Cross Domain Recommender Systems: A Systematic Literature Review

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Cross domain recommender systems (CDRS) can assist recommendations in a target domain based on knowledge learned from a source domain. CDRS consists of three building blocks: domain, user-item overlap scenarios, and recommendation tasks. The objective of this research is to identify the most widely used CDRS building-block definitions, identify common features between them, classify current research in the frame of identified definitions, group together research with respect to algorithm types, present existing problems, and recommend future directions for CDRS research. To achieve this objective, we have conducted a systematic literature review of 94 shortlisted studies. We classified the selected studies using the tag-based approach and designed classification grids. Using classification grids, it was found that the category-domain contributed a maximum of 62%, whereas the time domain contributed at least 3%. User-item overlaps were found to have equal contribution. Single target domain recommendation task was found at a maximum of 78%, whereas cross-domain recommendation task had a minor influence at only 10%. MovieLens contributed the most at 22%, whereas Yahoo-music provided 1% between 29 datasets. Factorization-based algorithms contributed a total of 37%, whereas semantics-based algorithms contributed 6% among seven types of identified algorithm groups. Finally, future directions were grouped into five categories.

Categories and Subject Descriptors: H.5.5 [**Information Systems - information retrieval**]: Recommender Systems

General Terms: Survey, comparison, trend

Additional Key Words and Phrases: Cross domain recommender systems, systematic literature review, cross domain transfer learning, multi domain recommender systems

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1. INTRODUCTION

Recommender systems are special software programs designed to recommend items to users based on their observed interest [Ricci et al. 2011]. A user's interest with respect to recommended items is stored in the form of interaction, for example, numerical rating, inside a rating matrix. Therefore, users, items, and the rating matrix create a recommender systems ecosystem known as a domain.

These days, recommender systems focus on item recommendation to a single domain. For example, AMAZON recommends items for sale to its interested users; Netflix

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presents its viewers with a list of media content, whereas Last.fm recommends songs and music albums to its users. Such recommender systems are increasing rapidly and are found to focus on users having specific interests, rather than relying on the wisdom of the majority, that is, covering a broad range of users [Ivàn Cantador 2015].

Single-domain recommender systems face a variety of problems, including cold start, sparsity, issues related to new users, items, and so on [Ricci et al. 2011]. Although these problems are being researched under the single-domain perspective, cross domain recommender systems (CDRS), on the other hand, add a new dimension in solving these problems. This is achieved by transferring knowledge available in other domains (known as the source domain) to the target domain.

In recent years, CDRS has gained momentum, and researchers have started contributing from diverse viewpoints. They are using a variety of versatile approaches including the following:

—Graph-based approach [Jiang et al. 2012; Shapira et al. 2013; Biadsy et al. 2013; Guo and Chen 2014] to identify the connection between source and target domain users and items.
—Factorization-based approach [Shi et al. 2011; Wang et al. 2012; Gao et al. 2013b; Xin et al. 2014] for extracting common features of users and items from both domains.
—Semantics-based approach [Moe and Aung 2014a; Kumar et al. 2014b] for generation of knowledge map using source domain attributes for application in the target domain.
—Tag-based approach [Dong and Zhao 2012; Yang et al. 2014; Guo and Chen 2013b; Moe and Aung 2014b] to generate meta-data association between participating domains, and so on.

Each primary study tries to identify itself with respect to domain type, user-item overlap scenario, and recommendation tasks, respectively. These three identification attributes are building blocks of CDRS and were proposed by different researchers as follows: Li [2011] and Ivan [Ivàn Cantador 2015] proposed domain definitions, Cremonesi [Cremonesi et al. 2011] and Fernández-Tobías et al. [2012] suggested recommendation scenarios, whereas Cremonesi et al. [2011], Fernández-Tobías et al. [2012], and Ivàn Cantador [2015] advised recommendation tasks.

Although Cremonesi et al. [2011], Li [2011], Fernández-Tobías et al. [2012], and Ivan Ivàn Cantador [2015] proposed CDRS definitions, they were not actually supporting each other; rather, some of them were pointing in different directions. For example, Li [2011] described "system," "data," and "time" domain, whereas Ivàn Cantador [2015] identified domains with respect to item attributes. Cremonesi et al. [2011] described user-item overlap scenarios, whereas Fernández-Tobías et al. [2012] extended them. In relation to recommendation tasks, although Cremonesi et al. [2011], Fernández-Tobías et al. [2012], and Ivàn Cantador [2015] proposed their own definitions, without citing each other, they were found to be technically similar.

Difference of opinion partitioned researchers into different groups, while existing CDRS secondary studies do not identify common features of proposed definitions. In this article, we selected the systematic literature review approach to gather and analyze primary studies, using a widely accepted and recognized review methodology [Brereton et al. 2007] to present a broad view of CDRS research and achieve our objectives. To this end, 94 studies were shortlisted, classified, and compared using classification grids built using building blocks. Building blocks served as horizontal and vertical dimensions of grids resulting in two grids being formed: "domain" vs. "user-item overlap scenarios" and "recommendation tasks" vs. "user-item overlap scenarios." These are similar to the classification parameters used by Ivàn Cantador [2015]. The domain vs recommendation tasks classification was excluded because recommendation tasks are not dependent on domain change. The research synthesis resulted in the formulation of research trends based on clustered primary studies inside the classification grid.

In response to systematic literature review (SLR) research questions, this study first attempts to identify common features among the identified building-block definitions. Second, it classifies primary studies with respect to proposed domain vs. user-item overlap and recommendation tasks vs. user-item overlap grid. Third, algorithms that enable CDRS knowledge transfer are grouped, and datasets having a maximum contribution in CDRS research are identified. Fourth, conventional recommender systems problems addressed by CDRS are identified and problems faced by CDRS are described. Finally, future directions of CDRS research are highlighted. Therefore, the results of this SLR are beneficial for the following individuals:

—Researchers who are new to cross domain recommender systems and are looking for open research issues, problems, and future directions in CDRS research.
—Researchers who are confused by different CDRS definitions and need a comprehensive study to identify common features between them.

This article is split into seven sections starting with Section 1, which gives an introduction, followed by Section 2, which contain related research. Section 2 presents the following scenarios: First, it identifies associated studies describing building blocks of CDRS; second, it groups together the most widely used CDRS definitions and discusses them; and, finally, it compares studies on reviews about CDRS research. In Section 3, objectives of this review article are outlined and a list of criteria for empirical (primary) studies classification is defined. Section 4 identifies our research questions, search strategy, inclusion and exclusion criteria, and data extraction procedure in accordance with systematic literature review approach. This is followed by Section 5 where results are presented to answer research questions leading to Section 6, which discusses threats to validity. Finally, in Section 7, the conclusion is presented along with the suggestions for future work.

2. RELATED RESEARCH

This section attempts to gather existing research by initially identifying CDRS attributes, highlighting multiple definitions associated with these attributes and outlining how some researchers have classified CDRS primary studies with respect to these attributes.

2.1. Building Blocks of Cross Domain Recommender Systems Research

Primary studies in CDRS usually classify their work with respect to knowledge transfer between domains, based on similarity of users and items occurring in both domains, as shown in the following examples: Gao et al. [2013b] and Li et al. [2009] transferred knowledge from EachMovies to the MovieLens dataset based on similar items; Berkovsky et al. [2007] and Zhang et al. [2012] transferred knowledge between different movie genres among the same users; Pan et al. [2015a] and Pan et al. [2015b] transferred knowledge from binary interactions to numerical ratings between same users and items; while Huang et al. [2012] and Xin et al. [2014] transferred knowledge between rating matrices having different time stamps between same users and items. Similarly, once knowledge is transferred, primary studies classify themselves according to generated recommendations, for example, Gao et al. [2013b] and Li et al. [2009] generated recommendation for users in target domain, that is, MovieLens [Berkovsky et al. 2007], while Zhang et al. [2012] generated recommendation for users of both domains. Generated recommendation is presented to either target or source users or both; hence this process is known as the recommendation task. In conclusion, domain difference, user-item overlap, and recommendation tasks can be regarded as the most essential aspects attributed for cross domain recommender systems research. Hence, these attributes are named as building blocks of cross domain recommender systems.

Given that these attributes are being used widely, we find it necessary to describe them separately according to their proposed definitions.

2.1.1. Notion of Domain. Two studies that define the notion of the domain were written by Li [2011] and Ivàn Cantador [2015]. Li [2011] defined system, time, and data domain, whereas Ivàn Cantador [2015] defined item attribute level domain, item type level domain, item level domain, and system domain, respectively. At the time of the writing of this review, Li [2011] was found to be more popular and was cited by many researchers [Hu et al. 2013a; Moreno et al. 2012; Gao et al. 2013a, 2013b; Hu et al. 2013b; Ren et al. 2015; Li et al. 2015; Biadsy et al. 2013]. The respective domains in both of these studies are described as follows:

• *Li's domain definitions*

System Domain: When data in the target recommender system rating matrix (e.g., MovieLens) are sparse as compared to some related recommender system (e.g., Netflix), each recommender system is considered as a distinct domain. In such cases, knowledge is transferred from a domain having dense ratings to a weak target domain [Xu et al. 2011b].

Data Domain: In recommender systems, users' interactions with items can be stored in the form of numeric ratings (1–5) or binary ratings, for example, item likes or dislikes. These multi-dimensional data for similar interaction is considered to be a different data domain [Pan et al. 2011].

Time Domain: A Time Domain is formed when a rating matrix having time stamps is split into different time slices; each slice is then considered as a separate temporal domain [Li 2011].

• *Ivan's domain definitions*

(Item) Attribute level: Two items are considered to belong to different domains if their attribute values are found to differ (e.g., movies from different genres such as comedy or action are supposed to belong to different domains).

(Item) Type level: Two items are supposed to belong to different domains if some of their attributes differ while others remain the same. For example, movies and TV shows are regarded as different domains, because, although their items can have the same title and genre, their other attributes differ, for example, play time. An example is *The X-Files* (the movie) and "The X-Files" (TV show).

Item level: Items in which the majority of their attributes differ are labeled as item level domains. For example, movies and books can have items sharing the same name but having a different medium type.

System level: Items belonging to different systems are considered as belonging to different domains; for example, MovieLens and Netflix are considered as different domains.

Both Li and Ivan concludes that system domain was found to be common, whereas other domain definitions were distinct in nature. Ivan's definitions were proposed recently [Ivàn Cantador 2015]. However, the first three definitions related to item attributes were found to be confusing. They did not clearly specify the amount of attributes required to differ to change domain from (Item) type level to Item level. Also, their

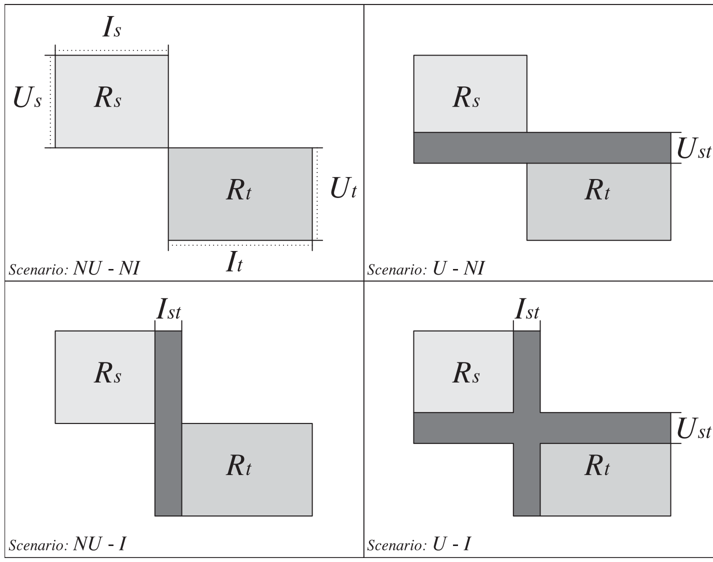


Fig. 1. User-item overlaps scenarios.

claim of "being first" to define domains was incorrect, since Li's definitions had been proposed earlier and were cited by more researchers as compared to Ivan.

2.1.2. User-Item Overlaps Scenarios. The most prominent study related to user-item overlap was conducted by Cremonesi et al. [2011] where he identified four user-item overlap scenarios. Although these four scenarios were found to have been cited by many researchers [Gao et al. 2013a, 2013b; Enrich et al. 2013; Sahebi and Brusilovsky 2013; Iwata and Takeuchi 2015; Li et al. 2015; Hoxha et al. 2013; Kille 2013; Fernández-Tobías et al. 2012], there were extended overlap scenarios.

• *Cremonesi scenarios*

To assist in the transfer of learning between domains, some relation needs to exist between users and items of participating domains. Usually, this relation is formed when users and items are found to be common in both domains. This relation overlap was highlighted by Cremonesi et al. [2011] and is shown in Figure 1. In relation ship to overlaps, four scenarios exist and are described as follows:

—**No User–No Item overlap (NU-NI):** In this scenario, no user and no item are found to be common between participating domains. Ratings of both domains are analyzed to identify similarity of user and items.
—**User–No Item overlap (U-NI):** Users are found to be common between participating domains hence assisting in recommendation generation.
—**No User–Item overlap (NU-I):** Items are found to be common between participating domains hence assisting in recommendation generation.
—**User–Item overlap (U-I):** Users and items are found to be common between participating domains; hence both assist in recommendation generation.

• *Fernandez scenarios*

Fernandez states that, in the case of a small overlap between users and items of both domains, the generated recommendations may be inaccurate. For such scenarios, Fernandez proposes a "characteristics" overlap between the user and item profile of both domains. Characteristics can be defined as a feature vector extracted from ratings provided by the user and items of both domains.

2.1.3. Recommendation Tasks. Cross domain recommendation tasks are associated with user recommendation. Two main factors involved are the scope of recommended items and the scope of target users. Recommended items can come from both source or target domains or from only one of the two domains. Similarly, target users can reside in either one or both of the two domains. This leads to multiple scenarios of recommendation, but for simplicity, recommendation tasks proposed in Cremonesi et al. [2011], Fernández-Tobías et al. [2012], and Ivàn Cantador [2015] will be discussed as follows:

- *Cremonesi's recommendation tasks*

A study by Cremonesi et al. [2011] distinguished recommendation tasks under three scenarios as follows:

Single-domain: When items of the target domain are recommended to target users based on knowledge learned from the source domain, it is referred to as a "single-domain recommendation task."

Cross-domain: When items in the source domain are recommended to users of the target domain or vice versa, such a recommendation is labeled as a "cross-domain recommendation task."

Multi-domain: When items of both domains are recommended to users of both or one domain, sucha recommendation is known as a "multi-domain recommendation task."

- *Ivan's recommendation tasks*

Ivàn Cantador [2015] described recommendation tasks as follows:

Multi-domain recommendation: When items of both domains are recommended to users of either one or both domains, such a recommendation is known as a "multi-domain recommendation task."

Linked-domain recommendation: When items of the target domain are recommended to target users based on knowledge learned from the source domain, it is referred to as a "linked-domain recommendation task." Ivan also described another task named "cross-domain recommendation"; however, its definition was found to be the same as the linked-domain recommendation.

- *Fernandez's recommendation tasks*

Fernández-Tobías et al. [2012] explained recommendation tasks, although he did not propose names for them. His definitions were as follows:

(Scenario 1): Recommending items in the target domain to users of the target domain based on knowledge learned from the source domain.

(Scenario 2): Making a joint recommendation, that is, recommending items of both domains to users of both domains.

Although different researchers proposed definitions for CDRS building blocks, most of them do not correlate them to each other hence raising concerns that are highlighted in the next section.

2.2. Concerns Associated with CDRS Building Blocks

Q1 Why do different people have different definitions?

Different researchers approach CDRS building blocks in different ways for the following reasons:

1. Until now, no effort has been made by the recommender systems community to standardize definitions related to CDRS building blocks.
2. No survey study exists that attempts to summarize existing definitions related to CDRS building blocks and shows common features between them.
3. Existing studies that define CDRS building blocks do not cite or relate to each other.

Researchers of primary studies do not find it necessary to cite an appropriate source that defines CDRS building blocks. If they do, then they bind their studies to specific definitions. As no secondary study exists that identifies the similarities between different definitions, it becomes difficult to analyze CDRS primary studies on a common ground. Therefore, this study attempts to identify existing definitions and highlight similarities between them in response to the first research question of this systematic literature review.

Q2 What are common features of different definitions ?

Proposed definitions are grouped together into three building blocks as highlighted in Section 2.1. All building blocks operate on a rating matrix, which is the most essential part of the recommender system. The rating matrix contains ratings provided by users for items existing inside a recommender system. Users, items, and the rating matrix have features such as the time at which ratings were provided, type of items, type of users, types of ratings, the scope of a rating matrix, and so on. Each domain definition attempts to group together users, items, and the rating matrix with respect to these features.

—**Domain:** The time domain is associated with the time feature of a rating matrix, that is, the time at which a rating is provided. The data domain is related to the data type of a rating provided inside a rating matrix, for example, numeric rating or binary rating such as like/dislike, and so on. The system domain is associated with the scope of a rating matrix. Time, data, and system domain were proposed by Li [2011] among which system domain is common with the definitions of Ivàn Cantador [2015]. The rest of the Ivan definitions rely on the item attributes that are related to metadata features associated with items inside a rating matrix.

—**Recommendation scenarios:** Recommendation scenarios use the similarity feature of a participating domain. It means that knowledge is transferred from the source domain to the target domain based on the similarity of user and item of both the domains. Usually, source domain is considered to have dense ratings as compared to the target domain.

—**Recommendation tasks:** A recommender system generates recommendations for the users, and this process is known as a "recommendation task." A recommendation task aims at empty ratings. Empty ratings can exist in both source and target domains, and, therefore, a recommendation task can produce recommendations for both or either one of the two domains.

Section 3.2 lists identified features in the form of TAGs and uses them for data extraction from primary studies. Extracted data are further used for classification of primary studies into a proposed classification grid as shown in Section 5.2.

Table I. Compared Secondary Studies

Secondary Studies	Fernández-Tobías et al. 2012	Iván Cantador 2015
Domain differences	✓	✓
User-Item overlap scenarios	✗	✓
Recommendation tasks	✓	✓
Enabling algorithm	✓	✓
Identified problems	✗	✓
Future directions	✓	✓

Q3 Will these definitions increase in the future?

Recommender systems are continuously evolving due to improving technology, which results in increased features related to users, items, and ratings. Any new set of features will open a new perspective of transferring knowledge from the source to the target domain. Hence, it is highly likely that, in the future, definitions related to CDRS building blocks will increase. This is highlighted in Section 5.4.2, which discusses future directions of cross domain recommender systems.

While definitions can grow, building-block types (domain, recommendation scenario, and recommendation tasks) are expected to remain the same, as they serve as steps according to which knowledge transfer is executed.

In conclusion, domain, user-item overlap and recommendation were found to be common in primary studies, and these attributes were also considered for classification by two secondary studies [Fernández-Tobías et al. 2012; Ivàn Cantador 2015]. A comparison performed by these secondary studies is briefly described in the next section.

2.3. Compared Secondary Study

In recent years, research into cross domain recommender systems research has been gaining momentum. However, only two secondary studies have been found that discuss research trends. Table I lists attributes found to be common in both secondary studies [Fernández-Tobías et al. 2012; Ivàn Cantador 2015] according to which primary studies were classified.

Among the mentioned attributes, the first three were described previously as building blocks, whereas enabling algorithms, identified problems, and future directions are related to experiments conducted by primary studies. Fernández-Tobías et al. [2012] analyzed cross domain recommender system primary studies with respect to collaborative and content-based techniques. It also grouped primary studies in different user-item recommendation scenarios and recommendation tasks. Similarly, Ivàn Cantador [2015] grouped primary studies with respect to domain, user-item recommendation scenarios and tasks differences, respectively, while it mostly focused on user and item modeling for cross domain recommender systems. Both studies highlighted future directions, whereas Ivàn Cantador [2015] also pointed out problems faced under cross domain recommender systems research.

3. AIM OF UESEARCH AND CLASSIFICATION CRITERIA

The aim of this research is to analyze existing research work in cross domain recommender systems with respect to CDRS building blocks that is, domain differences, user-item recommendation scenarios, recommendation tasks, and experimental attributes, which include enabling algorithms, addressed problems and broad future directions.

Table II. Classification TAG Groups

<table>
<tr><th colspan="5">Experimental attributes</th><th colspan="2">Conclusive attributes</th></tr>
<tr><td colspan="3">Classification group 1 (CG1)</td><td colspan="2">Classification group 2 (CG2)</td><td colspan="2">Classification group 3 (CG3)</td></tr>
<tr><td rowspan="4">A</td><td>Source system domain</td><td>Target system domain</td><td rowspan="3">A</td><td>Proposed Algorithm</td><td>A</td><td>Addressed problem</td></tr>
<tr><td>Source category domain</td><td>Target category domain</td><td>Auxiliary dataset name</td><td>B</td><td>Future direction</td></tr>
<tr><td>Source data domain</td><td>Target data domain</td><td>Target dataset name</td><td></td><td></td></tr>
<tr><td>Source time domain</td><td>Target time domain</td><td>B</td><td>Evaluation Matrix</td><td></td><td></td></tr>
<tr><td>B</td><td colspan="2">User-Item overlap scenario [U-I,U-NI,NU-I,NU-NI]</td><td></td><td></td><td></td><td></td></tr>
<tr><td>C</td><td colspan="2">Recommendation tasks [C1, C2, C3]</td><td></td><td></td><td></td><td></td></tr>
</table>

3.1. Need for SLR

Table I performs a comparison between secondary studies with respect to their categorization of gathered primary studies. Related secondary studies did cover parts of outlined aims; however, no one has yet provided a methodology and search strategy to validate their research. For instance, Ivàn Cantador [2015] indexed primary studies according to their own defined domains, whereas Ivàn Cantador [2015], Fernández-Tobías et al. [2012], and Cremonesi et al. [2011] were focused on their conceptual contribution rather than categorizing existing research work to provide an overview of the research domain. Hence, we have adopted the systematic literature review approach to achieve our objectives and used the tag-based approach for classification of primary studies.

3.2. Classification Criteria

We used the tag-based approach, also known as knowledge tagging, to classify primary studies. Knowledge tag is a type of meta information that describes some aspect of the data under observation. In a tag-based approach, concepts related to a group of objects are shortlisted in the form of keywords and each object is represented by associated tags.

The tag-based approach has been in existence for a long time and has been used by researchers to group, classify, and shortlist primary studies. Maria da Conceição and Figueiredo [2013] supported the concept of tagging proposed by Miles and Huberman [1994] as units of meaning assigned to a study and used it for classification of their primary studies. Boell and Cecez-Kecmanovic [2015] used the tag-based approach to identify and associate primary studies with concepts relating to literature in the form of keywords. Cocchia [2014] shortlisted primary studies associated with smart cities using TAGGING, Razavi and Ahmad [2014] classified primary studies according to TAGs related to development, organization, customers, and teams concepts, whereas Mailk and Yusof [2013] and Maria da Conceição and Figueiredo [2013] used a tag-based approach for inclusion and exclusion of searched studies.

Keeping in mind the attributes used by compared secondary studies, we grouped essential CDRS concepts as tags (as shown in Table II) to use them for classification of our shortlisted primary studies.

The main reason for using the tag-based approach is to gather together as many primary studies as possible. Moreover, each primary study is not expected to cover all TAGs. For example, some studies may cover domain, user-item overlap, algorithm experiment, algorithm used, and addressed problems, that is, CG1A, CG1B, CG1C, CG2A, and CG3A, respectively, whereas others can have any combination they wish. To show organization, tags are grouped as each group precedes the other as follows:

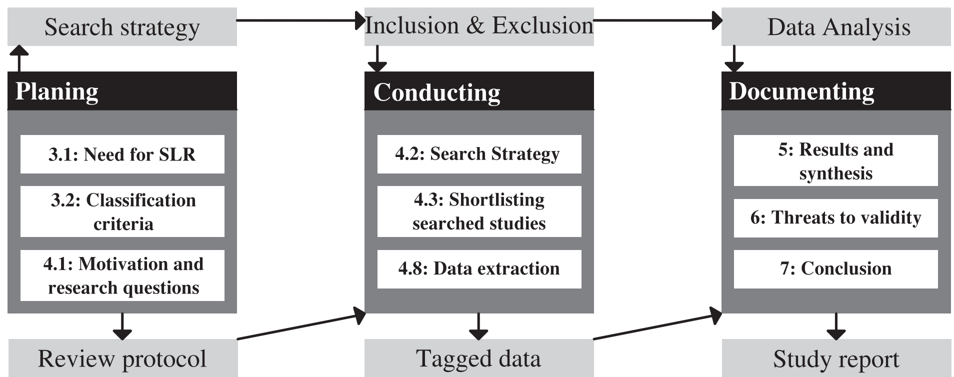


Fig. 2. Research phases.

domain knowledge transfer attributes (Classification Group 1: CG1), algorithm and evaluation attributes (CG2), and address problem and future research attributes (CG3). In conclusion, the above-mentioned TAGs will be used for shortlisting (Section 4.3) and classification (Section 4.7) of primary studies.

4. RESEARCH METHODOLOGY

A systematic literature review (SLR) attempts to execute a detailed sequence of specialized steps to gather maximum related research in contrast to a non-structured review process [Kitchenham 2004]. We followed guidelines provided in Brereton et al. [2007] comprising a three-step review process that consists of planning, conducting, and documenting of phases. Figure 2 shows the components of each phase and outlines outcomes that will drive consequent phases. To illustrate the flow of research, components of each phase are labeled as actual headings of this research article.

4.1. Motivation and Research Questions

In contrast to the secondary studies discussed in Section 2.3, we decided to summarize primary studies with respect to domain differences, user-item recommendation scenarios, recommendation tasks, addressed problems, and future directions, respectively, using a systematic literature review approach. Our research motivation led to objectives being defined in Section 3.1. In this section, research questions are derived and listed in Table III.

We have also identified PICOC (population, intervention, comparison, outcome and context) [Petticrew and Roberts 2008] criteria in Table IV to define the scope of SLR.

PICOC outlines five criteria that each SLR attempts to fulfill. The first criterion (population) is related to the identification of participants in each of the research questions. Interventions are actions that are a prerequisite to a comparison of a gathered population. Outcome is related to an analysis performed based on comparison, and, finally, context is associated with contribution claimed by a systematic study.

4.2. Search Strategy

Primary studies analyzed by the secondary studies compared in Section 2.3 were gathered. From each primary study, search keywords were then gathered into a single file. A word frequency analysis was then carried out for this file and the terms occurring most frequently were shortlisted. The most-frequently occurring terms with respect to secondary studies are shown in Figure 3.

Table III. Motivation and Research Questions

SNO	Research Questions	Motivation
RQ1	How can definitions of CDRS building blocks be associated in order to classify a broad range of primary studies?	Aim is to reduce confusion caused by a variety of definitions associated with CDRS building blocks.
RQ2	What percentage of cross domain recommender systems research is contributed by most of the relevant scenarios constructed under domain difference, recommendation scenario and recommendation tasks?	Aim is to highlight which scenarios are receiving the most research interest and why others are lagging behind.
RQ3	What are the existing methods and techniques to enable cross domain recommender systems and which existing approaches are used to evaluate them?	Aim is to compare existing techniques and methods that enable cross-domain recommendation.
RQ4	Which research issues have been addressed by existing approaches and what lies in future research?	Aim is to uncover existing research for future research purposes.

Table IV. PICOC Criteria

Criteria	RQ1	RQ2	RQ3	RQ4
Population	domain, user-item overlap and recommendation tasks definitions	Domain Difference, user-item overlap scenarios and recommendation tasks	propsed algorithms and evaluation criteria	research problems and future work
Intervention	Characterization, data extraction and synthesis			
Comparison	Comparison of primary studies with respect to characterization framework			
Outcome	A characterization framework, classification and comparison, hypothesis for future research.			
Context	Systematic investigation to consolidate research undertaken			

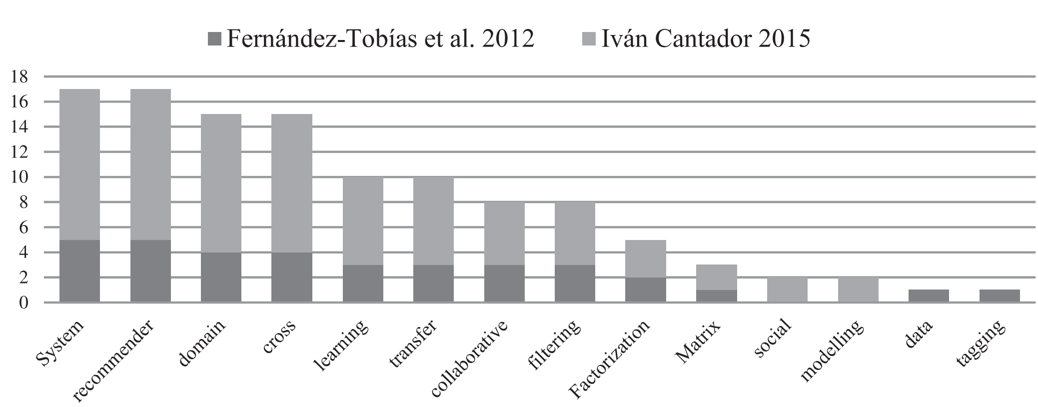


Fig. 3. Term frequency.

Table V. Search Keywords and Search Query

Terms	Group 1 (g')	Group 2(g'')
1	Cross domain	Recommender system
2	Multi domain	Recommendation
3	Transfer learning	Collaborative filtering
4	Cross model	Factorization

$$(g_1{}' \text{ OR } g_2{}' \text{ OR } g_3{}' \text{ OR } g_4{}') \\ \text{AND} \\ (g_1{}'' \text{ OR } g_2{}'' \text{ OR } g_3{}'' \text{ OR } g_4{}'')$$

Table VI. Search Results

Source	Results	Source	Results
IEEE	250	Web of science	82
ACM	72	Google scholar	95
Springer link	170		
Science direct	30		

Frequently occurring terms were found to exist as pairs in primary studies, for example, cross domain, recommender systems, collaborative filtering, transfer learning, matrix factorization, and so on. The search string for this study was generated using terms shown in Table V, which are based on terms counted earlier.

In addition, terms were grouped based on similarity. Therefore, Group 1 (g') terms were related to existence of a relationship among multiple entities and Group 2 (g'') was related to the research domain. Hence, a pseudo search string was formulated, shown alongside Table V.

To gather the primary studies, a highlighted pseudo search string was implemented as a search query in literature indexing systems. We selected ACM, IEEE, Springer Link, and Science Direct under digital libraries. To gather any leftover studies, broad indexing services like Web of Science and Google scholar were searched. Based on the search control provided by each source, it was intended to set a search scope to the title and abstract. In addition, a search was conducted independent of the time frame, hence covering studies up to 2016.

Table VI shows the number of articles uncovered from each source. In the next section, we describe our inclusion and exclusion criteria for shortlisting of primary studies.

4.3. Shortlisting Searched Studies

Shortlisting of primary studies was carried out in three stages starting with scanning the title, moving on to reading the abstract, and, finally, ending with a tagging process, as shown in Figure 4. Articles gathered from the search were listed in a spreadsheet, and, for each article, the title and its abstract were mentioned. This file was used during scanning of the title and reading of the abstract stage. Next, inclusion and exclusion criteria were used to assist with the shortlisting procedure.

4.4. Inclusion and Exclusion Criteria

For inclusion, 383 studies were shortlisted, since their title and mentioned keywords were found to be similar to searched keywords. Next, the abstract of each shortlisted study was read and the concept of the study was analyzed. During this phase, some studies were found to be exactly aligned with CDRS research concepts as discussed in Section 2; while others were found to be completely out of context. At the end of the abstract reading phase, 98 studies were shortlisted among which four [Cremonesi et al. 2011; Li 2011; Fernández-Tobías et al. 2012; Ivàn Cantador 2015] were found to have

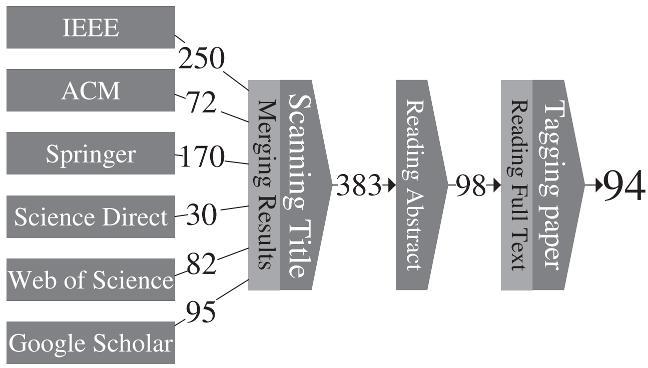


Fig. 4. Shortlisting searched studies.

conceptual contributions to CDRS research while others included experiments related to CDRS. In the tagging stage, 94 primary studies were tagged for data extraction.

In relation to exclusion, first, those searched articles that did not include searched keywords in their title and abstract were excluded. Some of the search results included Masters and Ph.D. theses, some were from the electrical and telecommunication domains, while others were found to have repeated search results. The most difficult to exclude were those that existed under recommender systems but did not include knowledge transfer between domains. Finally, those studies that existed under the CDRS domain but only had a conceptual contribution were also excluded.

4.5. Tagged Studies

Each of the 94 shortlisted primary studies was thoroughly reviewed and tagged using the tags grouped in Table II. Two “tag” concepts of classification group 1 (CG1), that is, domain (CG1A) and user-item overlap (CG1B), were found to be coexisting in 86 primary studies. Recommendation tasks (CG1C) tags were found in 65 studies. Classification group 2 (CG2A),(CG2B) concepts were found in a total of 70 and 72 studies, respectively. Finally, 67 of the articles identified addressed problems (CG3A) while 46 provided future direction of their work that came under classification group 3 (CG3). The list of studies having respective TAGs is shown in Table IX in the appendix to this article.

This study assigned a unique id to shortlisted articles as shown in Table VIII in the appendix. Paper id (PID) was used to represent each primary study relative to the other while keeping illustrations in this study flexible enough to accommodate all tagged studies, as presented in Section 5.

4.6. Publication Trend

Among the 94 shortlisted primary studies, 57% were conference publications, 25% were journal publications, and 18% were book chapters. Figure 5 shows the oldest study (including CDRS-related keywords), which dated from 2005. Since 2013, journal publications have been gaining momentum. A gradual decline was observed in conference and book chapters due to the delays caused by indexing services. A similar trend was also observed in an existing review study [Khalili and Auer 2013].

4.7. Data Extraction

Tagged primary studies were further passed through a data extraction process. In this process, each primary study was downloaded from the internet and given a file id. Based on TAGs identified in Table II, a spreadsheet was created where each column

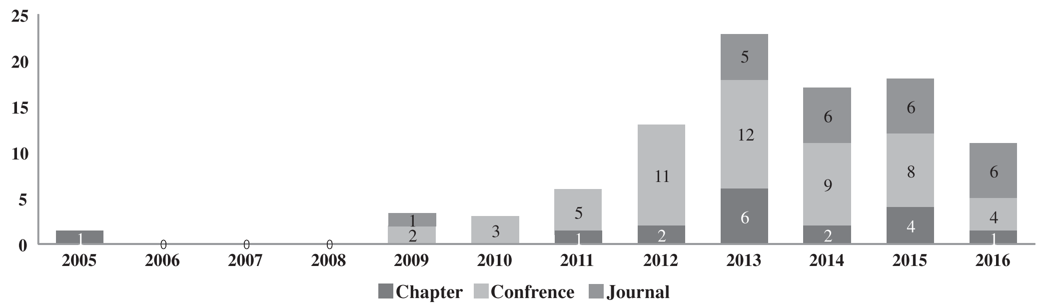


Fig. 5. Primary studies trend.

represented classification group labels (i.e., CG1A, CG1B). From each primary study, information related to the corresponding tag was gathered and put in its respective file. Additional information such as dataset information, evaluation method, compared algorithm, future work, and conclusion were also stored in the respective columns for each file. Accordingly, the extracted data was then used for analysis purpose as described in the next section.

5. RESULTS

This section presents results for research questions as mentioned in Section 4.1. This section is further divided into four subsections. The first subsection attempts to identify common features among CDRS building-block definitions. The second subsection attempts to classify primary studies with respect to the proposed classification grid. The third subsection highlights existing algorithms enabling CDRS, and, finally, the fourth subsection identifies future directions.

Each subsection also attempts to synthesize results using a cross-case analysis [Miles and Huberman 1994]. The cross-case analysis includes a variety of representation techniques such as tables and graphs to manage and present qualitative data, without destroying its meaning, through intensive coding. In our case, we have used the tag-based approach to code data that is, primary studies and proposed a grid as meta-metrics for classification and clustering of primary studies.

5.1. RQ1: *How CDRS Building Block Definitions Can be Generalized in Order to Classify a Broad Range of Primary Studies?*

This research question aims to identify common features between building blocks of CDRS. To do so, first, the domain definitions that are common are identified. Second, the category domain definition is proposed to compensate for the Ivàn Cantador [2015] (Item) Attribute level, (Item) Type level, and Item level definitions. Third, user-item overlap scenarios are selected based on citation of the candidate's studies. Fourth, recommendation tasks are defined using existing definitions proposed by the candidate's studies. In conclusion, the proposed set of definitions has been utilized for generation of classification grid used for classification of primary studies in later sections.

- *Domain*

To simplify understanding of domain definitions, Figure 6 was generated. This figure shows that the system domain definition was found to be common in both studies, that is, Li [2011] and Ivàn Cantador [2015], whereas Ivàn Cantador [2015] definitions related to item attributes were grouped into one domain, that is, category domain. This was performed because, although Ivan's definitions ("(Item) Attribute level," "(Item) Type level," and "Item level") used item attributes and types for differentiation, they did

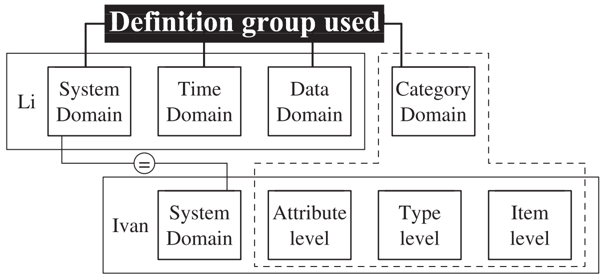


Fig. 6. Domain definitions used.

not specify the quantity of attributes required to differ. This is necessary to differentiate between “(Item) Attribute level” and “(Item) Type level.”

Category domain: Recommender systems items can be grouped with respect to item attributes or types as far as they reside inside a single system domain. Hence, each attribute or type can be described as a different category. When knowledge is transferred between different categories for recommendation generation, it is considered as category domain transfer, for example,

—Hu et al. [2013a] and Loni et al. [2014] transferred knowledge among AMAZON items having type book, Music CD, DVD, and VHS.
—Tang et al. [2012] and Shapira et al. [2013] transferred knowledge among Facebook items having type Music, Movie, TV, and books.
—Berkovsky et al. [2007] and Nakatsuji et al. [2010] transferred knowledge between EachMovies items having different genres.

• *User-Item overlap*

For user-item overlap scenarios, the Cremonesi et al. [2011] definitions were found to be widely accepted by primary studies, and, therefore, we continued with their definitions for classification of primary studies.

• *Recommendation tasks*

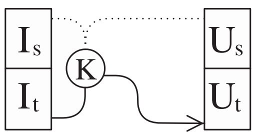
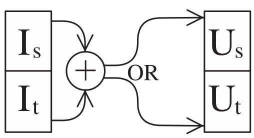
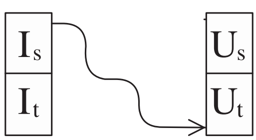
Recommendation tasks proposed by Cremonesi et al. [2011], Fernández-Tobías et al. [2012], and Ivàn Cantador [2015] had different names; however, they represented similar concepts. For simplicity, we have created three types of recommendation tasks as shown in Table VII where each type provides a precise explanation of similar recommendation tasks proposed by Cremonesi et al. [2011], Fernández-Tobías et al. [2012], and Ivàn Cantador [2015].

C1: Single target domain recommendation. Items in one domain are recommended to users of the respective domain based on knowledge acquired another domain. This scenario is similar to the single domain and recommendation quality improvement scenario in Cremonesi et al. [2011] and Fernández-Tobías et al. [2012], respectively.

C2: Combined Recommendation. Items from both domains contribute to the generated recommendation that is then presented to users of either one or both of the two domains. This scenario is similar to multi-domain recommendation and the joint user-item overlap recommendation scenario in Cremonesi et al. [2011], Ivàn Cantador [2015], and Fernández-Tobías et al. [2012], respectively.

C3: Cross domain recommendation. Items residing in one domain are recommended to other domain users based on knowledge learned from users and items of

Table VII. Recommendation Tasks Comparison

Recommendation Tasks	Cremonesi et al. 2011	Fernández-Tobías et al. 2012	Iván Cantador 2015
C1 	Single-domain	(Scenario 1)	
C2 	Multi-domain	(Scenario 2)	Multi-domain recommendation
C3 	Cross-domain		Linked-domain recommendation

I_s : Source items U_s : Source Users K : Knowledge
I_t : Target items U_t : Target Users + : Combined

both domains. This scenario is similar to the linked-domain recommendation and cross domain scenario in Ivàn Cantador [2015] and Cremonesi et al. [2011], respectively.

• *Summary*

This section answers respective research questions by first identifying the similarities between domains and proposing the category domain. Second, recommendation scenarios are discussed. Finally, recommendation tasks are then grouped together for classification of primary studies in the next section.

5.2. RQ2: *What Percentage of Cross Domain Recommender Systems Research Is Contributed by Most of the Relevant Scenarios Constructed Under Domain Difference, Recommendation Scenario, and Recommendation Tasks?*

Cross domain recommender system research stands on the foundation of three pillars, that is, domain knowledge transfer, user item overlap, and recommendation generation (known as recommendation tasks). The purpose of this research question is to properly position primary studies in a grid of identified pillars. During classification of primary studies, the "user-item" overlap was found to be common in articles containing both domain and recommendation task attributes. Therefore, to conveniently represent studies in a grid, it was designed in two variations as follows:

—Domain vs user-item overlap
—Recommendation tasks vs user-item overlap

5.2.1. Domain vs User-item Overlap. A total of 86 studies were found to identify domain difference and user-item overlap. These studies, according to their article id, are listed in Table VIII and are presented in Figure 7.

Grid Description: On the x-axis, the user-item overlap scenarios are mapped. "User-Item," "User-No Item" are placed in the left quadrant and "No User-Item," "No User-No Item" are placed in the right quadrant. Similarly, on the y-axis system and

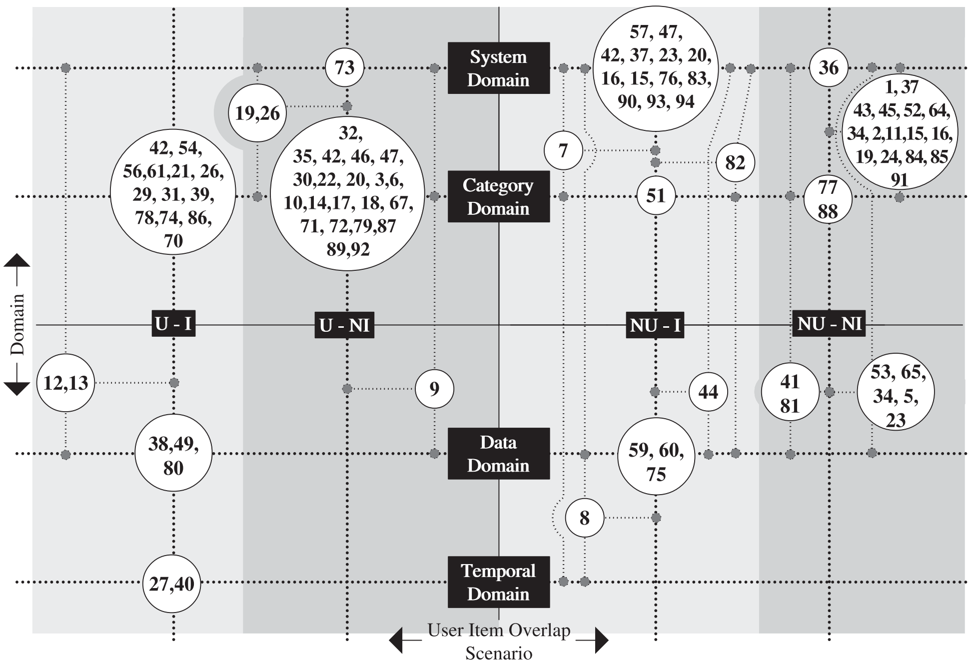


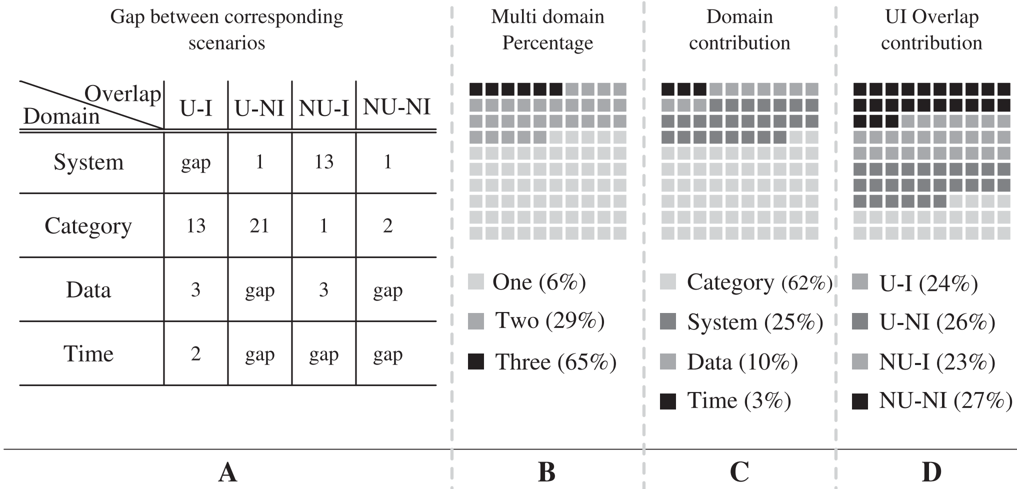
Fig. 7. Domain vs user-item overlap.

category domain are placed in the upper quadrant; while data and time domain are placed in the lower quadrant. This grid does not show any negative value but rather circles consisting of article id. The grid contains dotted lines that show the connection to respective axis elements. The horizontal dotted lines show a connection with domains, whereas vertical dotted lines indicate a connection with the user-item overlap scenario.

A simple glance at the circles placed in the grid will reveal two outcomes. In the first outcome, circles will exist at the intersection of strong dotted lines. For example, in the lower left quadrant, a circle containing two PID (27, 40) are placed at the intersection of dotted lines connected with "User-Item overlap" and time domain. This means that these primary studies transfer knowledge from the source to the target domain with respect to changes in the temporal domain. Moreover, they have the same users and items residing in both domains.

The second outcome shows circles existing in square blocks with narrow dashed lines connecting them to domain and user-item overlap dotted lines. In this grid, there exist 10 circles inside square blocks that can be split into two groups. The first group consists of those circles that are connected to two domains, and a single user-item overlap dotted line (e.g., the circle containing (19,26) in the upper left corner is connected to the system, category domain, and User-No Item overlap, respectively). The second group of circles comprises those that are connected to three domains, while a single user-item overlap, for example, (8), is connected to data and temporal and system domains along with the No User-Item overlap.

A circle connecting two domains indicates that it is involved in knowledge transfer from two domains while keeping the "user-item" overlap the same. Similarly, a circle connected with three domains shows a knowledge transfer among three domains.



Domain \ Overlap	U-I	U-NI	NU-I	NU-NI
System	gap	1	13	1
Category	13	21	1	2
Data	3	gap	3	gap
Time	2	gap	gap	gap

Fig. 8. Analysis of gathered primary studies using domain vs. user-item overlap.

• *Synthesis:*

Open for research contribution : *Single Domain vs. User-Item Overlap*
No study was found for scenarios between the following: system domain vs. user-item overlap, date domain vs. user-no item overlap, and no user-no item overlap; time domain vs. user-no item; no user-item, and no user-no item overlap as shown in Figure 8(A). The reason highlighted by Fernández-Tobías et al. [2012] for such a trend is non-availability of the appropriate dataset. In fact, an artificial data split of the same source was exercised by several authors to simulate different domain scenarios, for example, Berkovsky et al. [2008], Winoto and Tang [2008], and Zhang et al. [2012].

Open for research contribution: *Multi domain vs User - Item Overlap*
Some studies were found that transferred knowledge with respect to two domains, whereas only a few transferred knowledge with respect to three domains. One reason found for the decline in studies with respect to increasing domain was related to algorithm complexity. Still, there are many possible combinations open for research.

Figure 8(B) shows a comparison between overlap scenarios with respect to the number of domains involved. Single domain scenarios are abundant, whereas three domain overlap scenarios are the least common.

Mature Scenarios
The domain vs. user-item overlap scenarios are considered to be mature if they can gain maximum contribution from shortlisted primary studies. To calculate the overall domain contribution, the primary studies contributing to a unique domain were selected. Following this, the category domain obtained a maximum contribution of 37 studies, whereas the time domain received input from only two studies. This resulted, in domain contribution as shown in Figure 8(C).

In the case of a user-item overlap comparison, all of the scenarios were found to be participating nearly as equals, as shown in Figure 8(D).

5.2.2. Recommendation Tasks vs User-Item Overlap. A total of 65 studies were found that identified recommendation tasks and user-item overlaps. Figure 9 shows short-listed primary studies along with PID, as listed in Table VIII.

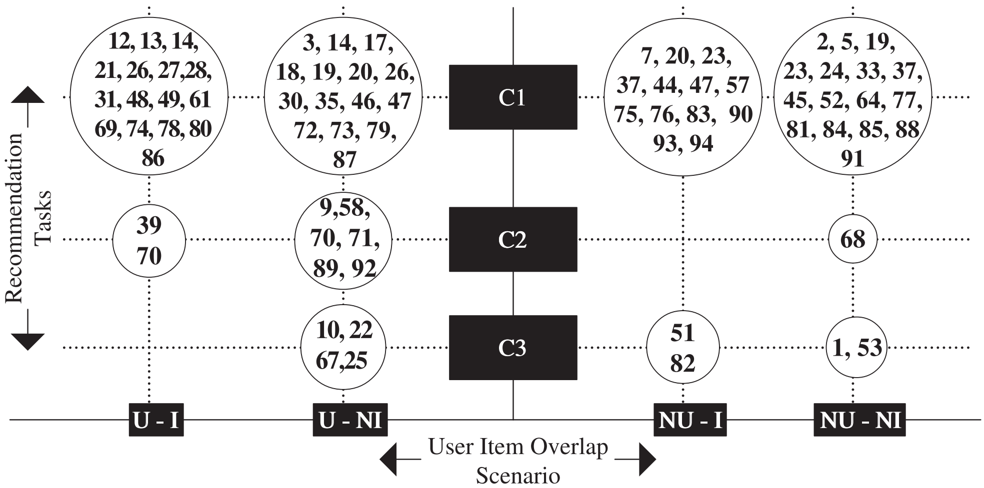


Fig. 9. Recommendation tasks vs. user-item overlap scenario.

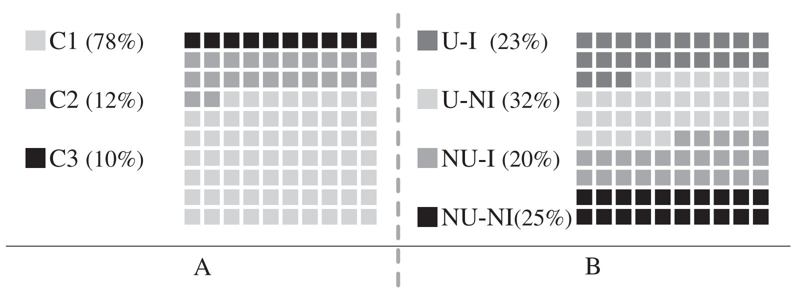


Fig. 10. Analysis of gathered primary studies using recommendation tasks vs. user-item overlap.

Grid description: The x-axis of the grid was labeled with a user-item overlap where User-Item, User-No Item existed in the left quadrant while No User-Item, No User-No Item existed in the right quadrant, respectively. The y-axis of Figure 9 represented recommendation tasks. Similarly to the previous grid, there is no negative information present, and the circles present on the grid contain PID of the corresponding primary study.

- *Synthesis:*

Open for research contribution: ***C2, C3***

Among all recommendation tasks, the single target domain recommendation (C1) provides the majority contribution followed by combined recommendation (C2) and, finally, cross domain recommendation (C3), respectively. Based on the gathered primary studies, the research gap was found at the intersection of the cross domain recommendation (C3), User-Item overlap and combined recommendation (C2), No User-Item overlap. Percentage for each recommendation task is shown in Figure 10(A).

For recommendation tasks vs. user-item overlap scenarios, user-no item overlap scenario was found to have maximum contribution whereas the no user - item overlap had a minimum contribution of 20% as shown in Figure 10(B).

• *Summary:*

This section classified CDRS primary studies with respect to domain vs. user-item overlap and recommendation tasks vs. user-item overlap. Classification resulted in the identification of the mature and developing CDRS research scenarios while, at the same time, also highlighting scenarios that are lacking research focus.

5.3. RQ3: *What are Existing Methods and Techniques to Enable Cross Domain Recommender Systems and Which Existing Approaches are Used to Evaluate Them?*

Algorithms that enable cross domain recommender systems research can be grouped into seven categories, specifically: clustering, semantics, graph-based, probability-distribution, factorization, tag-based association, and others. To gain a deeper insight into each group, an example is provided in the next section.

5.3.1. Algorithms.

Clustering: One of the primitive algorithms for cluster-based cross domain recommender system research was proposed by Moreno et al. [2012]. They designed a method to cluster ratings in a source domain based on users and items having similar rating patterns. This cluster was then transferred to a target domain and expanded according to similar user and items. Other studies based on clustering algorithm are those by Chen et al. [2013], Wang et al. [2012], Gao et al. [2013b], Yi et al. [2015], Li et al. [2009], Berkovsky et al. [2007], Li et al. [2016], Tang et al. [2013], Li et al. [2011], and Li et al. [2016], respectively.

Semantics: Semantic-based approaches find their root in knowledge engineering and ontology. The main idea behind semantic-based approaches is to generate a knowledge map using information available in the source domain and then transferring this knowledge map to the target domain for appropriate classification of items according to generated ratings. This approach was used by Moe and Aung [2014a] and Kumar et al. [2014b].

Graph-based approaches: The graph-based approach attempts to identify the connection between users and items in the source domain to generate a connection between similar users and items in the target domain. Studies that carry out a graph-based approach are those by Jiang et al. [2012], Shapira et al. [2013], Iwata and Takeuchi [2015], Biadsy et al. [2013], Guo and Chen [2014], and Nakatsuji et al. [2010] respectively.

Probability distribution: Probability distribution works for similar items identified in both domains. It attempts to learn the probability for each item with respect to all users of the source domain to find a probable recommendation score. Once learned, knowledge is transferred to the target domain for recommendation purposes. Studies utilizing probability distribution are Aizenberg et al. [2012], Ren et al. [2015], and Lu et al. [2013], respectively.

Factorization: Factorization techniques attempt to factorize a source rating matrix into a couple of feature matrices that are further combined with a target rating matrix to generate missing ratings. Papers covering factorization techniques are Shi et al. [2011], [Hu et al. 2013a], Huang et al. [2012], Gao et al. [2013b], Xin et al. [2014], Zhao et al. [2013], Loni et al. [2014], Shi et al. [2013a], Pan et al. [2012], Pan and Yang [2013], Shi et al. [2013b], Jing et al. [2014], Pan et al. [2015a], and Pan et al. [2015b], respectively.

Tags-based association: This refers first to TAG-based association first group source users and items with respect to their assigned TAGs. Second, on the association between source and target domain TAGs being identified, a rating pattern can be shared. Dong and Zhao [2012], Yang et al. [2014], Guo and Chen [2013b], and Moe

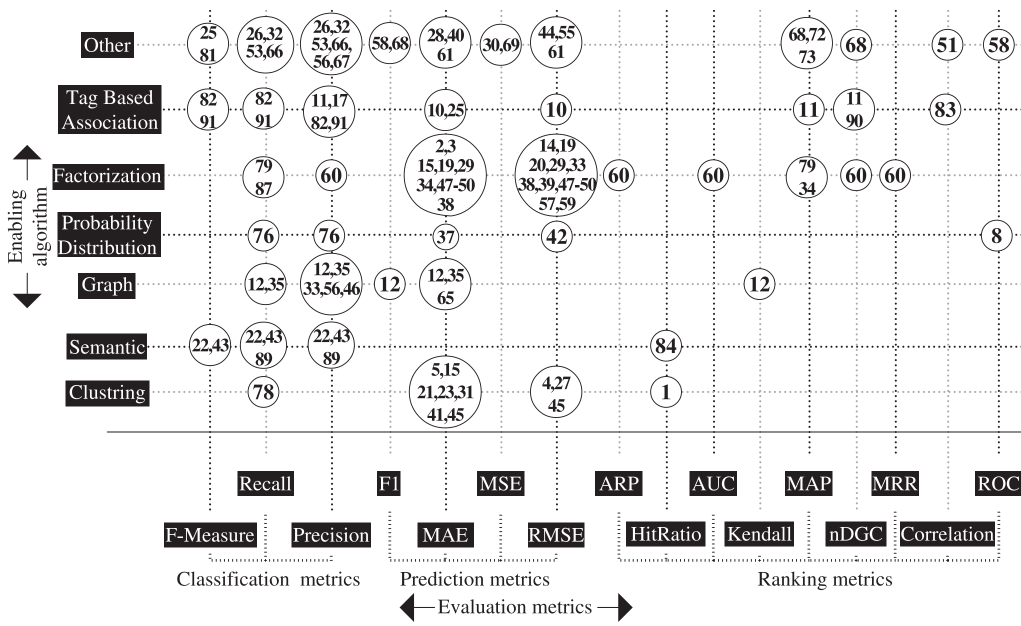


Fig. 11. Algorithms vs. evaluation metrics.

and Aung [2014b] utilized TAGs-based association to transfer knowledge from source to target domain.

Others: This refers to studies that proposed techniques for transfer learning between participating domains, which were application specific. Thus, in some cases related or compared techniques were not provided.

Evaluation techniques are required to measure performance of proposed algorithms and to identify evaluation techniques used for CDRS research. These techniques were extracted from each of the 72 shortlisted primary studies and grouped. Three groups were formed to identify evaluation metrics, that is, classification metrics, prediction metrics, and ranking metrics. Classification metrics are used to measure an algorithm's ability to identify true positives, true negatives, false positives, and false negatives with respect to an external judgment. Prediction metrics are similar to classification metrics and are usually used for algorithms that tend to improve with each iteration. Prediction metrics find the amount of error between the algorithms generated values and the actual values. Ranking metrics are usually used for measuring the degree of similarity between two ranked lists of items. A total of 16 evaluation techniques were found, with 3 contributing to classification metrics,3 contributing to prediction metrics, and 9 contributing to ranking metrics. In conclusion, classification grid 11 is generated between algorithms and evaluation metrics.

Grid description: To present algorithms in a comparative manner, primary studies are placed in a grid consisting of algorithms represented on the y-axis and evaluation metrics on the x-axis, as shown in Figure 11. Evaluation metrics are further grouped into three categories, namely classification metrics, prediction metrics, and ranking metrics. The grid only contains circles, which include primary studies and PID as listed in Table VIII. The circle is placed at the intersection of dotted lines where each of the dotted lines represents either an algorithm or an evaluation metric.

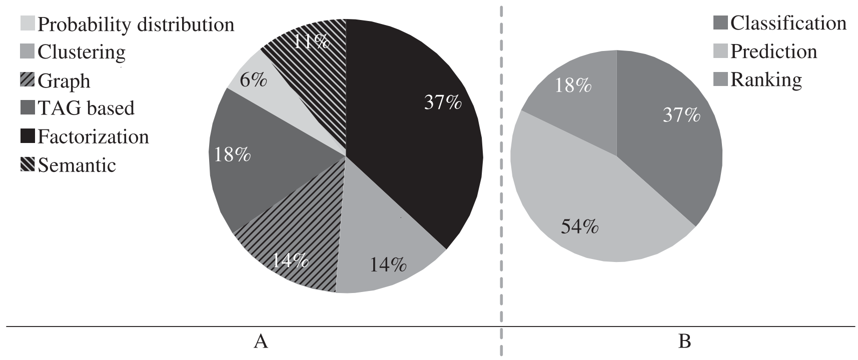


Fig. 12. Research contribution with respect to algorithm and evaluation metrics.

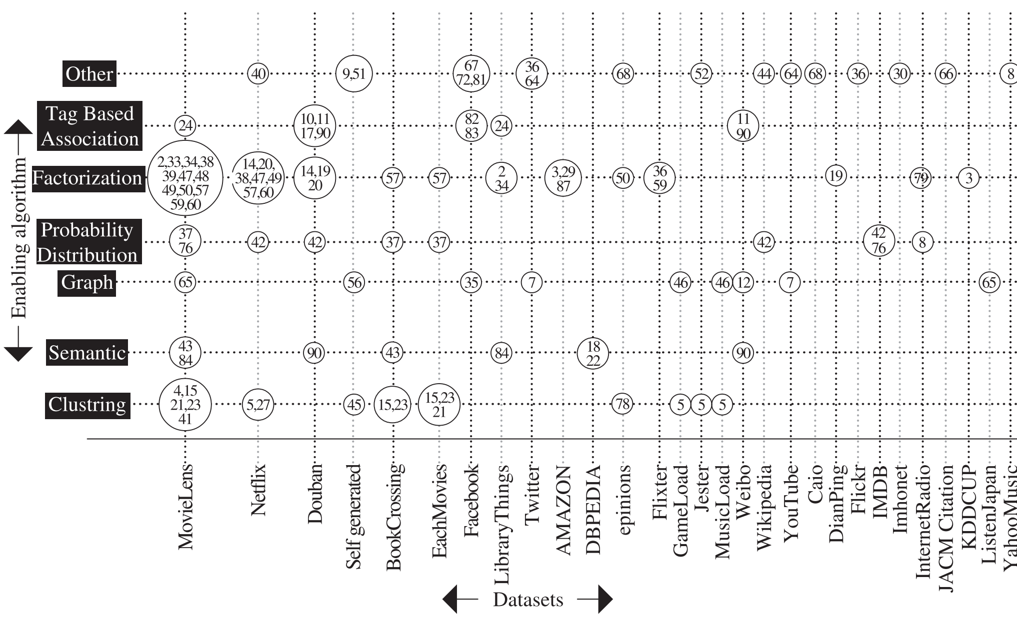


Fig. 13. datasets contribution.

• *Synthesis:*

The majority of research concentrates on factorization, graph and clustering based approaches as shown in Figure 12(A), while in fact the most often used evaluation metrics are prediction followed by classification and ranking metrics, respectively, as shown in Figure 12(B).

5.3.2. Used Datasets. Dataset information was also gathered while collecting algorithms and evaluation metrics. It was observed that the MovieLens dataset gained the maximum contribution from 23 studies at 22%, followed by Netflix, which was used by 11 studies. Moreover, many publicly accessible sources were used as datasets, as shown in Figure 13, in which 4 studies generated datasets of their own. In conclusion, 29 datasets were used in shortlisted primary studies, whereas the majority of the researchers focused on the popular datasets only.

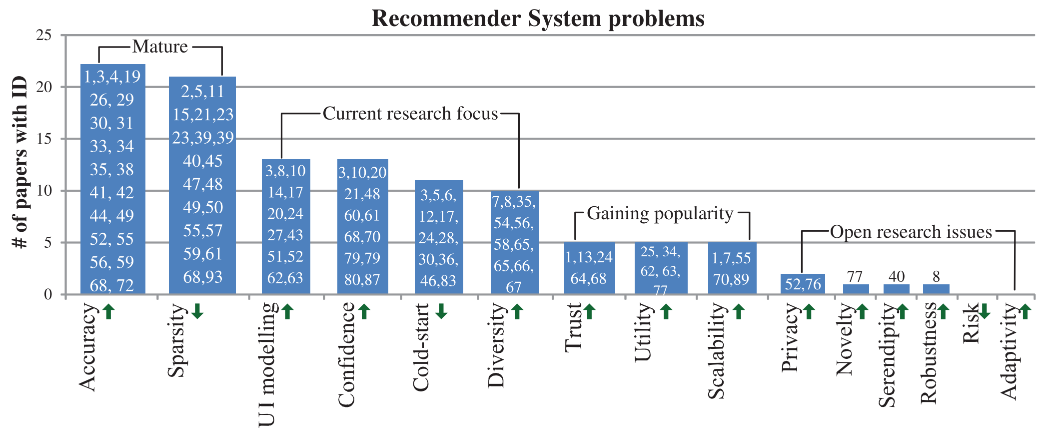


Fig. 14. Cross domain solution for recommender system problems.

• *Summary:*

This section first identifies the algorithms and their respective primary studies with respect to evaluation metrics, which can help CDRS in transferring knowledge from the source to the target domain. Second, datasets used by primary studies are identified with respect to the algorithm used.

5.4. RQ4: *Which Research Issues Have Been Addressed by Existing Approaches and Shat Lies Ahead in Terms of Future Research?*

5.4.1. Problems. Cross domain recommender systems attempt to address conventional recommender systems problems by transferring knowledge from the related domain. This section identifies, first, problems addressed by conventional recommender systems; second, CDRS studies that attempt to address conventional recommender system problems; and, finally, the problems faced by CDRS.

Conventional recommender systems problems: Conventional recommender systems research attempts to improve problems such as accuracy and diversity among others. Ricci et al. [2011] list the most researched recommender system problems as properties, which are shown as x-axis attributes in Figure 14. Some of these problems are directly proportional to the quality of recommender systems, for example, accuracy, confidence, diversity, and so on, whereas some properties are inversely proportional, for example, sparsity, coverage, coldstart, and so on. The green arrow in Figure 14 shows the relation between respective problems and recommender system quality.

CDRS studies addressing conventional problems: Cross domain recommender systems aim at addressing identified recommender system problems. Recommender system problems are arranged into four groups based on the gathered primary studies, shown in Figure 14. Problems in the first group are considered to be "mature" because they are the most researched problems, that is, accuracy and sparsity. Second, group problems are labeled as "current research focus" because they are the focus of research in recent years, that is, User-Item modeling, confidence, coverage, and diversity. The third group, "gaining popularity," consists of problems that were recently researched and have few studies in their favor, that is, trust, utility, and scalability. Finally, the fourth group, labeled "open research issues," is nearly empty or has very few studies that were found to address them, that is, privacy, novelty, serendipity, robustness, risk, and adaptivity.

Problems faced by CDRS: Cross domain recommender system research lacks appropriate datasets for multiple recommendation scenarios and tasks, as was highlighted previously in Section 5.2. This gives rise to the requirement for new datasets compatible with respective recommendation scenarios as mentioned in the selected primary studies [Wang et al. 2012; Moe and Aung 2014a, 2014b; Ren et al. 2015]. Some researchers have proposed new datasets such as MovieTweetings by Dooms et al. [2013], whereas others have attempted to use existing datasets based on assumptions.

Another problem faced by CDRS is that of context-based recommendations. Most of the time, the source domain used for assisting target recommendation comes with extra information. This extra information is meta-data related to shared information, hence referred to as context. Context can act as a domain itself; however, it has not been defined, and primary studies are still in their initial stages and thus maybe unsuitable for use as a domain. Some studies that use context for cross domain recommendation are Fernández-Tobías et al. [2011], Roy et al. [2012a], and Cao et al. [2015], respectively.

5.4.2. Future Directions. Future research directions for cross domain recommender systems can be arranged into five groups, namely domain similarity enhancement, algorithm improvement, using of "big data" as a source domain, conventional recommender systems problems, and dataset extensions. These groups are further explained as follows:

1. **Domain similarity enhancement:** Existing cross domain recommendation techniques rely on similarities between participating domains, Researchers are seeking to enhance domain similarity based on the following techniques.
   a. **Analyzing heterogeneous data:** User interaction exists in a variety of data types such as likes-dislikes, playing music, numeric ratings, and so on [Loni et al. 2014; Li et al. 2015; Pan et al. 2010]. This highlights heterogeneous data transfer as a promising future direction for cross domain recommender systems.
   b. **Analyzing user interest drift:** User interest can change over time; therefore, to generate recommendation with updated user interest, user interactions can be analyzed with respect to time. This specific scenario is related to time domain cross domain recommendation, and Hu et al. [2013a] highlighted it as their possible future work.
   c. **Including related domain:** Multiple researchers have identified experimental expansion as their future direction. In this direction, they intend to use more than one source domain, execute the same experiment over different domain, or analyze multiple domains to identify which domain would yield the best recommendation accuracy [Ren et al. 2015; Iwata and Takeuchi 2015; Shapira et al. 2013; Yan et al. 2013; Kumar et al. 2014b; Guo and Chen 2013a, 2014; de Campos et al. 2005; Wang and Ke 2014].
   d. **Context enhancement:** Researchers have found that the source domain can contain additional attributes related to the same user or item in the target domain [Roy et al. 2012b; Kaminskas 2009; Shi et al. 2013a; Shapira et al. 2013; Tang et al. 2011; Roy et al. 2012a; Hoxha et al. 2013]. These attributes can enhance the user or item context, resulting in generation of better recommendations.
2. **Improving algorithm:** Domain similarity can be enhanced by improving the algorithm used. For this reason researchers are striving to improve cross domain

recommendation generation algorithms as their future work [Moreno et al. 2012; Zhang et al. 2012; Li et al. 2016; Kumar et al. 2014a; Cao et al. 2015].

3. **Big data compatibility:** Using big data as the source domain leads to three future directions. These are as follows:
   a. **Big data as a source domain:** Cross domain recommender systems can utilize big data services to tune target recommendation as proposed by Roy et al. [2012b], Aizenberg et al. [2012], Yan et al. [2013], and Lu et al. [2013]. Big data are enriched with demographic and other statistical information that can help in personalized recommendation.
   b. **Distributed implementation:** Researchers are seeking to improve cross domain recommendation by proposing distributed algorithms that can be scaled as per the requirement. This research direction was highlighted by Su et al. [2010]
   c. **Utilizing social media:** Social media contains valuable user interactions related to different items, and the majority of these interactions are publicly available on Facebook, twitter, LinkedIn, and so on. Researchers have highlighted social media public interactions as a potential source of improving target recommendations [Zhao et al. 2013; Pan and Ming 2014; Xu et al. 2011a; Tang et al. 2013; Pan et al. 2012; Dong and Zhao 2012; Fernández-Tobías et al. 2011]. Recently, Khan et al. [2016] has illustrated the use of Facebook public social interactions for external recommendations that have not been used before.
4. **Conventional recommender system problems:** Conventional recommender system problems are those highlighted in Ricci et al. [2011] and that have little or no related CDRS studies.
   a. **Risk:** As described in Ricci et al. [2011], the risk is associated with loss of customers as a result of the wrong or inappropriate recommendation. CDRS can assist in avoiding risk by utilizing the user review sentiments available in other domains, hence reducing recommendation risk.
   b. **Adaptivity:** Adaptivity is related to user interest drift over time. CDRS can assist with adaptivity by transferring knowledge from the source domain within a recent time frame. A time-based CDRS recommendation will not only help adaptivity but also novelty and serendipity.
   c. **Robustness:** Robustness is related to avoiding recommendation based on fake ratings. CDRS can assist with robustness by transferring knowledge from more than one related domain, hence reducing the probability of fake ratings.
   d. **Novelty:** Novelty is related to the items that the user did not know about and found interesting when recommended by recommender systems. CDRS can assist by transferring source items related to items that were already rated by the user but are not exactly the same.
   e. **Privacy:** Privacy is associated with revealing the identity of people who like similar items or are connected to target users. CDRS recommendation does not face a privacy problem for recommendation across the system domain because no system declares user similarity for other systems. For CDRS recommendation within the system domain, CDRS relies on algorithms that merely map ratings from the source to the target domain rather than providing user information.
5. **Compatible datasets:** Cross domain recommender systems rely on datasets for recommendation assistance; however, existing datasets were created for conventional recommender systems. This provides CDRS researchers with the freedom to use them as they want. However, sometimes researchers use them in scenarios for which they were not made, for example Pan and Yang [2013] used the MovieLens dataset for numeric as well as binary ratings and Pan and Yang [2013] converted numeric ratings into binary by applying a threshold to numeric values for

mimicking like/dislike behavior. Although transformed data can run a developed algorithm, it cannot, however, be related to a real-world scenario. Dataset incompatibility can be reduced by the following future works.

a. **New dataset:** This refers to creating new datasets that classify their association with the appropriate domain, recommendation scenario, and recommendation tasks. Although this is possible, it may take considerable time.
b. **Existing dataset:** To use existing datasets for CDRS, efforts are required to standardize conditions and limits that should be considered when using existing datasets for scenarios having a specific domain, recommendation scenarios, and recommendation tasks.

• *Summary:*

This section highlights problems addressed by CDRS related to conventional recommender systems. Also, problems specifically faced by CDRS are then discussed. Finally, future directions of CDRS are grouped together under five categories.

6. THREATS TO VALIDITY

This SLR tries to compare and classify the cross domain recommender system's primary studies. This secondary study can have some potential limitations. However, systematic literature reviews are considered reliable in general [Zhang and Babar 2013]. Expected limitations are restricted to primary studies identification and selection, insufficient data extraction, and unconcluded results.

6.1. Threats to Primary Studies Identification and Selection

To provide a deeper insight to CDRS, we try to gather as many primary studies as possible for extraction of maximum cross domain recommendation scenarios and to avoid bias. Another challenge that we faced was related to the changing definition of domain and recommendation tasks

To avoid bias and to ensure that all experimental studies were covered, common keywords were selected from existing secondary studies for construction of a search string. The search string was applied to renowned research indexing services mentioned in Section 4.2. Moreover, while this strategy decreased bias, it significantly increased identification tasks.

Classification criteria wwere designed to short list and appropriately classify as many primary studies as possible. Although a rich bank of 94 primary studies was generated, our approach did not provide a relative quality score for each primary study as done in some systematic literature reviews. Instead, we used the tag-based approach to gather primary studies and analyze all of them equally.

6.2. Threats to Data Extraction

Although we gathered as much data as possible, still it was based on our perspective of the research question asked. There is a possibility that the reader can identify some attributes that were not considered by this study and can make a contribution that will result in better research trends. Second, a threat to data extraction is the unavailability of quality score that could help in prioritizing the result outcome and research trends. Also, to keep things precise and short, some studies that included multiple CDRS research scenarios were considered for only one prominent scenario.

6.3. Threats to Synthesis and Results

Quality score of primary studies could lead to better results and synthesis. However, our objective was to enable readers to visualize CDRS research based on common TAGs, as identified in primary studies. To achieve this objective, primary studies were placed in a classification grid, as shown in Section 5.2 with respect to assigned TAGs and domain scenarios, to provide a sense of current research trends. Further datasets relations with domain scenarios were not found to be associated to the research question but still can provide better understanding of CDRS. This leads to an overall conclusion and future work of this research in the next section.

7. CONCLUSION

The objective of this study was to identify the widely used CDRS building-block definition and to classify and visualize current CDRS research in the frame of identified building-block definitions. It also aimed to facilitate group research with respect to algorithm types and present existing problems, as well as future directions of CDRS research. To achieve the aforementioned objectives, we used a systematic literature review approach for gathering relevant primary studies while keeping our methodology unbiased and open for review.

Research questions were asked according to SLR guidelines and, as a result, this study made two contributions. The first contribution is an attempt to reduce confusion in CDRS research related to its building blocks by grouping together widely used domain definitions, user-item overlap scenarios, and recommendation tasks. Second, there is an aim to arrange shortlisted primary studies into proposed classification grids to show existing research trends.

Although this study attempts to answer the research questions, there are still some areas that were not explored. This study indicated a gain in momentum of CDRS research in Section 4.6. While this study was not able to find any toolkit related to CDRS research, in future literature reviews, available toolkits for CDRS research can provide helpful information for new researchers. Also it would be interesting to see the datasets and CDRS building blocks overlap to properly identify dataset features used by a specific scenario.

In conclusion, we believe that, in order for CDRS to grow, building-block definitions need to be standardized and a dedicated toolkit would also be of great help boosting CDRS research.

APPENDIX

In this appendix, we assign unique ID (PID) to shortlisted primary studies, as shown in Table VIII. PID was used to represent each primary study relative to the other while keeping presentations flexible enough to accommodate all tagged studies, presented in Section 5.

Assigned PID are further used to represent articles tagged with respective classification groups, as shown in Table IX.

Table VIII. Paper ID (PID) with Corresponding References

1 [Chen et al. 2013]	33 [Iwata and Takeuchi 2015]	65 [Nakatsuji et al. 2010]
2 [Shi et al. 2011]	34 [Shi et al. 2013a]	66 [Su et al. 2010]
3 [Hu et al. 2013a]	35 [Shapira et al. 2013]	67 [Tiroshi and Kuflik 2012]
4 [Wang et al. 2012]	36 [Yan et al. 2013]	68 [Zhang et al. 2013]
5 [Moreno et al. 2012]	37 [Ren et al. 2015]	69 [Abdollahi and Nasraoui 2014]
6 [Tang et al. 2012]	38 [Pan and Ming 2014]	70 [Sedhain et al. 2013]
7 [Roy et al. 2012b]	39 [Zhang et al. 2012]	71 [Guo and Chen 2013c]
8 [Aizenberg et al. 2012]	40 [Li et al. 2015]	72 [Fernández-Tobías and Cantador 2015]
9 [Kaminskas 2009]	41 [Li et al. 2016]	73 [Wongchokprasitti et al. 2015]
10 [Dong and Zhao 2012]	42 [Lu et al. 2013]	74 [Liu et al. 2015]
11 [Yang et al. 2014]	43 [Kumar et al. 2014b]	75 [Pan et al. 2016]
12 [Jiang et al. 2012]	44 [Xu et al. 2011a]	76 [Okkalioglu et al. 2016]
13 [Jiang et al. 2015]	45 [Tang et al. 2013]	77 [Fernández-Tobías et al. 2015]
14 [Huang et al. 2012]	46 [Biadsy et al. 2013]	78 [Rafailidis and Crestani 2016]
15 [Gao et al. 2013b]	47 [Pan et al. 2010]	79 [Parimi and Caragea 2015]
16 [Gao et al. 2013a]	48 [Pan et al. 2012]	80 [Wang et al. 2015]
17 [Guo and Chen 2013b]	49 [Pan and Yang 2013]	81 [Vinayak et al. 2016]
18 [Fernández-Tobías et al. 2011]	50 [Shi et al. 2013b]	82 [Ozsoy et al. 2016]
19 [Xin et al. 2014]	51 [Tang et al. 2011]	83 [Khan et al. 2016]
20 [Zhao et al. 2013]	52 [Nakamura et al. 2013]	84 [Shrivastva et al. 2016]
21 [Yi et al. 2015]	53 [Roy et al. 2012a]	85 [Cremonesi and Quadrana 2014]
22 [Moe and Aung 2014a]	54 [Guo and Chen 2013a]	86 [Sahebi and Brusilovsky 2015]
23 [Li et al. 2009]	55 [Kumar et al. 2014a]	87 [Mirbakhsh and Ling 2015]
24 [Enrich et al. 2013]	56 [Guo and Chen 2014]	88 [Fang et al. 2015]
25 [Moe and Aung 2014b]	57 [Jing et al. 2014]	89 [Elkahky et al. 2015]
26 [Tan et al. 2014]	58 [Hoxha et al. 2013]	90 [Yang et al. 2015]
27 [Li et al. 2011]	59 [Pan et al. 2015a]	91 [Saraswat et al. 2016]
28 [Hu et al. 2013b]	60 [Pan et al. 2015b]	92 [Fernández-Tobías et al. 2016]
29 [Loni et al. 2014]	61 [Wang and Ke 2014]	93 [Kotkov et al. 2016]
30 [Sahebi and Brusilovsky 2013]	62 [Kille 2013]	94 [Alanazi et al. 2016]
31 [Berkovsky et al. 2007]	63 [de Campos et al. 2005]	
32 [Wang et al. 2013]	64 [Cao et al. 2015]	

Table IX. Tagged Papers with Respect to ID

Classification group	Tagged Studies
CG1A	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 56, 57, 59, 60, 61, 64, 65, 67 ,70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94
CG1B	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 56, 57, 59, 60, 61, 64, 65, 67 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94
CG1C	1, 2, 3, 5, 7, 9, 10, 12, 13, 14, 17, 18, 19, 20, 21, 22, 23, 24, 26, 27, 28, 30, 31, 33, 35, 37, 39, 44, 45, 46, 47, 48, 49, 51, 52, 53, 57, 61, 64, 67, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94
CG2A	1, 2, 3, 4, 5, 7, 8, 10, 11, 12, 14, 15, 17, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 53, 54, 55, 56, 57, 58, 59, 60, 61, 65, 66, 67, 68, 69, 72, 76, 78, 79, 81, 82, 83, 84, 87, 90, 91
CG2B	1, 2, 3, 4, 5, 7, 8, 10, 11, 12, 14, 15, 17, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 53, 54, 55, 56, 57, 58, 59, 60, 61, 65, 66, 67, 68, 69, 72, 73, 76, 78, 79, 81, 82, 83, 84, 87, 89, 90, 91
CG3A	1, 2, 3, 4, 5, 6, 7, 8, 10, 11, 12, 14, 15, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 61, 62, 63, 64, 65, 66, 67, 68,72,83,91,93
CG3B	2, 3, 4, 5, 6, 7, 8, 9, 10, 14, 17, 18, 20, 22, 29, 30, 33, 34, 35, 36, 37, 38, 39, 43, 40, 41, 44, 45, 47, 48, 51, 53, 54, 55, 56, 58, 63, 61, 64, 66, 67, 70

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