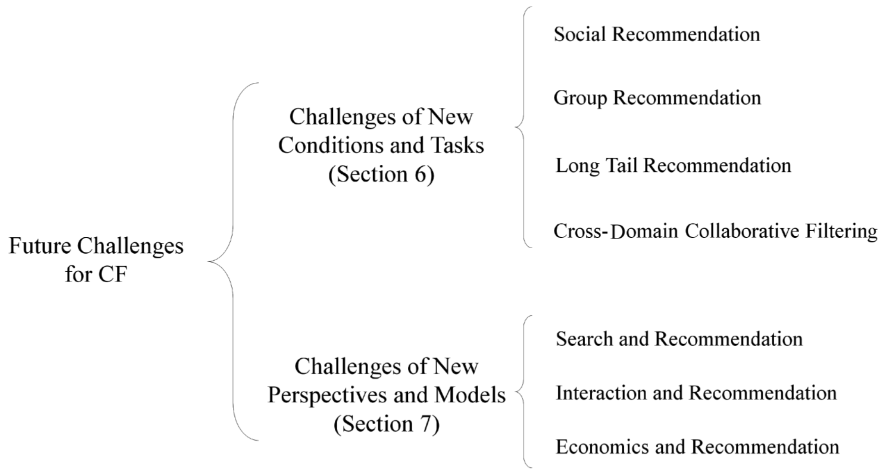


Fig. 8. Overview of the challenges for CF.

is only linear to the number of all the entities (users, items, interaction-associated variables). However, in graph-based approaches, we have to store all of the transition probabilities for modeling the edge connections between different entities, which makes the space complexity higher than for TF and FM. Regarding the model complexity, the number of model parameters in TF and FM models is much higher than in graph-based models, because in TF and FM models, many parameters need to be defined, such as those for regularization, learning rate, and latent dimensionality. As opposed to this, graph-based approaches such as random walk with restarts only require one parameter determining the restart probability. As mentioned in the beginning of this section, *time-dependent CF* differs from the other three categories of algorithms due to the unique information source, time, in which it does not represent a general framework for incorporating a variety of interaction-associated information sources. For this reason, we leave this category of approaches aside. However, we provide more information on exploiting temporal information for recommendation in Section 4.2.1.

5. OVERVIEW OF CHALLENGES

In the first half of this survey, we provided an overview of recommender system techniques that use the information reaching beyond the U-I matrix. We now turn to consider the future of these techniques. We maintain our focus on additional information, which includes both rich side information concerning users and items as well as the interaction information associated with the interplay of users and items. Based on this focus as well as the existing recommender system techniques that we have just covered, we identify a series of challenges that face the recommender system research.

We group the challenges into two main categories in the following two sections, as structured in Figure 8. We refer to the first category of challenges as the Challenges of New Conditions and Tasks. They are covered in Section 6 and have their origins within the recommender system research community. Initial work has been carried out in these areas, but they can still be considered to be newly emergent, as they have just started to attract significant research attention. We point out that these challenges are general challenges in the sense that they are independent of specific applications and appear across the range of recommender system domains. As recommender system research moves forward, innovative new techniques and frameworks must be developed in order to face these challenges. We refer to the second category of challenges as the

Challenges of New Perspectives and Models. They are covered in Section 7 and have their origins outside the recommender system research community. Their emergence is due to the interaction between recommender systems and other areas of research. In contrast to the first class of challenges, the second class of challenges serves as sources of techniques and frameworks. If recommender system research succeeds in harnessing these sources, conventional recommender system concepts could change considerably, bringing about a new era of success and productivity for the recommender system technology. In the next two sections, we present a discussion for each of the challenges in the two categories. The discussion is organized at three levels. At the level of Significance, we illustrate the importance of the challenge being discussed. Then, at the level of Open Issues, we discuss a set of specific issues that must be faced for addressing each challenge. Finally, at the level of State of the Art, we summarize the achievements of the existing work in addressing each challenge. In order to better highlight the challenges and provide a clearer view of the possibilities for addressing these challenges, we also discuss the relationship between each challenge and the past contributions to CF as presented in the first part of the survey.

6. CHALLENGES OF NEW CONDITIONS AND TASKS

Rapid growth and the emerging new concepts of systems and platforms accommodating recommendation mechanisms have resulted in increasing demands posed on these mechanisms to adjust to new conditions and tasks. Innovative recommendation concepts are required that can operate in the Web context, which is becoming increasingly social, where much more can be derived about relations between users or between a user and an item than from the traditional U-I matrix. Furthermore, increasing accessibility of the Web to new social groups, like elderly people, opens new perspectives for designing recommendation algorithms, like those that can satisfy not a single user but groups of users, such as those in elderly homes. In the same way, increasing demands for improved and personalized (mobile) services, like travel location recommendation, force the recommender systems to get the most from the available information resources, such as by focusing on the long tail of the popularity-based item list. Finally, service providers exploiting different commercial domains have discovered a high potential of learning user preferences across these domains, which gives rise to cross-domain recommendation. For each of these challenges, we describe in the following subsections its significance, open issues to be addressed by new research, and the state-of-the-art approaches that in one way or the other have attempted to address these challenges.

6.1. Social Recommendation

Significance. As discussed in Section 3.1.1, social networks are a valuable side information source about users for CF. Their ability to improve recommendations has been demonstrated by multiple research contributions, reviewed in Section 4.1. Adopting the dominant usage in the literature, we use the term *social recommendation* to refer to recommender systems that incorporate a social aspect. Figure 9 illustrates a typical scenario of social recommendation, in which we have observations of both users' social connections to (such as friendship) and users' preferences for different items.

Social recommendation naturally plays a central role in social networks and social media sites. One example is contact recommendations *People You May Know* that are offered to users of the LinkedIn professional network.[8] Another example, is the *Recommendations Bar* offered by the Facebook social network. In addition, in more general social media sites, users' social relationships can be exploited together with CF approaches for recommending content items, such as videos, photos, and news. We

[8]http://www.linkedin.com/.

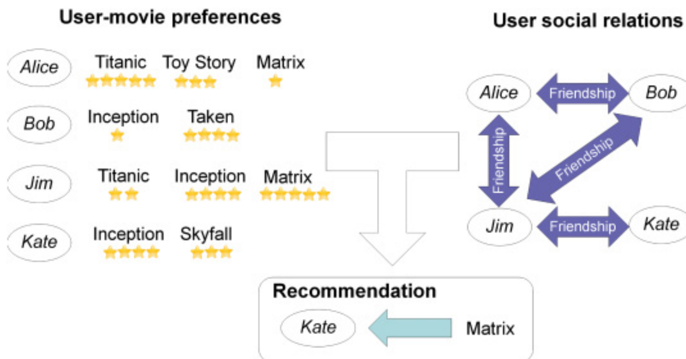


Fig. 9. An example of a social recommendation scenario. Kate may like movie *Matrix* because Jim, who shared similar interest in *Inception* and is also a friend to her, liked this movie.

anticipate that increasingly more information and content sources that are derived from social networks will be exploited by recommender systems in the future.

Open Issues. Here, we discuss two major issues faced by social recommendation and sketch the possibilities for future research directions.

—*How do inherent properties of social networks interact with social recommendation?* Existing work in this direction, as discussed in Section 4.1, generally neglects the intrinsic nature of social networks and its influence on recommendation. For example, connectivity in online social networks is known to be characterized by *Power Law* distributions [Clauset et al. 2009; Newman 2005]. In other words, it is a defining characteristic of social networks that few users have many connections, whereas many users only have few connections. If social recommendations are influenced by users' connectivity degrees, some users stand to benefit much more than others from the integration of a social network into recommender system algorithms. The impact of varying levels of connectivity on recommender system performance is, of yet, only poorly understood and deserves further investigation. Similar questions can be raised concerning the impact of other social network properties on recommender systems, such as their "small world" property [Watts and Strogatz 1998] or their "shrinking diameters" property [Leskovec et al. 2005]. In short, researchers have yet to fully explore the benefits that social relationship can bring to recommendation. An example of a method that can be used to investigate this issue has been introduced in preliminary work by Shi et al. [2010b]. This work proposes to exploit social network modeling techniques, such as those of Leskovec et al. [2010a], to simulate the social relationship between users in the recommender system. The simulation makes it possible to investigate the upper bounds of the benefit that the exploitation of social networks can be expected to provide for recommender system algorithms.

—*How can mutual benefits between recommender systems and social networks be promoted?* In other words, how can we improve both the content item recommendation and user social engagement via social recommendation? As discussed in Section 4.1, recommender system researchers have devoted significant effort to exploiting user social relationship for improving recommendation performance, whereas research on how to exploit recommendations for learning more about social relations has remained relatively limited. For this reason, an open issue is to investigate the potential of using the U-I matrix simultaneously for social relationship prediction and recommendation. A pioneering contribution in this area was made by Yang et al. [2011a], who demonstrated the mutual benefit between recommenders and social networks in terms of product recommendation and social connection prediction. However, a fundamental question that researchers need to address in this direction is the exact nature of the correlation between the similarity of users' interests and the social relationship. This question is important because the core assumption that must hold in order to guarantee mutual benefit is that socially related users share similar interests. Previous work has shown that there is a correlation between user online communication behavior and social relationships [Singla and Richardson 2008], which may also indicate the potential correlation between recommender system users and their social relationships. An initial study, performed by Said et al. [2010], investigated the impact of user social relationships on their tastes in movies and showed a positive correlation between the two. However, more convincing research in this direction is still needed to provide evidence for understanding the predictability between the users' interests in recommender systems and their social relationships. A productive avenue for exploring this predictability could be to address the question, *How should negative social relationships be exploited for social recommendation?* Examples of negative relationships in social networks involve distrust and blacklisting. One example of the relatively limited work in this area is by Ma et al. [2009a], who proposed to regularize the factorization of the U-I matrix by imposing a constraint that users with distrust relationships should have dissimilar latent factors. This work suggests that exploiting distrust relationships could have a positive effect for improving recommendation performance. However, another recent study by Victor et al. [2011] has compared several trust-based and distrust-based recommendation approaches, and observed that distrust relationships make only a marginal contribution. In the future, we believe that one of the challenging issues that researchers need to tackle in order to effectively use negative relationships for recommendation is the propagation of negative relationships in social networks. We expect this propagation to demonstrate a fundamentally different dynamics than the propagation of positive relationships. The simple assumption that "a friend's friend is a friend" captures the natural propagation of positive relationships relatively well. However, the assumption that "an enemy's enemy is a friend" is less reliable and suggests that the propagation of negative relationship is much more complicated. The research on social network analysis has started investigating the propagation of the negative relationships and its predictability [Guha et al. 2004; Leskovec et al. 2010b]. It can be expected that findings from research in this related area could inform the exploitation of the negative relationship for social recommendation.

State of the Art. In the literature, in addition to using social networks for item recommendation, as presented in Section 4.1, a few contributions have been made to social connection recommendation. One of the first contributions to use recommender system techniques for people recommendation in social networks was conducted in the domain of an enterprise social network by Guy et al. [2009]. This work empirically investigated user profile representations by structured information sources, for example, the user's co-authorship, and the effectiveness of content-based recommendation approaches. The results demonstrated the feasibility and the usefulness of exploiting rich side information sources for online connection recommendation. Inspired by this work, Hannon et al. [2010] have carried out comprehensive research on followee recommendation in the Twitter social network, by means of content-based approaches, CF approaches, and the combination of the two. Their work also demonstrated the usefulness of the content features from tweets (which, in contrast to the information sources used by Guy et al. [2009], consist of unstructured data) for improving recommendation over that solely based on the social graph. We also notice that other similar work investigated different user profile representations with structured data in Flickr social network for

Fig. 10. An example of a group recommendation scenario. Family 1 seems to have no interest in Sci-Fi movies (*Matrix* and *Inception*), which, however, may be preferred by Family 2.

a variety of recommendation purposes, including friend recommendation [Siersdorfer and Sizov 2009]. In the area of social tagging networks, Symeonidis et al. [2010] and Zhou et al. [2010] exploited user tagging data for user connection recommendation but did not examine the usefulness of the social graph. As mentioned previously, more recent work related to the topic of people recommendation has been carried out by Yang et al. [2011a]. This work proposed to jointly exploit both the user-service/item relations and the user-user social graph for both service/item and friend recommendation. In addition to people recommendation, community recommendation in social networks has also been attempted. *Combinational CF* [Chen et al. 2008] was one of the first attempts proposed for community recommendation. Vasuki et al. [2011] investigated both MF and graph-based approaches for community recommendation, exploiting both the user-user friendship network and the user-community network.

Summarizing, research work in social recommendation has mainly focused on the exploitation of social networks for item recommendation; however, an effective model/framework of social recommendation that can introduce mutual benefits between social networks and recommender systems is still missing. As addressed in Section 4.1, social networks can be taken as a type of side information for improving CF-based recommender systems. In turn, we would expect that the user behavior in the recommendation context can be taken as a type of side information for a social network, for which similar approaches as presented in Section 4.1 can be developed for analyzing and predicting social connections. In addition, we may explore side information sources about users to link their different behaviors in a recommender domain and a social network. Since social recommendation, due to its myriad applications, is expected to remain a productive research topic in recommender systems, the effort toward addressing the two open issues covered here holds the potential for high payoff in terms of impact on the recommender system community.

6.2. Group Recommendation

Significance. Although most recommender systems aim at providing quality recommendations for individual users, in some scenarios, recommendations are required that satisfy the needs of a group, for example, as movie recommendation for a family, restaurant recommendation for dating partners, and event recommendation for online communities. Figure 10 illustrates a scenario of group recommendation, which involves four users affiliated with two groups (i.e., families) and their preferences for different items. The item recommendations are expected to be provided to each group so as to be enjoyed by all group members. Therefore, the success of a given recommendation does not depend on the opinion of one user, but rather on the group as a whole. Because the recommendation needs of groups are complex and go beyond the sum of the needs of the individual group members, group recommendation has been identified as a research challenge in recommender systems [Jameson and Smyth 2007].

Open Issues. We cover three issues that distinguish group recommendation from recommendation for individual users. These issues constitute the key aspects that need to be addressed for this research challenge. We note that a recent overview work by Pazos Arias et al. [2012] has also discussed the new perspectives on group recommendation. In this survey, we restrict ourselves to highlighting only those group recommendation issues that are most critical in our viewpoint, with the goal of complementing the information already provided by Pazos Arias et al. [2012].

—*How to model group-level preference?* Intuitively, a good recommendation for a group should be something that fits the group-level preference. However, modeling the group-level preference is difficult, because in most scenarios we only have the preferences of individual users, and the side information of individual users and items. A simple model could take the group-level preference to be the intersection of all members' individual preferences [Masthoff 2011]. However, such an aggregation approach potentially suffers from two drawbacks. First, it might result in more severe data sparseness for CF, as the common interests among all the members could be rather limited. Second, it might overlook the relationship between the members and the group, as members can possibly adjust their personal preference to accommodate those of other group members, who they know to enjoy or consume different sorts of items. To overcome the drawbacks of this simple model, significant research effort toward effective recommendation algorithms that can model the group-level preference in a reasonable and interpretable manner is needed.

—*What is the impact of group structure, and how to exploit it for group recommendation?* Members in a social system/organization sometimes have different roles, such as leaders and followers. In this case, members in a group should have different types of influence on the items recommended to the group as a whole. Here, again, we note that a good group recommendation is not necessarily the "common" interest of all group members. For example, if plenty of research themes are available/relevant to be recommended to a research group, the group leader, who holds a 10-year strategic view on this group but also understands the expertise among the group members, should have much stronger opinion on the relative importance of different themes than the group members with less experience, who may only consider the relevance of those themes based on their own expertise and a significantly narrower understanding of the field. In this case, a good recommendation should be more biased to the group leader's preference. Another example is if a parent takes a young child to see a movie, in which case the recommendation should be more heavily based on what will interest the child rather than the parent. Because of such asymmetries, group structure needs to be investigated and exploited for steering group recommendation. Although the explicit group structures may not be available for individual groups, there could exist possibilities for mining group structures from the side information about group members, such as the interaction information and the social relationship. Then, one could further study how the inferred group structures benefit group recommendation. To the best of our knowledge, the issue of group structures has not been raised or studied in the community, although it is clear that research addressing this issue stands to make a significant contribution to group recommendation.

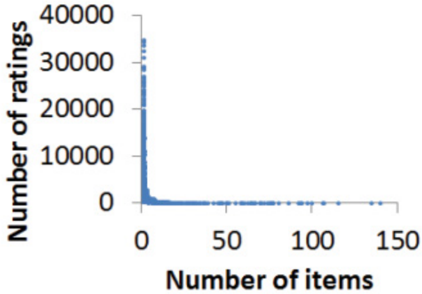
—*How to take into account the dynamics of a group for group recommendation?* This issue has been raised in the work of Pazos Arias et al. [2012]. We also highlight this issue because we consider dynamics to be a key characteristic that makes group recommendation different from other recommendation tasks. For example, it is natural that online groups can be growing (i.e., new members joining in) or dying (i.e., members leaving) [Kairam et al. 2012]. Little is known about the impact of such trends on group recommendation. Further, research has yet to explore how changes in the group structure can best be deployed to inform recommendations. For example, the information that a particular member left a group could potentially shed light on the ways in which recommendation could be improved for the remaining group members. The challenge is how to infer the implications of the changes, for example, if the member dropped out due to interests that diverged with those of the group. Conversely, if a member is observed to join the group, this information could be useful for improving recommendations as long as the reason for joining can be inferred.

State of the Art. A few research contributions have been made to address the challenge of group recommendation. Most of them have focused on the first open issue mentioned earlier, namely preference modeling. Two strategies have been attempted—that is, one is to first generate a group profile by aggregating the user profiles in the group and then make recommendations for the group profile, and the other is to first generate recommendations for all users in the group and then aggregate the results as the final output for the group [Amer-Yahia et al. 2009; Campos et al. 2009]. The effectiveness of the two strategies for group recommendation has been investigated in recent studies by using either simulated data of user groups [Baltrunas et al. 2010] or real data about families of users [Berkovsky and Freyne 2010]. In addition, some recent work has exploited the social relationship of group members for group recommendation [Gartrell et al. 2010]. Other recent work has exploited items' content features or metadata for modifying group recommendation that is solely based on the joint preferences of group members [Seko et al. 2011]. However, the two challenges—namely, the increasing data sparseness and conditional relationship between the members and their group—have not been addressed, nor have they even been widely recognized. A recent competition focusing on the group recommendation task [Said et al. 2011] has, again, highlighted the difficulty of addressing these challenges.[9] Finally, we emphasize that the other two open issues, group structure and dynamics, also present challenges in need of attention from the research community. We notice that the group information can be regarded as a type of side information about users (in the case that users' group memberships are stable) or a type of interaction-associated information (in the case that users' group memberships are dynamic). For this reason, we may expect that the algorithms as discussed in Sections 4.1 and 4.2 could be investigated, modified, or specialized for addressing the challenge of group recommendation as well.

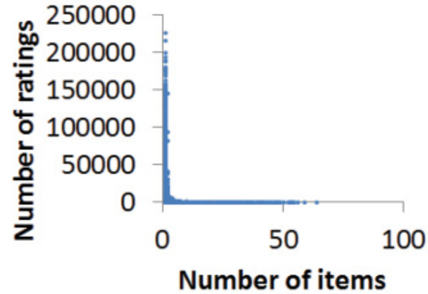
6.3. Long Tail Recommendation

Significance. According to the terminology introduced by Anderson [2006], the *long tail* within the area of recommender systems refers to the items that have low popularity. In other words, those items have only been rated or viewed by very few users. In Figure 11, we show the long tail phenomenon in two datasets, the MovieLens 10 million dataset[10] and the Netflix dataset, which are commonly used in recommender system community. As can be observed in both datasets, there are a small number of items that received a huge number of ratings from users (e.g., in the Netflix dataset, one item may have more than 200,000 ratings), but many items only received a few ratings (e.g., in the Netflix dataset, one item may have fewer than 10 ratings). Note that the tail items are different from *cold-start* items, which are typically new items in a system, but they may become more and more popular (receiving more interactions from users) over time. The ability of a recommender system to recommend items from the long tail is a critical indicator of the usefulness of recommender systems. For example, a user may like a popular movie (she may already know it) that suits her interest but may

[9]http://2011.camrachallenge.com/news/.
[10]http://www.grouplens.org/node/73.



(a) MovieLens



(b) Netflix

Fig. 11. The long tail distribution in the MovieLens dataset and the Netflix dataset. Note: A point (x, y) in the plot means that there are x items in the dataset that have y ratings.

be more in favor of a movie recommendation that is less obvious and surprises her. The ability to recommend items that users would not have otherwise found or thought of raises their appreciation of the system. Similarly in the travel domain, a traveler could appreciate a recommendation for a place hidden in the long tail more than a popular location that is described in every tour guide. In short, long tail recommendation plays an important role in most recommendation applications because it helps, to a large extent, to improve users' satisfaction and, by stimulating curiosity, also their engagement.

Open Issues. We summarize our perspective on three issues that make long tail recommendation challenging:

—*How to promote the recommendation of tail items?* As mentioned previously, the difficulty of recommending long tail items lies in the fact that such items have very limited user preferences in their history. One possibility is to address this problem by taking into account either content information derived from the items or rich side information associated with them when applying CF approaches. Another possibility is to first explicitly identify the tail items in a given collection and then generate recommendations intentionally biased to those tail items [Park and Tuzhilin 2008]. However, both of these options involve heuristics.

—*What is the added value of tail items, and how to exploit it in recommendation algorithms?* We also notice that there has been little investigation on how recommendation of tail items can influence user satisfaction, or how additional revenue can be generated by the recommender systems from the tail items. In general, principled answers are lacking to the question of why, and in which cases, recommending a tail item is more important than a head item. Extensive experimental research may be necessary in order to understand and explain the potential added value to be derived from long tail recommendation. Pioneering work on this issue was carried out by Oestreicher-Singer and Sundararajan [2012], who studied the revenue influenced by recommendation of tail items and head items in Amazon.com. They found that the recommender system helps to improve the revenue from the tail items but at the same time reduces the revenue from the head items, resulting in a decreased overall revenue. Although this survey does not directly address the challenge of improving tail recommendations, it serves as an example of a work that could inform future research that addresses the underlying question, *Why recommend tail items?*

—*How to match long tail recommendations and users' topical needs?* Recommendation in the long tail may not only mean recommending items receiving less overall user attention but also satisfying user needs that are, relatively speaking, more exotic. Adapting recommender systems not only to niche items but also to niche preferences is a formidable research challenge. Consider a travel recommender system that recommends that a user visit a relatively popular destination, the London Eye. The user can be satisfied with this recommendation for a relatively popular reason, namely because of a general desire to visit famous attractions. However, the user can also be satisfied with this recommendation because of a technical interest in large *observation wheels*, which is shared by relatively fewer people. Because this interest applies to a very small group of users, it will not be well represented in the traditional U-I matrix. In other words, the matrix does not contain the information on the rationale behind the ratings. Facing the challenge of recommending items for long tail reasons requires methods capable of adapting recommendations to a user's topical interests. Approaches to this challenge could derive benefit from analyzing user's topical interests from various information sources in order to determine the specific nature of the long tail adaptation that would best suit a user. One of the recent contributions exploited the category information of geographic landmarks from Wikipedia[11] for the purpose of nontrivial landmark recommendation [Shi et al. 2013]. However, in a broad scope, awareness of the importance of this open issue is not widespread, and significant efforts are necessary to understand the nature of highly specialized user interests and also how to adapt recommendation to address them.

State of the Art. The long tail problem in recommender systems was first formulated by Park and Tuzhilin [2008], who specifically focused on improving recommendations of items in the long tail. The authors proposed to first split the item set into head items and tail items and then only use the ratings in the clusters of tail items to generate the recommendations for the tail items. The effectiveness of their approach relies, however, on achieving the proper split between head and tail items. More recently, Steck [2011] has proposed to specifically exploit item popularity (i.e., the number of ratings for an item) for refining the evaluation metric used to measure recommendation accuracy so that it places more emphasis on successful recommendations of tail items. We also note that long tail recommendation is closely related to the issue of *novelty / serendipity* in recommender systems [Grossman 2010]. Researchers focusing on this issue have argued that it is important to recommend items that are not only relevant but also can provide users with a positive sense of surprise [Hurley and Zhang 2011; Nakatsuji et al. 2010; Oh et al. 2011; Onuma et al. 2009]. In short, the contributions that have been made thus far in this area have mainly focused on mechanisms that promote the recommendation of tail items—that is, they address the first technical problem discussed earlier. There has been a marked shortage of contributions that treat the theoretical aspects of long tail recommendation models and the second and the third issues discussed previously remain, therefore, open research challenges. As discussed in Section 4.1, the side information of users and items usually has the effect of compensating for data sparseness in recommender systems. For this reason, it is promising to explore possible side information sources of long tail items for discovering their potential match with the users' topical interests. In addition, the additional information about the interaction between users and tail items may indicate the reason why a user likes a tail item and the particular value that this item brings to the user. In this sense, long tail recommendation is also in need of exploring interaction-associated information sources and may benefit from previous contributions as discussed in Section 4.2.

[11]http://www.wikipedia.org/.

Fig. 12. An example of CDCF scenario. In Domain A, Alice's preferences are not similar to any of the other users in this domain. However, in Domain B, we discover that users who like "My Heart Will Go On" (the theme song to *Titanic*) may also like "There You'll Be" (the theme song to *Pearl Harbor*). This knowledge can be exploited for recommending the movie *Pearl Harbor* to Alice.

6.4. Cross-Domain Collaborative Filtering

Significance. Cross-domain collaborative filtering (CDCF) has recently started to draw significant research attention [Li 2011]. The core concept of CDCF is to exploit information from multiple U-I matrices (i.e., domains) in order to allow the recommendation performance of one domain to benefit from the information from one or more other domains. In other words, we can regard CDCF as CF on one U-I matrix/domain that takes other U-I matrices as additional information sources. The CDCF techniques hold particular importance for recommender systems for two reasons. First, they can be exploited by megadata owners (e.g., Internet companies with a variety of online services) for further optimizing recommendations for their users under different sites. Second, they can introduce mutual benefit for different data owners (e.g., two companies running businesses that offer different online products) for further improving their service quality. We illustrate in Figure 12 an exemplified scenario where two domains (A and B) are involved. The two domains may have different users and also different category of items (e.g., movies vs. music). Then, it is expected to have knowledge transfer between different domains so as to introduce benefits for recommendation in both domains. Recently, a new online application, *Tipflare*,[12] has been developed at MIT as a pioneering application of cross-domain recommendation.

Open Issues. As a new research topic in recommender systems, CDCF is in search of answers to two fundamental questions: first, what could be the common knowledge/data that can be transferred/shared between different domains, or simply, "What to share?" and, second, what could be the optimal way to transfer/share knowledge between different domains, or simply, "How to share?" [Pan and Yang 2010; Pan et al. 2010]. In the following, we elaborate on our understanding of these two issues:

—*What to share?* This problem focuses on the usefulness and the reliability of information patterns that could be exploited for CDCF. Users (or items) in different domains could be mutually exclusive, thus making it difficult to establish links between users (or items) from different domains. In that case, an interesting direction is to explore the user-contributed information, such as tags shared between domains [Shi et al. 2011b]. In addition, since social networks can interconnect users across different domains, it might also be promising to derive knowledge that is common between two

[12] https://www.tipflare.com/.

domains by analyzing information, such as votes/likes on different domain products, contributed by socially connected users. It is important to pay careful attention to the reliability of information that is common between two domains. In other words, in cases in which it is possible to automatically identify information about characteristics shared between two domains, it is still questionable whether, or which of, those characteristics are reliable enough to improve CDCF. For this reason, it is important that researchers also gain an understanding of cases in which CDCF could degrade the recommendation quality.

—*How to share?* Addressing this issue requires the development of new algorithms for maximizing the mutual benefit from multiple domains. On one hand, the link (or the correlation) between user preferences in different domains may be hidden. Methods that focus on discovering cross-domain correlations hold promise to improve the performance of CDCF. On the other hand, there might be multiple links between different domains that could be used for knowledge transfer. In this case, algorithms are needed that are not only capable of exploiting multiple links simultaneously but that are also able to automatically discover the relative importance of different links. In addition, as mentioned earlier, there are typically many information sources available in each of the individual domains. Individually, the domains may already be large, and taken together they may pose an even more serious scale challenge for CDCF. Massive amounts of information from multiple domains need to be processed with a reasonable computational cost.

State of the Art. Some of the earliest work on CDCF was carried out by Berkovsky et al. [2007], who deployed several mediation approaches for importing and aggregating user rating vectors from different domains. Recently, research on CDCF has been influenced by, and has benefited from, the progress in the area of transfer learning [Pan and Yang 2010], a machine learning paradigm for sharing knowledge among different domains. For example, the approach called *coordinate system transfer* [Pan et al. 2010] first learns latent features of users and items from an auxiliary domain (which has relatively more user preference data) and then adapts them to a target domain (which has relatively less user preference data). Further, an extension of this approach has been proposed that exploits implicit user feedback, rather than explicit user ratings, to constitute the auxiliary domain [Pan et al. 2011]. However, these approaches require that either users or items are shared between the domains, which is a condition not commonly encountered in practical applications. Codebook transfer (CBT) [Li et al. 2009a] and the rating-matrix generative model (RMGM) [Li et al. 2009b] are two approaches that transfer the knowledge from an auxiliary domain by learning an implicit cluster-level rating pattern that can be shared with a target domain. Similarly, multidomain CF is an approach that extends PMF to multiple domains involving explicit user preference [Zhang et al. 2010] or implicit user feedback [Tang et al. 2011] by learning an implicit correlation matrix, which links different domains for knowledge transfer. One of the latest contributions has adopted the CDCF framework of RMGM [Li et al. 2009b] to address the problem of dynamic CF [Li et al. 2011]. However, those approaches rely on implicit domain correlations that are mined solely from user preference data, and no explicit links are exploited. Shi et al. [2011b] have proposed tag-induced cross-domain collaborative filtering (TagCDCF), which uses common tags as bridges to link different domains for improving CDCF. On the whole, very limited work has been devoted to exploiting explicit links between different domains for CDCF. For this reason, the first technical problem—that is, what to share—is still a significant open issue. In addition, as discussed with respect to the second CDCF issue, the exploitation of various information sources and the consideration of multiple cross-domain links have not been fully explored by the research community. Thus, many opportunities remain open for addressing the challenge of CDCF. We would like to emphasize that the side information of users and items may be one of the most critical information sources for CDCF, as it can serve as a common background for different domains (e.g., movies and books may share the same genre space). For this reason, we expect that previous contributions of incorporating side information, as discussed in Section 4.1, can be exploited for addressing the challenge of CDCF.

7. CHALLENGES OF NEW PERSPECTIVES AND MODELS

Outside of the core research area of recommender systems, there are a number of other research areas that are rapidly developing and that have the potential to inform and stimulate innovation and progress in the recommender system research. In this section, we cover three of these areas that we consider to be particularly promising sources of the new perspectives and models.

7.1. Search and Recommendation

Significance. Search and recommendation are two technologies that have come in to their own with the rise of the Internet. From the application perspective, the difference between the two lies in whether or not users are required to express their information need explicitly, that is, via queries (as in search), or whether the information needs are implicit, for example, encoded in rating and consumption behavior (as in recommendation). Because the function and benefit of the two technologies are complementary, it can be expected that many online applications will have the need for both, with various levels of integration. A recent example of the convergence of search and recommendation is the +1 button offered by *Google+*[13] that allows users to vote on search results. The quality of search results stands to benefit significantly from integrating explicit feedback from human users with similar search needs. In addition, another recent Google application, *Google Now*,[14] aims to achieve personalized search by integrating context-aware recommendation. Because of the wide reach and enormous importance of search engines, the integration of search and recommendation technologies has become an attractive research topic and presents a substantial challenge for researchers from both communities.

Open Issues. We would like to discuss two challenges that we expect to be of central importance for the future research on the integration of search and recommendation:

—*How can recommendation techniques help improve the quality of search results in the long tail?* In the case of Web search, which involves billions of webpages, millions of which can be relevant to a single query, there could be a tremendous number of webpages that are only visited by users an extremely limited number of times. If webpages are infrequently viewed, they will be infrequently voted upon by users, even when voting is effortless, as with *Google+* as described earlier. There is a real danger that a given relevant webpage does not accumulate any votes at all. We note that this challenge can be regarded as a special case of the general Long Tail Recommendation challenge (see Section 6.3) in the search scenario. However, we emphasize that one major/particular issue here is that the result webpages (which correspond to items) are conditioned on particular queries. It is important to keep in mind that in search scenarios, the long tail involves the interaction between the frequency of user votes and the frequencies of the queries. Note that there are many queries that are issued only infrequently, and for this reason, low voting volume

[13]http://www.google.com/+1/button/.
[14]http://www.google.com/landing/now/.

might fail to reinforce not only the importance of the webpage but also the relevance relationship between the webpage and the query. Another danger is that user votes will create a snowball feedback effect. In other words, a few user votes will lead to certain webpages being ranked higher, where they will be more easily seen and accumulate more votes. Webpages that are relevant but happen not to establish their popularity early risk falling to the bottom of the ranking and never being discovered. We would suggest two directions for addressing this problem. First, one could develop methods to predict votes for webpages and then use the inferred votes for improving search results. These methods would create a minimum vote volume for tail webpages and could also prevent webpages from being lost in the snowball voting patterns. Second, instead of the voting system for the search results, one could consider developing a voting system for queries so as to avoid the constraint from tail webpages. In this way, the search results are expected to improve not by the collaboratively recommended results, but by means of using collaboratively recommended queries [Sun et al. 2005; Yan et al. 2011].

—*How to allow search results to benefit from user votes but also maintain attack resistance?* Conventionally, *attacks* in recommender systems refer to cases in which malicious users (attackers) assign high ratings deliberately to particular items in order to promote (or denigrate) those items [Lam and Riedl 2004; Mobasher et al. 2007]. In the case of a voting system for search results, malicious users could also shill the system by giving deliberate votes to particular results (e.g., webpages). We emphasize that this issue could be more severe than that in recommender systems because the queries are used to express the users' information needs. For example, the query "New York" is often used by users who are planning travel to New York. This information need can be easily used by malicious users who may deliberately promote some results (e.g., a particular hotel) by assigning a lot of votes to them. This issue also opens plenty of opportunities for future research toward attack-resistant mechanisms for collaboratively recommending search results.

State of the Art. The relationship between search and recommendation was formally raised in a panel discussion in 2010 [Guy et al. 2010]. A few recent research contributions have demonstrated the possibilities of exploiting information from search engines for item recommendation [Li et al. 2010; Smyth et al. 2011], especially in social settings. However, to the best of our knowledge, there have been no specific attempts that address the open issues for the integration of search and recommendation that we have identified here. We anticipate that a sizable number of studies on this challenge will be carried out in the near future, leading to significant new developments in online applications. We would like to emphasize that there is a remarkable amount of interaction-associated information generated in the intersection of search and recommendation. For example, if a user is interested in an advertisement on a Web site, then, the query that was used by the user to find the Web site can be a valuable piece of information for the advertisement recommendation. In this sense, there is great potential to exploit the interaction-associated information from users' search patterns, by referring to previous contributions in Section 4.2, for improving recommendation performance, and vice versa.

7.2. Interaction and Recommendation

Significance. Today, the interaction between users and recommender systems is no longer focused on ratings, and most recommender systems have become more interactive than before. Note that the term *interaction* in this subsection refers to a process in which the system and the user are engaged in an information exchange. On one hand, the system may elicit particular information/reactions from the user and integrate this information to refine the recommendation results. On the other hand, the system may allow the user to assess the recommendation based on the explanations that it provides to the user.

Conversation has been recognized as one of the most important types of interaction for recommender systems [Tunkelang 2011]. Typically, a conversation is used to guide the users to express their information needs more explicitly, providing a basis for fine-grained adaption of recommendation to user needs [Mahmood and Ricci 2009]. For instance, a movie recommender may first ask the user some situational questions, such as "Are you alone or with friends?" before generating recommendations. The answers to this kind of questions could help the system increase the relevance of recommendations. Another example is that the system can ask the user for feedback on recommendations. One possibility would be that if a user did not choose any of the top (e.g., top 10) recommended items, the system may ask the user why she was disappointed. The answer to this question could also be used in improving recommendation algorithms by allowing them to adjust the recommendations for this user [Chen and Pu 2012].

Explanation of recommendations has also been considered as a critical function for recommender systems. Explanations provide the users with rationale that motivates why the items/products have been recommended [Friedrich and Zanker 2011; Herlocker et al. 2000; Knijnenburg et al. 2012; Symeonidis et al. 2008a]. Two main effects can be attained by explaining recommendation results. First, it helps users to better understand the mechanism of the system. Understanding, in turn, potentially improves user satisfaction, because users could learn to adjust their behavior and expectations to the system [Ye and Johnson 1995]. In addition, it also builds trust because the users can tell if they agree with the factors influencing recommendations produced by the system. Second, it may allow recommender systems to serve users better with serendipitous results, as the users may discover new interest inspired by the explanations [Yoo and Gretzel 2011]. For example, in the case that a user wants to enjoy some movies and consults a movie recommender, the user may like the recommended movies that are popular at that moment and fit his interest well. However, if the user has never heard of the recommended movie but the recommender system provides a convincing explanation as to why the user might like the movie, the user might prefer to watch this movie instead of other "predictable" suggestions. In view of the advantages sketched previously, the integration of interaction and recommendation is expected to become a trend for most online services. At the same time, it will remain a challenging research topic that requires effort from different research areas.

Open Issues. Although various types of interaction exist between recommenders and users, the key issue that we would like to highlight is *how can the information from the interactions, such as conversations and explanations, be exploited effectively for improving the recommendation quality?* In other words, we need to address the question, "Which algorithms/paradigms would be the most promising for interactive recommender systems?" One possibility to address this problem is to consult the results from the field of decision-making theory [Roe et al. 2001], which has been identified as a viable basis for developing new recommendation algorithms [Jameson 2011]. Another aspect of this problem is whether researchers should seek a generalized mechanism that can handle all kinds of interactions for recommendation, or whether different mechanisms that are specialized for different types of interaction are needed. This challenge also provides valuable opportunities for future research on interactive recommendation with different types of interaction data. Looking back on the past research progress in CF, we see that major innovations have been made in the face of the rise of new types of data, such as the information sources reviewed in this survey. We anticipate that along with the growing availability of various types of interaction data, a wave of new contributions to CF will be proposed for integrating interaction and recommendation.

State of the Art. In the most basic case, interactive recommendation is studied as a case of the problem of online CF [Liu et al. 2010; Stern et al. 2009]. Under such a view, the key issue is how to constantly take into account new user preference data for improving recommendation results. One recent contribution has exploited the information of user choice in recommendation sessions for model training [Yang et al. 2011b]. Here, a key constraint imposed is that the chosen items in a session should have higher relevance for the user than the unchosen items. In general, however, current research remains in a stage that focuses on users' explicit preference data. Research has yet to turn its attention to use cases in which information about a variety of interactions between users and recommenders is available. Clearly, the challenge of leveraging multiple information sources of interaction for recommendation calls for further investigation beyond current research of CF with interaction-associated information as presented in Section 4.2, including the aspects of both interpreting and exploiting the interactions.

7.3. Economics and Recommendation

Significance. The study of economics provides a valuable source of models and insights that can be used to improve recommender systems. In economic systems, for example, in commodity markets, actors pursue specific objectives under the limitations of specific constraints. Recommender systems are also characterized by interactions between actors with objectives and constraints. As recommender system scenarios grow more complicated, multiple objectives of multiple actors and a growing number of constraints must be taken into consideration. For example, recommender systems play a key role in e-commerce because they mediate the interaction between buyers and sellers. Recommendations must be optimized in order to satisfy both sellers business metrics, such as sales and customer retention, and also to generate recommendations that buyers find interesting and useful. Economic models are ideally suited for capturing these complex interactions. The ability of economic models to reflect and explain the dynamics underlying recommendation scenarios makes them uniquely suited for understanding and improving recommender systems.

Open Issues. The main challenge that must be faced in order to allow recommender systems to productively exploit economic models is *selecting and integrating economic models to optimize the recommender system output*. Obviously, different economic theories may relate to different aspects of recommender systems. The discussion in this survey has focused on recommender systems that exploit context. We would like to explicitly point out that the availability of additional information, such as item categories or item prices, increases the complexity of the recommendation problem and thereby also of the ways in which economic models can be exploited by recommender systems.

State of the Art. Here we mention a few examples of the work in the area of recommender systems that has drawn on economic theories. These examples are chosen to illustrate the diversity of economic models that are relevant for recommendation scenarios.

Early work connecting economic models and recommender systems highlighted the correspondence between CF and social choice theory [Pennock et al. 2000]. Social choice theory is a framework for analyzing how the preferences of individuals can be combined to obtain decisions at the level of the social collective. Pennock et al. [2000] suggest that voting mechanisms provide a valuable source of possibilities for refined CF. Economic models have been used by Harper et al. [2005] in order to explain user rating behavior in recommender systems. These authors adopt a straightforward economic model that models raters as a set of agents who work to maximize their objectives given constraints. The model integrates factors that influence users' willingness to rate movies, including their desire for high-quality movie recommendations and the limited time and effort that they are willing to spend rating movies. The model is able to explain a significant portion of users' rating behavior. However, the authors caution that a thorough understanding of the user population under investigation is required in order to create economic models that explain user behavior. A marketplace model has been used by Wei et al. [2005]. This work is based on the insight that the strengths of multiple recommender systems can be combined, if these systems are allowed to compete in a marketplace for positions within the recommendation list that is presented to the user.

A consumer behavior model has been used by Wang and Zhang [2011]. This work makes use of the economic concept of *utility*, which is defined as the satisfaction or pleasure that an individual derives as a result of purchasing a product. In the work of Wang and Zhang [2011], an existing recommender system is extended to take into account the dependence of a product's utility on the user's past purchasing behavior. For example, a user who has just purchased a consumable item such as diapers will soon derive high additional utility from another similar purchase. For durable items, such as consumer electronics like cameras, more time must elapse before similar purchases provide high additional utility. Portfolio theory has been exploited by Shi et al. [2012] to improve the lists of recommended items. This work observes that the usefulness of an item recommendation depends not only on that particular recommendation but rather on the entire list of recommended items. The approach takes this list to be an investment portfolio and applies optimization techniques used in the financial world. The optimization handles uncertainty and also maximizes the diversity of the list in a way that respects the user's preference for topical breadth.

We envision that future research for addressing this challenge would build on previous contributions to CF with both side information and interaction-associated information. The side information of users and items can serve to identify the economic value of a recommendation, which, in turn, could be used for refining the recommendation model. The interaction-associated information, on the other hand, may be exploited for selecting a proper economic model in terms of specific interaction patterns.

8. CONCLUSIONS

We have presented a comprehensive survey on recent progress in CF methods that make use of various sources of information that stretch beyond the traditional U-I matrix. We have categorized different algorithmic contributions into different groups based on the type of information that is processed and the type of fundamental paradigm exploited. We have also discussed the challenges that we anticipate to be most significant to the future of research on CF and have discussed potential opportunities for addressing each of these challenges. The treatment that we have given the challenges presented in this survey is based on our understanding of application demands, fundamental problems, and outreach connections in the area of recommender systems. We expect that these challenges will attract significant research efforts and lead to productive research outcomes in the following 5 to 10 years.

Without a doubt, new challenges in the scope of CF with information, above and beyond those discussed in this survey, will continue to arise in the coming years. The emergence of new challenges is influenced by a variety of factors. These factors include the availability of new types of additional information in recommender systems, the development of new applications involving recommendation technology, the reform of evaluation methodologies for recommendation performance, the exploration of new crossovers between recommender systems and other areas, and the recognition of new fundamentals and theories in recommender systems. As a result of these new developments, we believe that recommender systems will continue to be a productive and interesting research field, and that the opportunities for research work to achieve high impact in this area will remain ample and attractive.

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