# Design and Evaluation of Cross-Domain Recommender Systems

**Maurizio Ferrari Dacrema, Iván Cantador, Ignacio Fernández-Tobías, Shlomo Berkovsky, and Paolo Cremonesi**

## 1 Introduction

Nowadays, the majority of recommender systems offer recommendations for items belonging to a single domain. For instance, Sky recommends movies and TV series, Zalando recommends clothing, and Spotify recommends songs and playlists. These domain-specific systems have been successfully deployed by numerous websites, and the single-domain recommendation functionality is not perceived as a limitation, but rather pitched as a focus on a certain market segment.

Nonetheless, large e-commerce sites like Amazon and Alibaba often store user feedback for items across multiple domains, and social media users often express their tastes and interests for a variety of topics. It may, therefore, be beneficial to leverage all the available user data provided in various systems and domains, in order to generate more encompassing user models and better recommendations. Instead of treating each domain (e.g., movies, books and music) independently, knowledge acquired in a *source* domain could be transferred to and exploited in another *target* domain. The research challenge of transferring knowledge and the business potential of delivering recommendations spanning multiple domains, have triggered an increasing interest in *cross-domain recommendations*.

M. F. Dacrema · P. Cremonesi (✉)
Politecnico di Milano, Milan, Italy
e-mail: maurizio.ferrari@polimi.it; paolo.cremonesi@polimi.it

I. Cantador · I. Fernández-Tobías
Universidad Autónoma de Madrid, Madrid, Spain
e-mail: ivan.cantador@uam.es; ignacio.fernandezt@uam.es

S. Berkovsky
Macquarie University, Sydney, Australia
e-mail: shlomo.berkovsky@mq.edu.au



F. Ricci et al. (eds.), *Recommender Systems Handbook*,
https://doi.org/10.1007/978-1-0716-2197-4_13

Consider two motivating use cases for cross-domain recommendations. The first refers to the well known cold-start problem, which makes it difficult to generate recommendations due to the lack of sufficient information about users or items. In a cross-domain setting, a recommender may draw on information acquired from other domains to alleviate such a problem, e.g., user's favorite movie genres may be derived from her favorite book genres. The second refers to the generation of personalized cross-selling or bundle recommendations for items from multiple domains, e.g., a movie accompanied by a music album similar to the movie soundtrack. This recommendation may be informed by the user's movie tastes, extracted from rating correlations within a joined movie-music rating matrix.

These use cases are underpinned by an intuitive assumption that there are correspondences between user and item profiles in the source and target domains. This assumption has been validated in several market basket analysis marketing, behavioral, and data mining studies, which uncover dependencies between various domains [69, 78]. Cross-domain recommender systems leverage these dependencies by considering, for example, overlaps between the user or item sets, correlations between user preferences, and similarities of item attributes. Then, they apply a variety of techniques for enriching the knowledge in the target domain and improving the quality of recommendations generated therein.

A vast literature exists on cross-domain recommender systems, with hundreds of papers on the topic being published since 2005. To this end, the goal of the chapter is not to provide a comprehensive review of that body of literature (see Khan et al. [39] for a recent review). Instead, the chapter provides an overview of the scenarios, where cross-domain recommendations are beneficial and categorizes the methodologies available to materialize such recommendations.

The chapter is structured as follows. In Sect. 2 we formulate the cross-domain recommendation problem, describing its main tasks and goals. In Sect. 3 we categorize cross-domain recommendation techniques, and in Sects. 4.1–4.5 we review these techniques. In Sect. 5 we overview cross-domain recommendation evaluation. In Sect. 7 we discuss practical considerations around cross-domain recommenders. Finally, in Sect. 6 we discuss open research directions.

## 2 Formulation of the Cross-Domain Recommendation Problem

The cross-domain recommendation problem has been addressed from various perspectives in different research areas. Aiming to unify these, we provide a generic formulation of the cross-domain recommendation problem, focusing on the existing domain notions (Sect. 2.1), as well as cross-domain recommendation tasks (Sect. 2.2) and goals (Sect. 2.3), and finally discuss the possible scenarios of data overlap between domains (Sect. 2.4).

## *2.1 Definition of Domain*

In prior literature, researchers have considered several notions of domain. For instance, some have treated items like *movies* and *books* as belonging to different domains, while others have considered *action movies* and *comedy movies* as different domains. Here we distinguish between several domain notions according to the attributes and types of recommended items. Specifically, *domain* may be defined at three levels (see Fig. 1):

- *Attribute level*. Items are considered as belonging to distinct domains if they differ in the value of certain attributes, e.g., movies might belong to distinct domains if they have different genres, like action and comedy movies. This definition is rather vague and is mainly used as a means to increase the diversity of recommendations (e.g., recommending thrillers to users, who only watch comedies).
- *Item level*. Items are not of the same type, differing in most, if not all, of their attributes. For instance, movies and books belong to different domains, even though they have some common attributes (title, release year).
- *System level*. Items belong to distinct systems, which are considered as different domains. For instance, movies rated in the MovieLens recommender and movies watched in the Netflix streaming service.

In many real world scenarios, the distinction between the above levels is not clear. For instance, we may have one domain that contains cinema movies and another domain that contains TV series. These domains could be considered either at the attribute or system level. Table 1 summarizes the notions of domains, listing

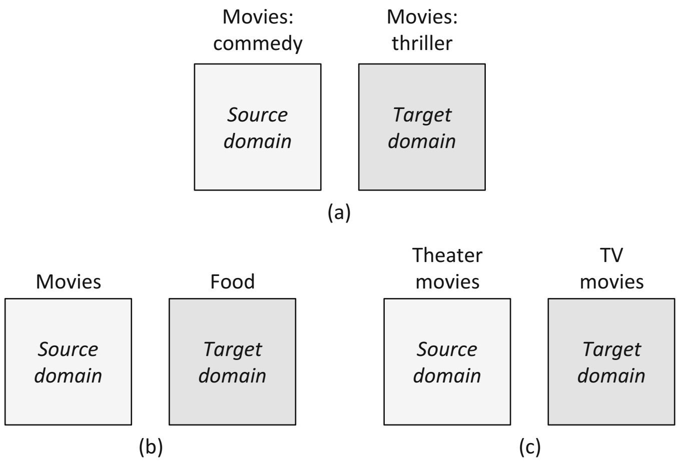


**Fig. 1** Notions of domain according to attributes and types of recommended items. (**a**) *Attribute level*: same type of items (movies) with different values of certain attributes (genre: comedy vs. thriller). (**b**) *Item level*: different types of items (books vs. movies). (**c**) *System level*: same type of items (movies) on different systems (theater vs. TV)

**Table 1** Summary of domain notions, domains, and datasets/systems used in the cross-domain recommendation literature

| Domain notion | Domains | Datasets/Systems | References |
|---|---|---|---|
| *Attribute* | Book categories | *BookCrossing* | Cao et al. [11] |
| | Movie genres | *EachMovie* | Berkovsky et al. [5] |
| | | *MovieLens* | Lee et al. [42] |
| | | | Cao et al. [11] |
| | Education, sport | *HVideo* | Ma et al. [55] |
| *Item* | Books, movies | *LibraryThing, MovieLens* | Zhang et al. [80] |
| | | | Shi et al. [70] |
| | | | Enrich et al. [18] |
| | | *Imhonet* | Sahebi and Brusilovsky [67] |
| | Movies, music | *Facebook* | Shapira et al. [69] |
| | Books, movies, music, TV shows | *Facebook* | Tiroshi and Kuflik [75] |
| | | | Tiroshi et al. [74] |
| | Music, tourism | – | Fernández-Tobías et al. [21] |
| | | | Kaminskas et al. [37] |
| | Books, movies, music | *Amazon* | Hu et al. [33] |
| | | | Loni et al. [52] |
| | | | Zhao et al. [84] |
| | | *Movielens, Douban* | Zhu et al. [86] |
| | Clothing, sport, home | *Amazon* | Liu et al. [50] |
| | Home, office, music | *Amazon* | Wang et al. [77] |
| | Various types of items | – | Winoto and Tang [78] |
| | | | Fu et al. [28] |
| | | | Li et al. [47] |
| | | *Amazon* | Hu et al. [34] |
| | | | Yuan et al. [79] |
| *System* | Movies | *Netflix* | Cremonesi et al. [14] |
| | | *MovieLens, Moviepilot, Netflix* | Pan et al. [64] |
| | Music | *Delicious, Last.fm* | Loizou [51] |
| | | *Blogger, Last.fm* | Stewart et al. [71] |
| | Various domains | *Delicious, Flickr, StumbleUpon, Twitter* | Abel et al. [1] |
| | | | Abel et al. [2] |
| | | *Yahoo! services* | Low et al. [53] |

example papers, along with the type of domain and, when available, the datasets or systems used for experimental evaluation. It can be seen that the focus of past research works has been distributed across the three definitions of domain.

## 2.2 Cross-Domain Recommendation Tasks

Cross-domain recommendation research generally aims to exploit knowledge from a source domain $\mathcal{D}_S$ to perform or improve recommendations in a target domain $\mathcal{D}_T$. Analyzing the literature, we observe that the addressed tasks are diverse, and an agreed-upon definition of the cross-domain recommendation problem has not been formulated yet. Hence, some researchers have proposed models aimed at providing joint recommendations for items belonging to multiple domains, whereas others have developed methods to alleviate the cold-start and sparsity problems in the target domain using information from the source domains.

Aiming to provide a unified formulation of the cross-domain recommendation problem, we define the tasks we identify as providing recommendations across domains. Without loss of generality, we consider two domains $\mathcal{D}_S$ (source) and $\mathcal{D}_T$ (target). The definitions are extensible to multiple source domains. Let $\mathcal{U}_S$ and $\mathcal{U}_T$ denote the sets of users, and let $\mathcal{I}_S$ and $\mathcal{I}_T$ – the sets of items in $\mathcal{D}_S$ and $\mathcal{D}_T$, respectively. The users of a domain are those who interacted with the items in that domain (e.g., ratings, reviews, purchases). Note that not all the items in a domain necessarily need to have interactions with the domain users, as some may have content attributes that establish their membership in the domain.

Sorted in an increasing order of complexity, we distinguish between three recommendation tasks (see Fig. 2):

- *Multi-domain recommendation*: recommend items in both the source and target domains, i.e., items in $\mathcal{I}_S \cup \mathcal{I}_T$ to users in $\mathcal{U}_S \cup \mathcal{U}_T$.
- *Linked-domain recommendation*: recommend items in the target domain to users from the source domain, i.e., items in $\mathcal{I}_T$ to users in $\mathcal{U}_S$, or vice versa, i.e., items in $\mathcal{I}_S$ to users in $\mathcal{U}_T$.
- *Cross-domain recommendation*: recommend items in the target domain to users in the target domain, i.e., items in $\mathcal{I}_T$ to users in $\mathcal{U}_T$.

Multi-domain approaches have focused on the provision of cross-system recommendations, by jointly considering user preferences for items in multiple systems. To generate such recommendations, a significant overlap between user preferences

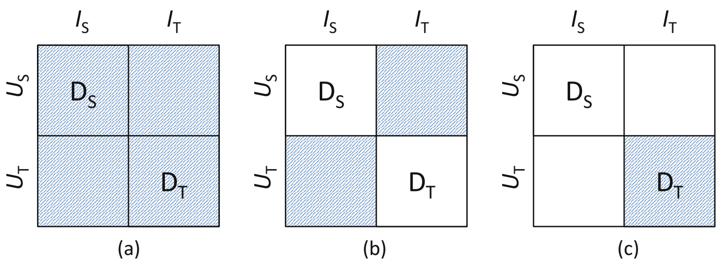


**Fig. 2** Cross-domain recommendation tasks. Colored areas represent the target users and items. (**a**) Multi-domain. (**b**) Linked-domain. (**c**) Cross-domain

across the domains is needed. This is becoming increasingly feasible, since users maintain profiles in various social media systems and there exist interconnecting mechanisms for cross-system interoperability [10] and user identification [9]. The benefits of multi-domain recommendations are also evident in e-commerce, where cross-selling recommendations were shown to boost customer satisfaction/loyalty and businesses profitability [17, 40]. For such purposes, approaches generally aim to aggregate knowledge from the source and target domains.

Linked-domain approaches have been mainly explored to improve recommendations in a target domain where there is a scarcity of user preferences, either at the user/item level (cold-start) or at the community level (data sparsity). To deal with these situations, a common solution is to enrich the available knowledge in the target domain with knowledge imported from the source domain. To generate this type of recommendations, data relations (or overlaps) between the domains are needed, and approaches aim to establish explicit or implicit knowledge-based links between the domains.

Finally, cross-domain approaches have been proposed to provide recommendations in the target domain, where no information about the users is available. In this case, there is no assumption of data relations or overlaps between the domains, and the approaches aim to establish knowledge-based links between domains or to transfer knowledge from the source domain to the target domain.

## *2.3 Cross-Domain Recommendation Goals*

From the research and practical perspectives, it is important to match the recommendation algorithms to the task in hand. For this reason, we initially present a taxonomy of cross-domain recommendation goals. The taxonomy is described in a solution-agnostic way: each problem is defined based solely on its goals—disregarding how they are achieved, which will be discussed in Sect. 3.

At the first level of the taxonomy, we consider the three recommendation tasks presented in Sect. 2.2, namely *multi-domain*, *linked-domain*, and *cross-domain* tasks, which are the columns of Table 2. At the second level, we distinguish between the specific goals addressed by cross-domain recommenders, which are the rows of Table 2. We distinguish between the following goals:

- *Addressing the cold-start problem*. This is related to situations, in which the recommender is unable to generate recommendations due to an initial lack of user preferences. One possible solution is to bootstrap the system with preferences from a data source outside the target domain.
- *Addressing the new user problem*. When a user starts using the recommender, this has no knowledge of the user's tastes and preferences, and cannot produce personalized recommendations. This may be solved by exploiting the user's preferences collected in a different domain.

**Table 2** Summary of cross-domain recommendation approaches based on goals and tasks

| *Goal* | Multi-domain task | Linked-domain task | Cross-domain task |
|---|---|---|---|
| *Cold start* | Wang et al. [77] | | Shapira et al. [69] |
| | | | Hu et al. [34] |
| | | | Zhao et al. [84] |
| *New user* | | Winoto et al. [78] | Berkovsky et al. [4, 5] |
| | | Cremonesi et al. [14] | Berkovsky et al. [6] |
| | | Low et al. [53] | Nakatsuji et al. [58] |
| | | Hu et al. [33] | Cremonesi et al. [14] |
| | | Sahebi et al. [67] | Tiroshi et al. [75] |
| | | | Braunhofer et al. [7] |
| | | | Man et al. [56] |
| | | | Fu et al. [28] |
| *New item* | | | Kaminskas et al. [37] |
| *Accuracy* | Cao et al. [11] | Shi et al. [70] | Pan et al. [64] |
| | Zhang et al. [80] | Pan et al. [59] | Stewart et al. [71] |
| | Li et al. [46] | | Pan et al. [63] |
| | Tang et al. [73] | | Tiroshi et al. [74] |
| | Zhang et al. [82] | | Loni et al. [52] |
| | Liu et al. [49] | | |
| | Taneja et al. [72] | | |
| | Zhu et al. [86] | | |
| | Ma et al. [55] | | |
| | Yuan et al. [79] | | |
| | Li et al. [47] | | |
| | Liu et al. [50] | | |
| *Diversity* | | Winoto et al. [78] | |
| *User model* | | Abel et al. [1] | |
| | | Abel et al. [2] | |

- *Addressing the new item problem*. When a new item is added to a catalog, no prior ratings for the item are available, so it cannot be recommended by a collaborative recommender. This problem is particularly evident when cross-selling new products from different domains.
- *Improving accuracy*. In many domains, the average number of ratings per user and item is low, which may negatively affect the quality of the recommendations. Data collected outside the target domain can increase the rating density, and upgrade the recommendation quality.
- *Improving diversity*. Having similar, redundant items in a recommendation list may degrade user experience. The diversity of recommendations can be improved by considering multiple domains, better covering the range of user preferences.
- *Enhancing user models*. The main goal of cross-domain user modeling applications is to enhance user models. Achieving this goal may have personalization-

oriented benefits, such as discovering new user preferences for the target domain [71] or enhancing similarities between users and items [1, 6].

Table 2 maps the key cross-domain recommendation papers across these tasks and goals. It is evident that cross-domain tasks are mainly used to address the cold-start problem and reduce data sparsity, while linked-domain tasks are used to improve accuracy and diversity.

## *2.4 Cross-Domain Recommendation Scenarios*

In order to leverage cross-domain recommendations, source and target domains must be linked. We refer to two domains being

- *collaborative-linked* if there are users or items with interactions in both domains
- *content-linked* if they share users or items with similar attributes
- *context-linked* if interactions share contextual attributes.

The type of overlap between domains may limit the choice of algorithms that can be used for cross-domain recommendations. For instance, if two domains have items or users that share attributes, but no users or items share interactions, collaborative algorithms cannot be used for cross-domain recommendations [15].

We denote by $\mathcal{U}_{ST}$ the set of linked users. In the content-based linkage, two cross-domain users are linked if they share attributes, e.g., linked in a social network, have the same age, or tagged an item with the same tag. In the collaborative case, users are linked if they have interactions in both the source and target domains. Similarly, we denote by $\mathcal{I}_{ST}$ the set of linked items. In the content-based linkage, items are linked if they share attributes, e.g., movies of the same genre. In the collaborative case, items are linked if they have interactions in both the source and target domains. Finally, we denote by $\mathcal{C}_{ST}$ the set of interactions linked by sharing contextual attributes. For example, the same tag might have been used by users from different domains or users might have rated items within the same context [60].

Extending the patterns described in [14], three basic scenarios of data overlap between two domains $S$ and $T$ can be identified:

- *User overlap*: there are linked users, i.e., $\mathcal{U}_{ST} \neq \emptyset$.
- *Item overlap*: there are linked items, i.e., $\mathcal{I}_{ST} \neq \emptyset$.
- *Context overlap*: there are linked interactions, i.e., $\mathcal{C}_{ST} \neq \emptyset$.

Note that not all the combinations of these scenarios are possible: if there is *no overlap* between users, items, and context, i.e., $\mathcal{U}_{ST} = \emptyset$, $\mathcal{I}_{ST} = \emptyset$, and $\mathcal{C}_{ST} = \emptyset$, cross-domain recommendations are not possible, as shown in [15].

The links between items, users and contexts are known a-priori and constitute an explicit input for cross-domain recommendations. However, *deep learning* techniques allows for a fourth scenario, where the domains are linked through semantic concepts extracted from unstructured information, e.g., user reviews for items, rather than by the means of structured attributes. These semantic concepts allow learning a-posteriori implicit relations between domains during the training of the model. We refer to this fourth scenario as *semantic overlap*.

## 3 Categorization of Cross-Domain Recommendation Techniques

Cross-domain recommendations have been addressed from various angles in different research areas. This has entailed the development of an array of approaches, which in many cases are difficult to directly compare due to the diversity in the user preferences they use, the cross-domain scenario they deal with, and the algorithms and data they harness. In this section, we overview the different categorizations proposed in the literature [8, 14, 22, 36, 43]. However, the published reviews and categorizations often do not reflect the complexity of the space. Thus, in the next section we will propose a unifying view for the existing cross-domain recommendation techniques.

Chung et al. presented in their seminal work [12] a framework that provides integrated recommendations for items that may be of different types and belong to different domains. The framework accounts for three levels of integration: *single item type recommendations* that consist of items of the same type, *cross item type recommendations* that consist of items of different types that belong to the same domain, and *cross domain recommendations* that consist of items that belong to different domains. The authors stated that integrated recommendations can be generated by following at least three approaches:

- *General filtering*. Instantiates a recommendation model for multiple item types that may belong to different domains.
- *Community filtering*. Utilizes ratings shared among several communities or systems that may deal with different item types and domains.
- *Market basket analysis*. Applies data mining to extrapolate hidden relations between items of different types/domains and build a model for item filtering.

Loizou identified three main trends in cross-domain recommendation research [51]. The first focuses on compiling unified user profiles for cross-domain recommendations. This is considered as integration of domain-specific user models into a single, unified multiple-domain user model, which is subsequently used for generating recommendations. The second involves profiling user preferences through monitoring their interactions in individual domains, which can be implemented by agents that learn single-domain user preferences and gather them across the domains. The third deals with combining (or mediating) information from several single-domain recommender systems. A number of strategies for mediating single-domain collaborative systems were considered: exchange of ratings, user neighborhoods, user similarities, and recommendations.

Based on these trends, Cremonesi et al. surveyed and categorized cross-domain collaborative systems [14]. They enhanced earlier categorizations by considering a more specific grouping of approaches: (i) Extracting association rules from rating behavior in a source domain, and using the extracted rules to recommend items in a target domain, as proposed by Lee et al. [42]; (ii) Learning inter-domain rating-based similarity and correlation matrices, as proposed by Cao et al. [11] and Zhang et al. [80]; (iii) Combining estimations of rating probability distributions in source domains to generate recommendations in a target domain, as proposed by Zhuang et al. [87]; (iv) Transferring knowledge between domains to address the rating sparsity in a target domain, as proposed by Li et al. [44, 45] and Pan et al. [62, 63].

For the last group, Li surveyed transfer learning techniques for cross-domain collaborative filtering [43]. They proposed a categorization based on the type of domain and distinguished between (i) *system domains* associated with different recommenders and representing a scenario, where the data in a target recommender are sparse, while the data in related recommenders are abundant; (ii) *data domains* associated with multiple sources of heterogeneous data and representing a scenario where user data in source domains can be obtained easier than in a target domain; and (iii) *temporal domains* associated with distinct data periods and representing a scenario where temporal user preference dynamics can be captured. Reflecting these categories, three recommendation strategies differing in the cross-domain knowledge transfer can be considered:

- *Rating pattern sharing*. Factorizes single-domain rating matrices utilizing user and item groups, encodes group-level rating patterns, and transfers knowledge between domains through the encoded patterns [44–46].
- *Rating latent feature sharing*. Factorizes single-domain rating matrices using latent features, shares latent feature spaces across domains, and transfers knowledge between domains through the latent feature matrices [62–64].
- *Domain correlation*. Factorizes single-domain rating matrices using latent features, explores correlations between latent features in individual domains, and transfers knowledge between domains through such correlations [11, 70, 80].

Pan and Yang identified in a survey of transfer learning three key questions [61]: (i) *what* to transfer—which knowledge should be transferred between domains; (ii) *how* to transfer—which algorithms should be exploited to transfer the knowledge; and (iii) *when* to transfer—in which situations the knowledge transfer is beneficial. Focusing on the first two, Pan et al. proposed a two-dimensional categorization of transfer learning-based approaches for cross-domain collaborative filtering [62, 63]. The first dimension takes the type of transferred knowledge into account, e.g., latent rating features, encoded rating patterns, and rating-based correlations. The second considers the algorithm, and distinguishes between adaptive and collective approaches, assuming, respectively, the existence of rating data in the source domain only, and in both the source and target domains.

More recently, Fernández-Tobías et al. stepped beyond collaborative recommendations, considering approaches that establish cross-domain relationships not necessarily based on ratings [22]. They identified three directions to the cross-domain recommendation problem. The first is through the integration of single-domain user preferences into a unified cross-domain user model, which aggregates user profiles from multiple domains and mediates user models across domains. The second direction transfers knowledge from a source domain to a target domain, and includes approaches that exploit recommendations generated for a source domain in a target domain, as well as approaches based on transfer learning [43]. The third direction is around establishing explicit relations between domains, which may be based either on content-based relations between items or rating-based relations between users/items. The authors then proposed a two-dimensional categorization of cross-domain recommendation approaches: (i) relation between domains: content-based relations (item attributes, tags, semantic properties, and feature correlations) vs. rating-based relations (rating patterns, rating latent factors, and rating correlations); and (ii) recommendation task: adaptive models (exploit source domain knowledge to generate recommendations in a target domain) vs. collective models (harness data from several domains to improve recommendations in a target domain).

## 4 Cross-Domain Recommendations Techniques

It is evident that the existing categorizations of cross-domain recommendation are diverse. In this section we reconcile these categorizations in a way that captures and unifies their core ideas. For this, we classify cross-domain recommendation techniques into five categories, generally reflecting their evolution:

- *Merging user preferences*. User preferences from both domains are aggregated in such a way that single-domain recommender systems can be used.
- *Linking domains*. Graph-based approaches, in which nodes from different domains are linked by the means of shared attributes or interactions.
- *Transfer learning*. Knowledge obtained while training a model on the source domain is transferred to make recommendations in the target domain.
- *Co-training of shared features (multi-task learning)*. Multiple tasks are solved at the same time in the source and target domains, to learn shared latent features.
- *Deep learning*. Neural network models are used to share/transfer latent features across domains through unstructured semantic features extracted during training.

This classification is not always clear-cut, as some technique capture aspects from different categories. We overview these five categories in the following sections.

### *4.1 Merging User Preferences*

Merging user preferences from different source domains is among the most widely used strategies for cross-system personalization, and the most natural way to address the cross-domain recommendation problem (see Fig. 3). This family of techniques requires a partial user overlap between the two domains. Table 3 summarizes the aggregation-based methods presented in this section.

Prior research has shown that rich profiles can be generated for users when multiple sources of personal preferences are combined, revealing tastes and interests not captured in isolated domains [2]. It has been also shown that enriching sparse user preferences in a target domain by adding data from the source domains can improve the generated recommendations under the cold-start and sparsity conditions [67, 69]. This, however, requires considerable user data in multiple domains and methods for merging the data, potentially represented in different ways.

The most favorable scenario for aggregation-based methods implies that different systems share user preferences of the same type and representation [3]. This scenario was addressed by Berkovsky et al. with a mediation strategy for cross-domain collaborative filtering [5]. The authors considered a domain-distributed setting, where a global rating matrix is split, so that single-domain recommenders store locally rating matrices having the same structure. In this setting, a target domain

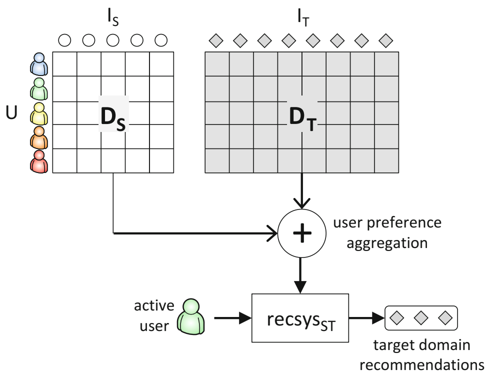


**Fig. 3** *Merging user preferences.* Data sources from different domains are merged, and traditional single-domain recommender system is used on the merged data

**Table 3** Cross-domain user modeling and recommendation approaches based on merging single-domain user preferences

| Cross-domain approach | Overlap | References |
|---|---|---|
| *Aggregating user ratings into a single multi-domain rating matrix* | *U I* | Berkovsky et al. [5] |
| | *U* | Winoto and Tang [78] |
| | *U* | Sahebi and Brusilovsky [67] |
| | *U* | Shapira et al. [69] |
| *Using a common representation for users* | *U* | Abel et al. [1] |
| | *U* | Abel et al. [2] |
| *Mapping user preferences onto domain-independent features* | *U* | Loni et al. [52] |

($U$) user overlap, ($UI$) user and item overlap recommender imports the rating matrices from the source domains, reconstructs the unified rating matrix, and applies collaborative filtering. Although this approach can be seen as a centralized recommender with user data split across multiple domains, smaller rating matrices can be efficiently maintained by local systems and shared with the target domain only when requested.

Berkovsky et al. showed an improvement in the accuracy of the target domain recommendations when aggregating ratings from several domains [5] . This was also observed by Winoto and Tang [78], where the authors collected ratings in several domains and conducted a study that revealed that even when there exists significant overlap between domains, recommendation accuracy in the target domain improved if only ratings from close domains were used. In addition, Winoto and Tang stated that cross-domain recommendations might benefit serendipity and diversity.

Apart from serendipity and diversity, other benefits of cross-domain recommendations have been identified. Sahebi and Brusilovsky examined the impact of the size of user profiles in the source and target domains on the quality of collaborative filtering, and showed that aggregating ratings from several domains improves the accuracy of cold-start recommendations [67]. Similarly, Shapira et al. showed substantial accuracy improvements yielded by aggregation-based methods, when the available user preferences were sparse [69].

Related to these, Abel et al. studied aggregation of tag clouds from multiple systems [1]. They evaluated a number of methods for semantic enrichment of tag overlaps between domains, via tag similarities and association rules deduced from the tagging data across systems. Analyzing commonalities and differences among tag-based profiles, Abel et al. also mapped tags to WordNet categories and DBpedia concepts [2]. They used the mapped tags to build category-based user profiles, which revealed significantly more user information than system-specific profiles.

The final type of cross-domain recommendations based on user preference aggregation is formed by approaches that map user preferences from multiple domains to domain-independent features, and use these feature-based profiles for building models that predict user preferences in the target domain. Loni et al. developed an approach that encoded rating matrices from multiple domains as real-valued feature vectors [52]. With these vectors, an algorithm based on factorization machines [66] found patterns between features from the source and target domains, and produced preference estimations associated with the input vectors.

Overall, this family of techniques constitutes one simple yet effective baseline that should be included in any evaluation protocol, unless the overall size of the merged domains makes the problem intractable.

### *4.2 Linking Domains*

Instead of aggregating user preferences directly, several works focused on directed weighted graphs linking user preferences from multiple domains. Such inter-domain correspondences may be established directly using common knowledge, e.g., item

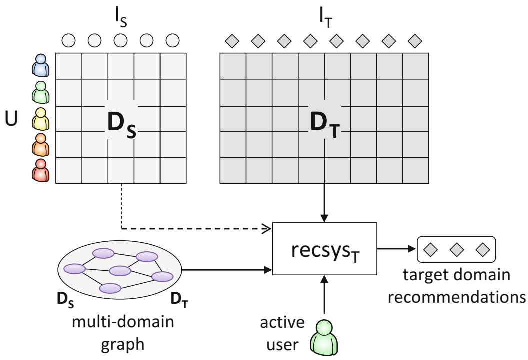


**Fig. 4** *Linking domains.* A graph is used to link items or users from different domains

**Table 4** Cross-domain recommendation approaches using graph methods

| Cross-domain approach | Overlap | References |
|---|---|---|
| *Linking user preferences via a multi-domain graph* | *U* | Nakatsuji et al. [58] |
| | *U* | Cremonesi et al. [14] |
| | *U* | Tiroshi et al. [74] |
| | *U* | Farseev et al. [20] |
| *Building semantic network linking domain concepts* | *I* | Fernández-Tobías et al. [21] |
| | *I* | Kaminskas et al. [37] |

($I$) item overlap, ($U$) user overlap

attributes, semantic networks, association rules, and inter-domain preference-based similarities or correlations (see Fig. 4). These offer valuable sources of information for cross-domain reasoning. A recommender could identify potentially relevant items in the target domain by selecting those that are related to others in the source domains, and for which the user has expressed a preference. Besides, inter-domain similarities and correlations can be exploited to adapt or combine knowledge transferred from different domains. Table 4 summarizes graph-based methods discussed in this section.

Nakatsuji et al. presented an approach that built domain-specific user graphs, where nodes were associated with users and edges reflected rating-based user similarity [58]. Domain graphs were connected via users, who either rated items in several domains or shared social connections, to create a cross-domain user graph. Over this graph, a random walk algorithm retrieved items liked by users associated with the extracted nodes. Cremonesi et al. built a graph, where nodes were associated with items and edges reflected rating-based item similarity [14]. The inter-domain connections were the edges between pairs of items in different domains. The authors enhanced inter-domain edges by discovering new edges and strengthening the existing ones. Tiroshi et al. collected a dataset containing user preferences in multiple domains extracted from social network profiles [74]. The data was merged into a bipartite user-item graph, and statistical and graph-based features of users and items were extracted. These features were exploited by an algorithm that addressed recommendations as a binary classification task. Farseev et al. [20] proposed a cross-network model, which combined the individual behavior, user communities, multiple social media sources, and heterogeneous data, such as text and images. The relationships between users were modeled as a multi-layered graph.

In a realistic setting, items can be heterogeneous, with no common attributes between domains [76]. To address this, more complex, likely indirect relations between items in different domains, may be established. Hence, when suitable knowledge repositories are available, concepts from several domains can be connected by the means of semantic properties, forming networks that explicitly link domains of interest. Along these lines, Fernández-Tobías et al. [21] and Kaminskas et al. [37] developed knowledge-based frameworks of semantic networks linking concepts across domains. These networks were weighted graphs, where nodes with no incoming edges represented concepts from the source domain, and nodes with no outgoing nodes represented concepts from the target domain. The framework facilitated an algorithm that propagated the node weights, in order to identify concepts most related to the source concepts. Implemented on top of DBpedia, the framework was deployed to recommend music suited to places of interest, related through concepts from several domains and spatio-temporal data.

## 4.3 Transfer Learning

We now survey cross-domain recommendation approaches that transfer knowledge between domains, enhancing the information available in the target domain. The knowledge transfer can be done explicitly via common item attributes, implicitly via shared latent features, or by the means of rating patterns transferred between the domains (see Fig. 5). Table 5 summarizes the methods presented in this section.

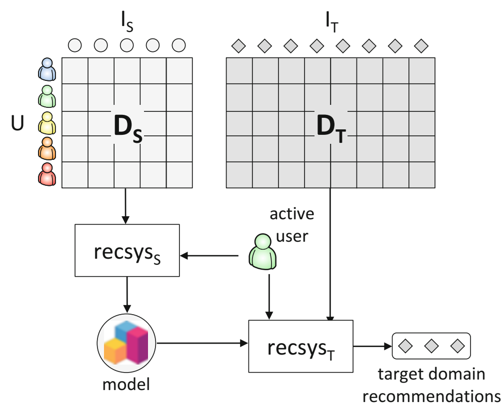


**Fig. 5** *Transfer learning.* A model is learned in the source domain and used in the target domain

**Table 5** Cross-domain recommendation approaches based on transfer learning. Other transfer learning approaches are described in Table 7

| Cross-domain approach | Overlap | References |
|---|---|---|
| *Aggregating neighbourhoods to generate recommendations* | $U$ | Berkovsky et al. [5] |
| | $UI$ | Tiroshi and Kuflik [75] |
| | $U$ | Shapira et al. [69] |
| *Exploiting user neighborhoods to enhance target user models* | $I$ | Stewart et al. [71] |
| *Combining probabilistic user models* | $U$ | Low et al. [53] |
| *Combining heterogeneous user preferences* | $UI$ | Pan et al. [64] |
| *Extracting association rules from user rating behavior* | $U$ | Lee et al. [42] |
| *Using latent features from source domains to regularize latent features in target domain* | $UI$ | Pan et al. [63] |
| *Using contextual bandits* | $U$ | Liu et al. [49] |
| *Modeling users, items and domains with tensors* | $C$ | Taneja et al. [72] |
| *Using a mapping function between the latent factors of the source and target domains* | $UI$ | Man et al. [56] |

($U$) user overlap, ($I$) item overlap, (C) context overlap, ($UI$) user and item overlap

The key idea behind transfer learning is that importing any user modeling data from source recommenders may benefit a target recommender. For example, in a collaborative system, cross-domain mediation may import the list of nearest neighbors. This example is underpinned by two assumptions: (i) there is overlap of users between domains, and (ii) user similarity spans across domains, i.e., if two users are similar in a source domain, they may be similar also in the target domain [5]. Aggregating the lists of nearest neighbors relies on their data in the target domain only, which may be sparse and result in noisy recommendations. Thus, one could import and aggregate also the degree of their similarity in the source domain.

Weighted k-NN aggregation was further enhanced by Shapira et al. [69]. They used multi-domain Facebook data to produce the set of candidate nearest neighbors, and compute their similarity degree in the source domain. This allowed overcoming the new user problem and the sparsity of ratings in the target domain. The authors compared several weighting schemes, the performance of which was consistent across metrics and recommendation tasks. Tiroshi and Kuflik also harnessed multi-domain Facebook data [75]. They applied random walks to identify source domain-specific neighbor sets, allowing to generate recommendations in the target domain. These cross-domain mediation scenarios assume an overlap in the sets of users. A similar scenario refers to a setting, where items overlap between the source and target domains that paves the way for further mediation. One of them, involving only two systems in the music domain, was studied by Stewart et al. [71]. The authors leveraged the tags assigned on Last.fm to recommend tags on Blogger.

Moving from collaborative to latent factor methods, we highlight two works compatible with the user modeling data mediation pattern. Low et al. developed a probabilistic model combining user information across multiple domains and facilitating personalization in domains with no prior user data [53]. The model was underpinned by a global user profile based on a latent vector and a set of domain-specific factors that eliminated the need for common items or features. Pan et al. dealt with transferring uncertain ratings, i.e., rating range or distribution derived from behavioral logs, using latent features of users and items [64]. The uncertainty was transferred from the source to the target domain and harnessed there as constraints for a matrix factorization model. Taneja et al. [72] proposed a tensor factorization algorithm, which transferred the knowledge in the two domains via the genre of the heterogeneous items, clustered according to their features.

Lee et al. exploited rating patterns for cross-domain recommendation [42]. There, global nearest neighbors were identified by adding the similarity scores from each domain. Then, patterns of items commonly rated together by a set of neighbors were discovered using association rule mining. Finally, rating predictions were computed by the standard user-based collaborative filtering, but enhanced with the rules containing the target items.

Pan et al. addressed the sparsity problem by exploiting user and item information from auxiliary domains, where user feedback might be represented differently [63]. In particular, they studied the case of binary like/dislike preferences in the source domain and 1–5 star ratings in the target domain. They performed singular value decomposition (SVD) in each auxiliary domain, in order to separately compute user and item latent factors, which were shared with the target domain. Specifically, transferred factors were integrated into a factorization of the rating matrix in the target domain and added as regularization terms, so that the characteristics of the target domain could be captured. Man et al. [56] instead addressed the problem of users and items with insufficient interactions in the target domain. The proposed method learned the embeddings with traditional matrix factorization and then trained a linear and non-linear mapping function to compute the embeddings in the target domain given the embeddings in the source domain.

Liu et al. [49] proposed a transferable contextual bandit for both homogeneous and heterogeneous domains. The use of transfer learning aimed to improve the exploitation steered by the policy of the contextual bandit as well as accelerate its exploration in the target domain. The proposed model leveraged both the source and target domain simultaneously via common users and items, and then exploited a translation matrix to match the different feature spaces.

Works by Li et al. [45], Moreno et al. [57], Gao et al. [30], Zang et al. [81] and He et al. [31] transferred rating patterns across multiple domains with simultaneous co-clustering of users and items. Clustering was achieved using a tri-factorization of the source rating matrix [16]. Then, knowledge was transferred through a *codebook*, a compact cluster-level matrix computed in the source domain. Missing ratings in the target domain were predicted using the same codebook. However, Cremonesi and Quadrana disproved the effectiveness of codebook-based transfer methods [15], showing that the codebook could not transfer knowledge when source and target domains did not overlap. Therefore, it is still an open question whether codebook-based approaches cab reliably perform knowledge transfer.

## 4.4 Co-Training of Shared Latent Features

Latent factors shared between domains can be exploited by cross-domain recommenders, as illustrated in Fig. 6. Instead of transferring knowledge, shared models can be learned simultaneously in both the source and target domains. Table 6 summarizes the co-training methods presented in this section.

Pan et al. proposed to learn latent features simultaneously in multiple domains [62]. Both user and item factors were assumed to generate the observed domain ratings and their corresponding random variables were shared between

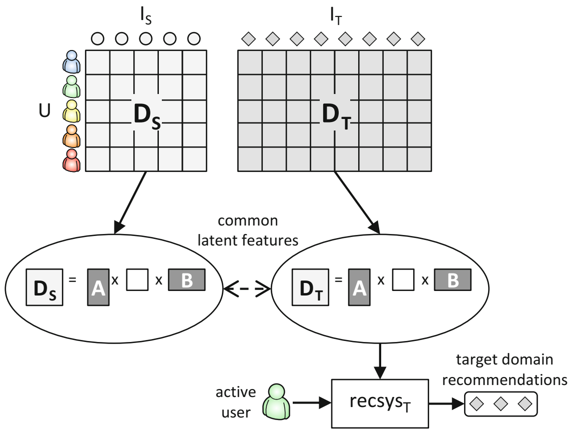


**Fig. 6** *Sharing latent features.* Latent features models are learnt simultaneously in the source and target domains, requiring identical user and/or item features across the domains

**Table 6** Cross-domain recommendation approaches based on co-training. Other co-training approaches are described in Table 7

| Cross-domain approach | Overlap | References |
|---|---|---|
| *Using latent factors to jointly factorize the rating matrices in the source and target domains* | *UI* | Pan et al. [62] |
| *Extending matrix factorization with latent factors associated to social tags* | *C* | Enrich et al. [18] |
| | *C* | Fernández-Tobías and Cantador [23] |
| *Sharing latent features via a user-item-domain tensor factorization* | *U* | Hu et al. [33] |
| *Constraining matrix factorization with inter-domain similarities* | *U* | Cao et al. [11] |
| | *U* | Zhang et al. [80] |
| | *C* | Shi et al. [70] |

(*U*) user overlap, (*C*) context overlap, (*UI*) user and item overlap probabilistic factorization models of each rating matrix. The factorization method was further extended by incorporating factors capturing domain-specific information, resulting in a tri-factorization scheme. A limitation of the approach was that the users and items from the source and target domains had to be identical. Zhang et al. adapted the probabilistic matrix factorization method to include a probability distribution of user latent factors that encoded inter-domain correlations [80]. One strength of this approach was that user latent factors shared across domains were not needed, allowing more flexibility in the heterogeneity of domains.

Rather than learning implicit correlations in the data, Shi et al. relied on shared social tags to compute cross-domain user-to-user and item-to-item similarities [70]. In similar to previous approaches, rating matrices from the source and target domains were jointly factorized, but user and item latent factors from each domain were restricted, so that their product was consistent with the tag-based similarities. Another way of exploiting co-training is to learn similarities from multiple domains simultaneously. For instance, Cao et al. developed an approach, which implicitly learned inter-domain similarities from the data as model parameters in a non-parametric Bayesian framework [11]. Since user feedback was used to estimate the similarities, user overlap between the domains was required.

Enrich et al. [18] and Fernández-Tobías and Cantador [23] studied the influence of social tags on rating predictions, as a knowledge transfer approach for cross-domain recommendations. The authors presented a number of models based on the SVD++ algorithm [41], aiming to incorporate the effect of tag assignment into rating estimation. The underlying hypothesis was that information about item annotation in a source domain could be exploited to improve predictions in a target domain, as long as a set of common tags between the domains existed. In the proposed models, tag factors were added to the latent item vectors and combined with user latent features to estimate ratings. In all the, models knowledge transfer was performed through the shared tag factors in a collective way, since these were computed jointly for the source and the target domains.

Hu et al. presented a more complex approach that considered also the domain factors [33]. The authors proposed a tensor factorization algorithm that exploited the triadic user-item-domain data. Specifically, they studied the use case, in which the same set of users consumed and rated different types of items. In this case, rating matrices from several domains were simultaneously decomposed into shared user, item, and domain latent factors, and genetic algorithm was then deployed to estimate the optimal weights of the domains.

### *4.5 Deep Learning*

Deep learning can be deployed to design sophisticated cross-domain architectures, where collaborative, content-based, and other features are shared across the domains. One of the key advantages of deep learning over traditional machine

**Table 7** Cross-domain recommendation approaches based on deep learning

| Cross-domain approach | Overlap | References |
|---|---|---|
| *Transfer-Learning* | $UI$ | Zhu et al. [85] |
| | $U$ | Yuan et al. [79] |
| | $U$ | Hu et al. [34] |
| | $U$ | Ma et al. [55] |
| | $US$ | Fu et al. [28] |
| | $US$ | Zhao et al. [84] |
| | $U$ | Li et al. [47] |
| | $US$ | Liu et al. [50] |
| *Co-Training* | $U$ | Lian et al. [48] |
| | $U$ or $S$ | Zhu et al. [86] |
| | $US$ | Wang et al. [77] |
| | $UI$ | Kang et al. [38] |

($U$) user overlap, ($S$) semantic overlap, ($UI$) user and item overlap, ($US$) user and semantic overlap

learning method is the ability to design cross-domain recommender systems between the domains without an explicit overlap of users, items, or attributes. This is possible when the links between domains are created using features extracted from the data. For instance, considering free-text reviews, users or items may be linked if they share reviews expressing a similar opinion. These algorithms cannot be directly mapped into one of the previous categories, although all of them adopt either *transfer learning* or *co-training* to share knowledge between the domains (Table 7).

### 4.5.1 Transfer Learning

Transfer learning is the most frequently used approach when implementing deep learning algorithms for cross-domain recommender systems. In general, a neural network model trained on the source domain is enriched with layers or components aimed to learn a new model in the target domain.

Zhu et al. computed benchmark latent factors by merging the user and item latent factors in both domains according to their sparsity and neighborhood [85]. Then, a deep function was used to map the benchmark factors with the ones computed in each domain. Hu et al. leveraged unstructured text for collaborative recommendations [34]. The model consisted of memory, transfer and prediction modules. The user and target item were first embedded in a low-dimensional space. The memory module modeled the relations between the text semantics, represented via a dictionary of word embeddings, and user preferences. The transfer module learned a non-linear function transferring knowledge from the embeddings of the source items the user interacted with to the target item. The prediction module was implemented as a multilayered perceptron (MLP) that predicted the user-item rating based on a concatenation of their embeddings. An additional layer considered the outputs of all three modules and computed the predicted user-item score.

Zhao et al. developed a review-based model, where aspects were extracted from reviews and used for knowledge transfer [84]. Users and items were represented by *documents* containing all their reviews. The aspects were extracted using text convolution and attention mechanisms, and the aspects were correlated across domains by training on the overlapping users. For an overlapping user and a target domain item, the user's document in the source domain and the item's document in the target domain were used for rating prediction. In addition to reviews, Fu et al. considered interactions and item features [28]. The model embedded reviews in the user profile encoding and MLP transferred the latent factors. The domains were linked by mapping the embeddings of overlapping users and the MLP generated embeddings in the target domain from the source domain embeddings.

Li et al. proposed a model for bidirectional recommendations, able to generate recommendations both in the source and target domains via a dual transfer learning mechanism [47]. For this, a latent orthogonal mapping represented user preferences in multiple domains in a way that preserved the relations between users across latent spaces and allowed learning user similarity in both domains simultaneously. The model represented users, items, and features by a latent vector computed with an autoencoder based on an MLP. The information was transferred across domains with a latent orthogonal matrix, which preserved the users' similarity and allowed for easy bidirectional transfer through a straightforward inverse. Liu et al. [50] incorporated into a similar model user's aesthetic preferences, associated with personality [13]. These were extracted using a pre-trained aesthetic network and assumed to be domain-independent. The embeddings of the user, source items, target items, and aesthetic traits were used as input for a cross-transfer network connecting the domains and facilitating bidirectional transfer.

### 4.5.2 Co-Training

Co-training in deep learning is used when there is a limited amount of labeled data, but a large amount of unlabeled data. In the case of cross-domain recommender systems, neural networks are used to jointly learn models for the source and target domains, aiming at balancing and complementing their available data.

Multiple tasks are solved at the same time in the source and target domains to learn shared latent features. Zhu et al. developed an algorithm building user and item embeddings from heterogeneous sources: reviews, tags, user profiles, and item features [86]. The embeddings were shared between the domains for overlapping users and items. The model consisted of an embedding layer for interaction and features, a sharing layer connecting the domains, and a layer aggregating domain-specific and shared embeddings. Wang et al. proposed an adversarial model that addressed the cold start and data imbalance problems [77]. The models learned latent representations for users, items and user-item pairs, which were transferred to the target domain. The functions used to transfer the embeddings were learned with a min-max adversarial game, in a way that the embeddings generated from the source and target domains were indistinguishable. Reviews and images of products were used to enhance the latent representation of items. Multiple strategies were proposed for various scenarios of user and item overlaps between the two domains.

Yuan et al. developed a pure collaborative model that transferred rating patterns between domains having the same set of users [79]. First, the embeddings of users and items were computed for each domain independently, and then all these were fed into a neural network that generated recommendations for both domains, balancing extraction of transferable rating patterns and predictive accuracy. Ma et al. studied sequential recommendations in multiple domains [55]. Their model contained a dedicated unit for cross-domain transfer that combined domain-specific models using gated recurrent units (GRUs) and trained according to the data timestamps. The representation learned in the target domain was combined with the one learned in another domain, such that the recommendations were computed using information from both the domains.

Lian et al. [48] proposed a hybrid model, where both collaborative and content-based data were represented in the same latent space and used a deep mapping function between the source and target embeddings. Kang et al. [38] addressed the issue of a limited number of overlapping users by proposing first to learn their embeddings in a metric space, and then to learn a mapping function by taking into account both the overlapping users in a supervised way and the non-overlapping items and users in an unsupervised way, therefore, including in the learning process the user's neighborhood.

## 5 Evaluation of Cross-Domain Recommender Systems

A central topic of research in cross-domain recommender systems lies in the evaluation of recommendation algorithms. Although the type of issues covered by cross-domain recommender systems has gradually expanded over the years, classical rating prediction and top-N recommendation problems still attract most of the attention, and the research community has developed a seemingly standardized way of evaluating these problems.

In the vast majority of published papers, algorithms are compared through offline experiments on historical data. Such experiments are typically easier to conduct than online studies and live evaluations, as they require no interactions with real users [27, 68].[1] With offline experiments, a system is evaluated by analyzing past user preferences. Thus, progress can be claimed if a new algorithm is better at predicting test data than previous ones in terms of predictive error measures (MAE,

[1] The reader is referred to Chap. 29 for an extensive discussion on the different methods used to evaluate recommender systems.

**Table 8** Metrics for evaluation of cross-domain recommender systems

| Category | References | |
|---|---|---|
| *Error metrics* | Berkovsky et al. [4, 5] | Hu et al. [33] |
| | Berkovsky et al. [6] | Sahebi et al. [67] |
| | Pan et al. [59] | Shapira et al. [69] |
| | Winoto et al. [78] | Loni et al. [52] |
| | Cao et al. [11] | Man et al. [56] |
| | Nakatsuji et al. [58] | Zhu et al. [85] |
| | Pan et al. [63] | Fu et al. [28] |
| | Zhang et al. [80] | Wang et al. [77] |
| | Li et al. [46] | Yuan et al. [79] |
| | Shi et al. [70] | Li et al. [47] |
| | Pan et al. [64] | Zhao et al. [84] |
| *Ranking metrics* | Abel et al. [1] | Man et al. [56] |
| | Tiroshi et al. [75] | Hu et al. [34] |
| | Abel et al. [2] | Kang et al. [38] |
| | Hu et al. [33] | Ma et al. [55] |
| | Shapira et al. [69] | Zhu et al. [86] |
| | Zhang et al. [82] | Liu et al. [50] |
| | Farseev et al. [20] | |
| *Classification metrics* | Stewart et al. [71] | Farseev et al. [20] |
| | Nakatsuji et al. [58] | Taneja et al. [72] |
| | Cremonesi et al. [14] | Ma et al. [55] |
| | Kaminskas et al. [37] | Li et al. [47] |
| | Tiroshi et al. [74] | |

MSE, etc), classification accuracy measures (Precision, Recall, Fallout, F1, etc), or ranking accuracy measures (MAP, NDCG, etc) [32]. Table 8 provides an overview of the evaluation metrics exploited in prior literature.

In this section, we discuss methods and best practices for offline evaluation of cross-domain recommender systems. The key point to bring up in this context is that such systems cannot be evaluated in a problem-independent way. That is, it is impossible to assess whether a cross-domain recommender system is an appropriate solution without taking into account for what it was intended for. The nature of the evaluation must be connected to the purpose, for which the recommendations were originally conceived, as outlined in Sect. 2.3.

Two key points in the evaluation of cross-domain recommender systems differ significantly from the evaluation of single-domain recommender systems: *data partitioning* and *sensitivity analysis* (e.g., studies of the relative density of domain-specific datasets and degree of user/item overlaps between the domains), as discussed in the following sections.

## 5.1 Data Partitioning

In order to evaluate algorithms offline, it is necessary to simulate the process, where the system makes recommendations, and users evaluate them. This requires a pre-recorded dataset of interactions between users and items. The dataset is then partitioned into the training and test sets. The former is used to build and tune the model used by the recommender algorithm, while the latter is actually used to evaluate the quality of the generated recommendations.

In cross-domain applications, there are (at least) two potentially overlapping datasets: the source dataset $\mathcal{D}_S$ and the target dataset $\mathcal{D}_T$. We assume $\mathcal{D}_S$ and $\mathcal{D}_T$ are chosen according to the recommendation task and goal in hand. For instance, when evaluating a cross-selling recommender, (i) $\mathcal{D}_S$ and $\mathcal{D}_T$ are set at the item level, as described in Sect. 2.1, (ii) contain items of a different nature, like movies and books, and (iii) have overlapping users. On the contrary, when evaluating a cross-domain recommender as a tool to increase recommendation diversity, $\mathcal{D}_S$ and $\mathcal{D}_T$ are set at the item attribute level, with items of the same type, but differing in the value of certain attributes, e.g., comedy and drama movies.

The exact way $\mathcal{D}_S$ and $\mathcal{D}_T$ are partitioned into training and test set depends on the cross-domain scenario and goal:

- **Scenario.** In the case of a multi-domain scenario, where recommendations target both the source and destination domains, the test set must contain interactions from $\mathcal{D}_S$ and $\mathcal{D}_T$. On the contrary, for a cross-domain scenario, test interactions should be collected exclusively from the target domain $\mathcal{D}_T$.
- **Goal.** When the main goal a cross-domain recommender system is to address the new user problem, the profiles of the tested users (i.e., their known ratings) should contain only interactions from $\mathcal{D}_S$. On the contrary, when the main goal is to increase accuracy, the profiles of the tested users should contain also interactions from $\mathcal{D}_T$.

## 5.2 Sensitivity Analysis

Performance of cross-domain recommenders is mainly affected by three parameters: data overlap between the source and target domains, density of the target domain data, and size of the target user's profile. Hence, the evaluation of cross-domain recommenders should analyze sensitivity with respect to these three parameters. Table 9 overviews the the sensitivity analyses reported in the literature.

Most works assume *data overlap* between the source and target domains materialized as an overlap of users, but only a few—Cremonesi et al. [14] and Zhao et al. [83]—study the sensitivity by varying the percentage of overlapping users. Fewer works assume to have the same catalog of items across the domains [6, 14]. Some works [2, 7, 37, 71] studied the case of overlapping features,

**Table 9** Variables for sensitivity analysis of cross-domain recommender systems

| Parameter | References | |
|---|---|---|
| *Overlap between domains* | Cremonesi et al. [14] | Abel et al. [2] |
| | Shi et al. [70] | Zhao et al. [84] |
| *Target domain density* | Pan et al. [59] | Cremonesi et al. [14] |
| | Cao et al. [11] | Shapira et al. [69] |
| | Pan et al. [63] | Hu et al. [34] |
| *User profile size* | Berkovsky et al. [4, 5] | Shi et al. [70] |
| | Berkovsky et al. [6] | Sahebi et al. [67] |
| | Li et al. [44, 45] | |

especially social tags. For example, Shi et al. studied the sensitivity of cross-domain recommendations by varying the number of overlapping tags between 5 and 50 [70].

Some works [6, 44, 45, 67, 70] studied the sensitivity of recommendations as a function of the *user profile size*, i.e., the number of ratings provided by the recipient of the recommendations. This is particularly critical for the cold-start and new user problems. Pan et al. [63] and Abel et al. [2] developed tag-based recommenders, and performed their analysis by varying the number of tags in the user profile in the 10 to 40 and 0 to 150 ranges, respectively. Others conducted a similar analysis on rating-based recommenders: Shi et al. varied the profile size from 20 to 100 ratings [70], Berkovsky et al. varied the profile size from 3% to 33% of ratings [6], and Sahebi et al. [67] varied the profile size in the range of 1 to 20 ratings.

Finally, some works [11, 14, 63, 69] studied the quality of recommendations as a function of the *dataset density*. Cao et al. varied the density of the multi-domain dataset, i.e., the union of the source and target datasets, between 0.2% and 1% [11]. Shapira et al. varied the density of the dataset between 1% and 40%, while evaluating cross-domain algorithms at the 1% density [69]. Cremonesi et al. varied the density of the target domain between 0.1% and 0.9% [14].

## 6 Open Research Questions

This section overviews the frontiers of cross-domain recommendations by providing some guidance to researchers looking for exciting future research directions. Open challenges mainly are in the areas of evaluation, privacy, fairness, session-based recommendations, and datasets.

- **Evaluation.** Close to 90% of works on cross-domain recommenders published since 2016 are based on deep learning. However, several indications show that using increasingly deeper learning methods in recommender systems is not as beneficial as one could expect. For example, four recent papers report that, for single-domain top-N recommendations, neural methods are not superior to long-existing non-neural ones [24–26, 54]. The observation that for certain tasks the reported improvements "don't add up" mainly lies in the choice of weak baselines and their poor optimization. These findings, however, are not limited to single-domain approaches, but also apply to cross-domain approaches. For instance, recognizing the progress made by transfer learning in cross-domain recommendations, it is not uncommon to find papers, where transfer-learning algorithms for cross-domain recommendations are compared against weak baselines [15]. The current methodological approach for benchmarking cross-domain recommender systems seems solid at first sight and suitable to determine if one algorithm outperforms another for a specific combination of goal, task, and overlap between the domains. However, cross-domain recommender systems researchers have ample freedom in selecting their experimental conditions: protocol, datasets, baselines, etc. This complicates reproducibility and direct benchmarking of results. Given these observations regarding potential methodological issues in the evaluation of cross-domain recommenders, we encourage researchers to publish reproducibility studies of cross-domain recommenders.

- **Privacy.** Privacy is an important and challenging consideration for cross-domain recommender systems, as they exploits information collected by multiple platforms. Sharing knowledge between domains can violate privacy policies and increase the risk of privacy leaks. For instance, if a social network is used as a source domain, it can be exploited to breach privacy in the target domain. Moreover, in many scenarios, different domains are managed by different companies, and sharing personal user data between companies may be prohibited or should comply with local policy regulations, such as the General Data Protection Regulation (GDPR) in Europe. However, existing researches on privacy-preserving recommendations are focused almost exclusively on single-domain scenarios, the only exception being the work from Gao et al. [29]. To this end, we call for an increased attention to privacy-preserving cross-domain recommendations.
- **Fairness.** Cross-domain recommender systems, as any recommender system, learn patterns from historical data, which conveys biases in terms of imbalances and inequalities. These biases, if not properly detected and controlled, potentially lead to discrimination and unfairness in recommendations [19]. Cross-domain recommender systems open new challenges in controlling biases and preventing unfairness, as imbalances and inequalities in the source domains might exacerbate unfairness of recommendations in the target domain. For instance, demographic characteristics within the source domain may not be representative of the target population. However, existing work on biases and fairness focused exclusively on single-domain scenarios. Research questions in cross-domain recommender systems are focused, among others, on controlling the effects generated by unbalances between domains, and transparently explaining why a recommender system provides a given result based on data collected from auxiliary domains. Hence, being able to detect, measure, characterize, and mitigate biases in cross-domain recommender systems is largely an open challenge.
- **Sequence-aware recommendations.** An under-explored research field is the one combining sequence-aware and cross-domain recommender systems. Cross-

domain sequential recommender systems predict the next item that the user is likely to interact with, based on past sessions behavior across multiple domains [35, 65]. Previous studies have investigated how to link interactions from different domains, regardless of their sequential nature, the only exception being the work of Ren et al. [65]. One of the key challenges in cross-domain sequential recommendation is around grasping and transferring sequential pattern of interactions from the source domain to the target domain. User behavior, in terms of temporal connections between the items they interact with, constitutes a new link that can be exploited to connect different domains and obtain better cross-domain sequence representations.

- **Datasets.** Finally, cross-domain recommender system research often lacks appropriate datasets allowing to assess diverse recommendation scenarios and tasks [39]. Rich datasets are necessary for a reliable evaluation of new cross-domain recommendation approaches, but these are quite scarce and hard to reach in practice. Large-scale cross-domain datasets are typically gathered by big industry players, such Amazon, eBay and Yelp, and these datasets rarely become available to the broader research community. This brings to the fore the emergent need for new datasets, openly available to the research community, allowing to clearly classify their association with the relevant cross-domain recommendation tasks, goals, and scenarios.

## 7 Conclusions

This chapter covered a wide spectrum of models and techniques applicable to cross-domain recommendations. Recommender system practitioners may find this list of overviewed papers and the variety of options overwhelming, when materializing a cross-domain recommender. Therefore, we list few practical considerations that drive the choice of cross-domain recommender systems.

The first consideration deals with the pivotal question of *why* to use cross-domain recommendations, which we have already raised in Sect. 2.3. Different goals require for different cross-domain recommendation approaches. Having a clear vision about the goal of the cross-domain recommender system is critical in designing the correct path and setting the expectations. A related consideration is *if* cross-domain recommendations are needed. The design of cross-domain recommenders is challenging not only from the algorithmic point of view, but also because cross-domain recommenders need access to reliable information, which needs to be collected, cleansed, deduplicated, and reconciled with the target domain data. This is a time consuming and potentially expensive task, which could compromise the benefits of cross-domain recommendations.

Last but not the least, special attention needs to be paid to *ethical* and *privacy* considerations. Transferring data and knowledge between systems may not conform with their privacy policies and existing privacy regulations. Moreover, it may allow malicious attackers not only to get access to a large volume of user data, but also to mine the combined knowledge, uncovering new potentially sensitive information. Developers of a cross-domain recommender system should keep the privacy considerations in mind when designing and evaluating their methods.

## References


1. F. Abel, S. Araújo, Q. Gao, G.-J. Houben, Analyzing cross-system user modeling on the social web, in *11th International Conference on Web Engineering*, pp. 28–43 (2011)
2. F. Abel, E. Helder, G.-J. Houben, N. Henze, D. Krause, Cross-system user modeling and personalization on the social web. User Model. User Adap. Inter. **23**(2-3), 169–209 (2013)
3. S. Berkovsky, T. Kuflik, F. Ricci, Entertainment personalization mechanism through cross-domain user modeling, in *1st International Conference on Intelligent Technologies for Interactive Entertainment*, pp. 215–219 (2005)
4. S. Berkovsky, T. Kuflik, F. Ricci, Cross-domain mediation in collaborative filtering, in *11th International Conference on User Modeling*, pp. 355–359 (2007)
5. S. Berkovsky, T. Kuflik, F. Ricci, Distributed collaborative filtering with domain specialization, in *1st ACM Conference on Recommender Systems*, pp. 33–40 (2007)
6. S. Berkovsky, T. Kuflik, F. Ricci, Mediation of user models for enhanced personalization in recommender systems. User Model. User Adap. Inter. **18**(3), 245–286 (2008)
7. M. Braunhofer, M. Kaminskas, F. Ricci, Location-aware music recommendation. Int. J. Multimedia Inf. Retr. **2**(1), 31–44 (2013)
8. I. Cantador, I. Fernández-Tobías, S. Berkovsky, P. Cremonesi, Cross-domain recommender systems. *Recommender Systems Handbook*, 2nd edn. (Springer, 2015), pp. 919–959
9. F. Carmagnola, F. Cena, User identification for cross-system personalisation. Information Sciences **179**(1-2), 16–32 (2009)
10. F. Carmagnola, F. Cena, C. Gena, User model interoperability: A survey. User Model. User Adap. Inter. **21**(3), 285–331 (2011)
11. B. Cao, N.N. Liu, Q. Yang, Transfer learning for collective link prediction in multiple heterogeneous domains, in *27th International Conference on Machine Learning*, pp. 159–166 (2010)
12. R. Chung, D. Sundaram, A. Srinivasan, Integrated personal recommender systems, in *9th International Conference on Electronic Commerce*, pp. 65–74 (2007)
13. P.T. Costa, R.R. McCrae, Revised NEO personality inventory (NEO-PI-R) and NEO five-factor inventory (NEO-FFI) manual. Psychol. Assess. Resour. (1992)
14. P. Cremonesi, A. Tripodi, R. Turrin, Cross-domain recommender systems, in *11th IEEE International Conference on Data Mining Workshops*, pp. 496–503 (2011)
15. P. Cremonesi, M. Quadrana, Cross-domain recommendations without overlapping data: myth or reality? in *8th ACM Conference on Recommender Systems* (2014)
16. C. Ding, T. Li, W. Peng, H. Park, Orthogonal nonnegative matrix tri-factorizations for clustering, in *12th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pp. 126–135 (2006)
17. R. Driskill, J. Riedl, Recommender systems for E-commerce: Challenges and opportunities, in *AAAI'99 Workshop on Artificial Intelligence for Electronic Commerce*, pp. 73–76 (1999)
18. M. Enrich, M. Braunhofer, F. Ricci, Cold-start management with cross-domain collaborative filtering and tags, in *14th International Conference on E-Commerce and Web Technologies*, pp. 101–112 (2013)
19. M.D. Ekstrand, R. Burke, F. Diaz, Fairness and discrimination in recommendation and retrieval, in *Proceedings of the 13th ACM Conference on Recommender Systems*, pp. 576–577 (2019)

20. A. Farseev, I. Samborskii, A. Filchenkov, T. Chua, Cross-domain recommendation via clustering on multi-layer graphs, in *40th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pp. 195–204 (2017)
21. I. Fernández-Tobías, I. Cantador, M. Kaminskas, F. Ricci, A generic semantic-based framework for cross-domain recommendation, in *2nd International Workshop on Information Heterogeneity and Fusion in Recommender Systems*, pp. 25–32 (2011)
22. I. Fernández-Tobías, I. Cantador, M. Kaminskas, F. Ricci, Cross-domain recommender systems: A survey of the state of the art, in *2nd Spanish Conference on Information Retrieval*, pp. 187–198 (2012)
23. I. Fernández-Tobías, I. Cantador, Exploiting social tags in matrix factorization models for cross-domain collaborative filtering, in *1st International Workshop on New Trends in Content-based Recommender Systems* (2013)
24. M. Ferrari Dacrema, S. Boglio, P. Cremonesi, D. Jannach, A troubling analysis of reproducibility and progress in recommender systems research. ACM Trans. Inf. Syst. **39**(2) 49 p. (2021)
25. M. Ferrari Dacrema, P. Cremonesi, D. Jannach, Are we really making much progress? A worrying analysis of recent neural recommendation approaches, in *13th ACM Conference on Recommender Systems*, pp. 101–109 (2019)
26. M. Ferrari Dacrema, F. Parroni, P. Cremonesi, D. Jannach, Critically examining the claimed value of convolutions over user-item embedding maps for recommender systems, in *29th ACM International Conference on Information & Knowledge Management*, pp. 355–363 (2020)
27. J. Freyne, S. Berkovsky, G. Smith, Evaluating recommender systems for supportive technologies, in *User Modeling and Adaptation for Daily Routines*, pp. 195–217 (2013)
28. W. Fu, Z. Peng, S. Wang, Y. Xu, J. Li, Deeply fusing reviews and contents for cold start users in cross-domain recommendation systems, in *33rd AAAI Conference on Artificial Intelligence*, pp. 94–101 (2019)
29. C. Gao, C. Huang, Y. Yu, H. Wang, Y. Li, D. Jin, Privacy-preserving cross-domain location recommendation. Proc. ACM Interactive Mobile Wearable Ubiquit. Technol. **3**(1), 1–21 (2019)
30. S. Gao, H. Luo, D. Chen, S. Li, P. Gallinari, J. Guo, Cross-domain recommendation via cluster-level latent factor model, in *17th and 24th European Conference on Machine Learning and Knowledge Discovery in Databases*, pp. 161–176 (2013)
31. M. He, J. Zhang, P. Yang, K. Yao, Robust transfer learning for cross-domain collaborative filtering using multiple rating patterns approximation, in *11th International Conference on Web Search and Data Mining, WSDM*, pp. 225–233 (2018)
32. J.L. Helocker, J.A. Konstan, L.G. Terveen, J. Riedl, Evaluating collaborative filtering recommender systems. ACM Trans. Inf. Syst. **22**(1), 5–53 (2004)
33. L. Hu, J. Cao, G. Xu, L. Cao, Z. Gu, C. Zhu, Personalized recommendation via cross-domain triadic factorization, in *22nd International Conference on World Wide Web*, pp. 595–606 (2013)
34. G. Hu, Y. Zhang, Q. Yang, Transfer meets hybrid: A synthetic approach for cross-domain collaborative filtering with text, in *The World Wide Web Conference 2019*, pp. 2822–2829 (2019)
35. D. Jannach, P. Cremonesi, M. Quadrana, Session-based recommender systems. *Recommender Systems Handbook*, 3nd edn. (Springer, 2021)
36. S. Jialin Pan, Q. Yang, A survey on transfer learning. IEEE Trans. Knowl. Data Eng. **22**(10), 1345–1359 (2010)
37. M. Kaminskas, I. Fernández-Tobías, F. Ricci, I. Cantador, Ontology-based identification of music for places, in *13th International Conference on Information and Communication Technologies in Tourism*, pp. 436–447 (2013)
38. S. Kang, J. Hwang, D. Lee, H. Yu, Semi-supervised learning for cross-domain recommendation to cold-start users, in *28th ACM International Conference on Information and Knowledge Management, CIKM*, pp. 1563–1572 (2019)
39. M. Khan, R. Ibrahim, I. Ghani, Cross domain recommender systems: A systematic literature review. ACM Comput. Surv. 36:1–36:34 (2017)

40. B. Kitts, D. Freed, M. Vrieze, Cross-sell: A fast promotion-tunable customer-item recommendation method based on conditionally independent probabilities, in *6th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pp. 437–446 (2000)
41. Y. Koren, Factorization meets the neighborhood: A multifaceted collaborative filtering model, in *14th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pp. 426–434 (2008)
42. C.H. Lee, Y.H. Kim, P.K. Rhee, Web personalization expert with combining collaborative filtering and association rule mining technique. Expert Syst. Appl. **21**(3), 131–137 (2001)
43. B. Li, Cross-domain collaborative filtering: A brief survey, in *23rd IEEE International Conference on Tools with Artificial Intelligence*, pp. 1085–1086 (2011)
44. B. Li, Q. Yang, X. Xue, Can movies and books collaborate? Cross-domain collaborative filtering for sparsity reduction, in *21st International Joint Conference on Artificial Intelligence*, pp. 2052–2057 (2009)
45. B. Li, Q. Yang, X. Xue, Transfer learning for collaborative filtering via a rating-matrix generative model, in *26th International Conference on Machine Learning*, pp. 617–624 (2009)
46. B. Li, X. Zhu, R. Li, C. Zhang, X. Xue, X. Wu, Cross-domain collaborative filtering over time, in *22nd International Joint Conference on Artificial Intelligence*, pp. 2293–2298 (2011)
47. P. Li, A. Tuzhilin, DDTCDR: Deep dual transfer cross domain recommendation, in *13th ACM International Conference on Web Search and Data Mining*, pp. 331–339 (2020)
48. J. Lian, F. Zhang, X. Xie, G. Sun, CCCFNet: A content-boosted collaborative filtering neural network for cross domain recommender systems, in *26th International Conference on World Wide Web Companion*, pp. 817–818 (2017)
49. B. Liu, Y. Wei, Y. Zhang, Z. Yan, Q. Yang, Transferable contextual bandit for cross-domain recommendation, in *32nd Conference on Artificial Intelligence (AAAI)*, pp. 3619–3626 (2018)
50. J. Liu, P. Zhao, F. Zhuang, Y. Liu, V. Sheng, J. Xu, X. Zhou, H. Xiong, Exploiting aesthetic preference in deep cross networks for cross-domain recommendation, in *The Web Conference 2020*, pp. 2768–2774 (2020)
51. A. Loizou, How to recommend music to film buffs: enabling the provision of recommendations from multiple domains. Ph.D. thesis, University of Southampton (2009)
52. B. Loni, Y. Shi, M.A. Larson, A. Hanjalic, Cross-domain collaborative filtering with factorization machines, in *36th European Conference on Information Retrieval* (2014)
53. Y. Low, D. Agarwal, A.J. Smola, Multiple domain user personalization, in *17th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pp. 123–131 (2011)
54. M. Ludewig, N. Mauro, S. Latifi, D. Jannach, Empirical analysis of session-based recommendation algorithms. User Model. User Adap. Inter., 1–33 (2020)
55. M. Ma, P. Ren, Y. Lin, Z. Chen, J. Ma, M. De Rijke, $\pi$-Net: A parallel information-sharing network for shared-account cross-domain sequential recommendations, in *42nd International ACM SIGIR Conference on Research and Development in Information Retrieval*, pp. 685–694 (2019)
56. T. Man, H. Shen, X. Jin, X. Cheng, Cross-domain recommendation: An embedding and mapping approach, in *26th International Joint Conference on Artificial Intelligence, IJCAI*, pp. 2464–2470 (2017)
57. O. Moreno, B. Shapira, L. Rokach, G. Shani, TALMUD: transfer learning for multiple domains, in *21st ACM Conference on Information and Knowledge Management*, pp. 425–434 (2012)
58. M. Nakatsuji, Y. Fujiwara, A. Tanaka, T. Uchiyama, T. Ishida, Recommendations over domain specific user graphs, in *19th European Conference on Artificial Intelligence*, pp. 607–612 (2010)
59. S.J. Pan, J.T. Kwok, Q. Yang, Transfer learning via dimensionality reduction, in *23rd AAAI Conference on Artificial Intelligence*, pp. 677–682 (2008)
60. R. Pagano, P. Cremonesi, M. Larson, B. Hidasi, D. Tikk, A. Karatzoglou, M. Quadrana, The contextual turn: From context-aware to context-driven recommender systems, in *10th ACM Conference on Recommender Systems*, pp. 249–252 (2016)

61. S.J. Pan, Q. Yang, A survey on transfer learning. IEEE Trans. Knowl. Data Eng. **22**(10), 1345–1359 (2010)
62. W. Pan, N.N. Liu, E.W. Xiang, Q. Yang, Transfer learning to predict missing ratings via heterogeneous user feedbacks, in *22nd International Joint Conference on Artificial Intelligence*, pp. 2318–2323 (2011)
63. W. Pan, E.W. Xiang, N.N. Liu, Q. Yang, Transfer learning in collaborative filtering for sparsity reduction, in *24th AAAI Conference on Artificial Intelligence*, pp. 210–235 (2010)
64. W. Pan, E.W. Xiang, Q. Yang, Transfer learning in collaborative filtering with uncertain ratings, in *26th AAAI Conference on Artificial Intelligence*, pp. 662–668 (2012)
65. Z. Ren, L. Zhao, J. Ma, M. de Rijke, Mixed information flow for cross-domain sequential recommendations. ACM Trans. Knowl. Discov. Data **1**(1), (2020)
66. S. Rendle, Factorization machines with libFM. ACM Trans. Intell. Syst. Tech. **3**(3), 1–22 (2012)
67. S. Sahebi, P. Brusilovsky, Cross-domain collaborative recommendation in a cold-start context: The impact of user profile size on the quality of recommendation, in *21st International Conference on User Modeling, Adaptation, and Personalization*, pp. 289–295 (2013)
68. G. Shani, A. Gunawardana, Evaluating recommendation systems. *Recommender Systems Handbook*, pp. 257–297 (2011)
69. B. Shapira, L. Rokach, S. Freilikhman, Facebook single and cross domain data for recommendation systems. User Model. User Adap. Inter. **23**(2-3), 211–247 (2013)
70. Y. Shi, M. Larson, A. Hanjalic, Tags as bridges between domains: Improving recommendation with Tag-induced cross-domain collaborative filtering, in *19th International Conference on User Modeling, Adaption, and Personalization*, pp. 305–316 (2011)
71. A. Stewart, E. Diaz-Aviles, W. Nejdl, L.B. Marinho, A. Nanopoulos, L. Schmidt-Thieme, Cross-tagging for personalized open social networking, in *20th ACM Conference on Hypertext and Hypermedia*, pp. 271–278 (2009)
72. A. Taneja, A. Arora, Cross domain recommendation using multidimensional tensor factorization. Expert Syst. Appl., 304–316 (2018)
73. J. Tang, J. Yan, L. Ji, M. Zhang, S. Guo, N. Liu, X. Wang, Z. Chen, Collaborative users' brand preference mining across multiple domains from implicit feedbacks, in *25th AAAI Conference on Artificial Intelligence*, pp. 477–482 (2011)
74. A. Tiroshi, S. Berkovsky, M.A. Kaafar, T. Chen, T. Kuflik, Cross social networks interests predictions based on graph features, in *7th ACM Conference on Recommender Systems*, pp. 319–322 (2013)
75. A. Tiroshi, T. Kuflik, Domain ranking for cross domain collaborative filtering, in *20th International Conference on User Modeling, Adaptation, and Personalization*, pp. 328–333 (2012)
76. D. Vallet, S. Berkovsky, S. Ardon, A. Mahanti, M.A. Kafaar, Characterizing and predicting viral-and-popular video content, in *24th ACM International on Conference on Information and Knowledge Management*, pp. 1591–1600 (2015)
77. C. Wang, M. Niepert, H. Li, RecSys-DAN: Discriminative adversarial networks for cross-domain recommender systems. IEEE Trans. Neural Netw. Learn. Syst. **31**(8), 2731–2740 (2020)
78. P. Winoto, T. Tang, If you like the devil wears prada the book, will you also enjoy the devil wears prada the movie? A study of cross-domain recommendations. N. Gener. Comput. **26**, 209–225 (2008)
79. F. Yuan, L. Yao, B. Benatallah, DARec: Deep domain adaptation for cross-domain recommendation via transferring rating patterns, in *28th International Joint Conference on Artificial Intelligence*, pp. 4227–4233 (2019)
80. Y. Zhang, B. Cao, D.-Y. Yeung, Multi-domain collaborative filtering, in *26th Conference on Uncertainty in Artificial Intelligence*, pp. 725–732 (2010)
81. Y. Zang, X. Hu, LKT-FM: A novel rating pattern transfer model for improving non-overlapping cross-domain collaborative filtering, in *Machine Learning and Knowledge Discovery in Databases - European Conference*, pp. 641–656 (2017)

82. X. Zhang, J. Cheng, T. Yuan, B. Niu, H. Lu, TopRec: domain-specific recommendation through community topic mining in social network, in *22nd International Conference on World Wide Web*, pp. 1501–1510 (2013)
83. L. Zhao, S.J. Pan, E.W. Xiang, E. Zhong, X. Lu, Q. Yang, Active transfer learning for cross-system recommendation, in *27th AAAI Conference on Artificial Intelligence*, pp. 1205–1211 (2013)
84. C. Zhao, C. Li, R. Xiao, H. Deng, A. Sun, CATN: Cross-domain recommendation for cold-start users via aspect transfer network, in *43rd International ACM SIGIR conference on research and development in Information Retrieval*, pp. 229–238 (2020)
85. F. Zhu, Y. Wang, C. Chen, G. Liu, M. Orgun, A deep framework for cross-domain and cross-system recommendations, in *27th International Joint Conference on Artificial Intelligence, IJCAI*, pp. 3711–3717 (2018)
86. F. Zhu, C. Chen, Y. Wang, G. Liu, X. Zheng, DTCDR: A framework for dual-target cross-domain recommendation, in *28th ACM International Conference on Information and Knowledge Management*, pp. 1533–1542 (2019)
87. F. Zhuang, P. Luo, H. Xiong, Y. Xiong, Q. He, Z. Shi, Cross-domain learning from multiple sources: A consensus regularization perspective. IEEE Trans. Knowl. Data Eng. **22**(12), 1664–1678 (2010)