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A review of the impacts of linked open data on cross-domain recommender systems for individual and groups

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ABSTRACT

As users' viewpoints on information searching change from information seeking to information receiving, new search paradigms are continuously emerging. Utilizing a recommender system (RS) is one of the modern ways to get information. The RS has succeeded in various traditional domains, including tourism, health, and books. However, some scenarios are more suitable to recommend to a group of users than an individual, such as listening to music at the same place and group traveling. The limited and incomplete number of user-item ratings triggers the challenges of the group and individual RSs. The data sparsity problem emerges because of this incompleteness. The quality of recommendations offered to individuals and groups suffers when there is data sparsity. Using knowledge gained from a source domain, cross-domain RSs can enhance recommendations in target domain. Cross-domain and linked open data approaches are two ways to increase recommendation systems' performance. The impacts of the two aforementioned approaches on individual and group RSs have been discussed. Furthermore, we highlighted various domains employed in cross-domain RSs for individuals and groups, examined diverse methodologies and algorithms, outlined current issues, and suggested future directions for cross-domain RSs research for groups leveraging linked open data technology.

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1. INTRODUCTION

The recommender system (RS) is a branch of information retrieval and artificial intelligence. It is a subclass of information filtering systems that aims to assist the user's search behaviour by suggesting items that best meet their interests and preferences [1]. It is considered a data filtering technique. The massive growth of data and information is inextricably tied to the 21st century's rapid technological advancements in information technology [2]. Nowadays, information is overloaded on the Internet as we generate vast amounts of diverse data, such as images and videos, daily [3]. Many people also would like to reduce their search costs for items when they want to carry out activities such as planning a family trip or buying books on Amazon. They would need valuable recommendations to help them decide the least incurring cost, such as time and money. Hence, RS can be beneficial in making appropriate decisions, especially with plenty of online choices that may lead to perplexity.

An RS aims to make suggestions to the users on a given software, platform, website, or application based on their historical behaviours and preferences. The RS required some user and item data to make predictions. The system must use the explicitly or implicitly collected user or item data to provide user recommendations. There are plenty of real-world examples of using RS on platforms. Recommendations for songs on Spotify or products on Shopee and Lazada are a few examples of the real-world application of RS. Given the various natures of the data, Yu *et al.* [4] designed different recommendation engines for e-commerce and movie domains in extensive experiments with Amazon and Netflix datasets, respectively. Hence, the design of these recommendation engines is influenced by the nature of the accessible data and the domain. For instance, Netflix users rate the movies they choose on a scale of 1 to 5 after they watch them. It can be converted into a user-item rating matrix for further processing and prediction. The rows of the matrix represent a collection of users, while the columns of the matrix represent a collection of items. This data collection will help record the interaction between the items and users.

Although RS are widely used to reduce data overload by making recommendations based on relevant historical data in various applications, they also have drawbacks. Data sparsity and cold-start issues are the fundamental problems in RSs [5]. This fact was supported by Behera and Nain [6], who state that the recommender environment always suffers from many issues, including data sparsity and scalability, that severely affect the accuracy of item recommendations. This is because the users only interact with a tiny portion of the items in the specific application domain, which causes a sparsity problem [7]. Due to most of the given user-item matrices being sparse, the RS struggles to make recommendations efficiently without complete information. Data sparsity is a problem that affects recommendation, and it is particularly severe for recently released systems that have not had the time to gather enough data [8]. This comes out with another serious RS problem: the cold-start issue. In recent years, cross-domain recommender systems (CDRS) and RS with linked open data technology were initiated to address the issue of data sparsity in RS. The CDRS has come to the forefront in recent years, and researchers have begun contributing diverse perspectives. These systems transfer knowledge from a dense data source domain to a sparse data target domain [9].

According to Masthoff [10], there are numerous situations where adapting to a group rather than an individual is necessary. For instance, choosing background music for a fitness center that is appropriate for a group of people exercising at a specific time, suggesting a show for a group to watch on television, and assisting a group in reaching a consensus on the qualities of tourist attractions they would like from a planned joint vacation. The implementation of group recommendation is based on user-specific recommendation paradigms [11]. As a result, if a problem arises in RS, the group recommender system (GRS) will undoubtedly experience the same issue. We discovered various techniques utilized to solve the data sparsity issue in RS. Cross-domain [12]–[16], linked open data (LOD) [17]–[19], neural network [6], [20], [21], and hybrid filtering [22], are a few examples. Similarly, some GRS research employed these techniques, including the cross-domain approach by Richa and Bedi [23] and Liang *et al.* [24], while the method of utilizing LOD technology in GRS by Nawi *et al.* [25]. We have not yet discovered a study that employs the integration of both the cross-domain and LOD techniques in GRS, even though several studies, such as the study by Natarajan *et al.* [26] and Jayaratne [27], used the integration of both approaches in individual RS.

In this paper, besides reviewing and examining the cross-domain approach alone in individual RS and GRS, we also focus on examining the CDRS by leveraging the LOD in both aspects of the application. Thus, our main motivations and purposes for this work are as follows: (i) to discuss the viewpoints using comparative analysis on various cross-domain algorithms and techniques for individual RS with and without leveraging LOD, (ii) to discuss the impacts of LOD technology and cross-domain approaches in individual RS and GRS, and (iii) to identify the possibility of the future direction of CDRS for groups by examining the potential and existing efficacy of these two methods in GRS.

2. RELATED STUDY

Khan *et al.* [28] reviewed CDRS but merely discussed a small portion regarding the methods of the LOD and its integration with cross-domain in individual RS. Hence, we aim to examine the CDRS more, focusing on LOD technology and its utilization with the cross-domain approach. One of our notable findings in this paper is a potential gap between the existing studies and the utilization of the cross-domain and LOD methods that may be applicable in GRS. This section will discuss the basic knowledge of the critical concepts of individual RS, GRS, CDRS, and LOD technology.

2.1. Individual recommender system

There are at least three main ways that learning algorithms can be used in the recommendation system. These three approaches—collaborative filtering (CF), content-based filtering, and hybrid filtering—can also be used in GRS. All the strategies are used on various platforms, each with advantages and disadvantages.

The recommendations in CF are based on similar users or similar items, and this method traditionally uses the concept of matrix factorization (MF), where a matrix contains users, items, and the ratings provided by the users for various items. According to Felfernig *et al.* [29], a user-item rating matrix identifies how much users enjoy a particular item. A recommender algorithm uses rating predictions to evaluate how much consumers want a product they have yet to consume or rate. In CF RS, the k-nearest neighbors machine learning technique is utilized. This algorithm anticipates and extrapolates unknown user's ratings based on user or item similarities. For instance, if two users that consume similar items are identified, the collaborative RS will suggest to the second user a new product that they have not yet consumed based on the historical behavior of the first user and vice versa. In this instance, the second user will be advised to purchase the additional product the first user consumed.

However, the machine learning model in content-based filtering can provide recommendations without requiring the interaction of users and items. It is simpler to scale the model because it simply has to know the user's interests. The content-based filtering method represents the items as keywords or descriptions. Bendouch *et al.* [30] extracted other semantic features from several item descriptions focusing on textual and visual information in content-based RS to provide better recommendations. Nevertheless, the model is incapable of recommending anything outside the users' area of interest to them. It cannot identify preferences or make recommendations for different keywords. Using a content-based filtering algorithm, the RS predicts and suggests to users the items that are close in content that they have previously enjoyed or that match their interests. According to Aggarwal [31], training data generates a user-specific classification or regression modeling issue from the item descriptions in the content-based method labeled with ratings. The training materials for each user are in accordance with the descriptions of the products they have purchased or rated. This content-based filtering is appropriate for the RS for recommendations tied to personal interests, like recommending politically relevant publications. Another illustration would be if someone is interested in data science and would like the recommended information about data science, analytics, and artificial intelligence.

In a nutshell, the algorithm in the content-based filtering strategy is based on the contents of things. However, the algorithm in the collaborative filtering approach considers the relationship between the user and the item. It can be challenging to forecast and give the user better recommendations when both methodologies for recommendation systems have some drawbacks. Introducing hybrid systems thereby addresses the fundamental disadvantages of these two approaches. These hybrid systems combine the advantages of collaborative filtering and content-based filtering to create a system that combines the best of both worlds. Utilizing hybrid systems enhances the quality of recommendations. Compared to collaborative filtering or content-based approaches, these hybrid systems are more reliable when deployed on websites or platforms. The majority of modern websites and platforms use hybrid RSs.

2.2. Group recommender system

The number of group activities available on the web has led to an increase in research on the GRS in recent years. GRS is capable of suggesting items or activities to groups of individuals who share a common goal or interest. Various methods have been developed to merge and align the individual preferences of users as a group to offer satisfactory recommendations. The group's preferences are modelled to create a group profile, which is greatly influenced by each user's preferences and the group's composition [32].

The GRS comprises two stages. The creation of the group profile comes first, followed by the recommendation of products to the group of consumers. There are two major groups in GRSs, namely stable groups and random groups, from the construction of the group profile's standpoint, regardless of the system domain [33]. According to Wang *et al.* [34], members of stable groups have the right to add their preferences to the group profile, and over time, the group's preferences may become centralized. In contrast, the random groups have no opportunity to express their opinions and have strongly contradictory group preferences [34].

As previously stated, the GRS and individual RS face some difficulties. The few and insufficient user-item ratings result in the GRS and individual RS problems. This incompleteness gives rise to the data sparsity issue. Data sparsity is stated by Liang *et al.* [32] as another problematic issue in GRS. The data sparsity issue in GRS is worse because the historical records of groups are significantly smaller than those of individuals. The quality of recommendations offered to a group suffers from a lack of data. It happens due to ineffective group creation, which frequently includes people with sparse user profiles.

There are some related studies on GRS other than LOD technology and cross-domain approach, such as the works done by Allaf and Kahani [35], Ali *et al.* [36], Villavicencio *et al.* [37] and De Pessemier *et al.* [38]. There are also some related studies on CDRS for groups with diverse algorithms to tackle the problems of GRS, such as the empirical study by Sun *et al.* [39].

2.3. Cross-domain recommender system

CDRS was developed to address the issue of data sparsity. Researchers have offered various opinions as the CDRS has gained prominence in recent years. According to Li and Tuzhilin [40], the most common

CDRS are extensions of single-domain recommendation models. The CDRS transfers knowledge from a source domain with a large amount of data to a destination domain with limited data [9]. CDRS is supposed to support enhancing the performance of recommendations for the target domain.

According to Zhu *et al.* [41], CDRS had different scenarios for the recommendations in the target domain, as shown in Figure 1, including single-target, dual-target, multi-target, and multi-domain. In the scenario of two domains, the conventional single-target solely focuses on alleviating a sparse target domain that aims to provide recommendations in that specific domain, while dual-target improves both domains and provides better recommendations in each domain. Similarly, a multi-target scenario will be used for more than three domains to increase the accuracy of each CDRS in each domain simultaneously using the auxiliary knowledge across domains. For multi-domain, the users and items overlap across multiple domains. This scenario recommends a collection of items across various domains to a set of users in different domains by leveraging auxiliary knowledge across domains. Therefore, multi-domain, dual-target, and multi-target CDRS are generally more sophisticated in model designs and their processes.

As shown in Figure 1, cross-domain data can be categorized from three perspectives, which are user-level relevance, item-level relevance, and content-level relevance [41]. Identifying the relevance of data between domains helps transfer knowledge to the target domain. It can be based on the overlapping of data. Hence, mapping between domains with common features, users, or items will be more straightforward.

However, Li and Tuzhilin [40] argued that some models in CDRS fail to adequately address the relationship between different domains since they do not simultaneously improve the effectiveness of recommendations in both domains, possibly restricting the applicability of cross-domain user interaction data. Generally, the CDRS supports enhancing the target domain's performance of recommendations. There are numerous approaches to building CDRS. There are some related studies on CDRS with diverse methods and algorithms to tackle the problems of individual RS based on various evaluation metrics on real-world domains and datasets [42]–[54]. The comparative analysis regarding CDRS will be critically analyzed in section 3.

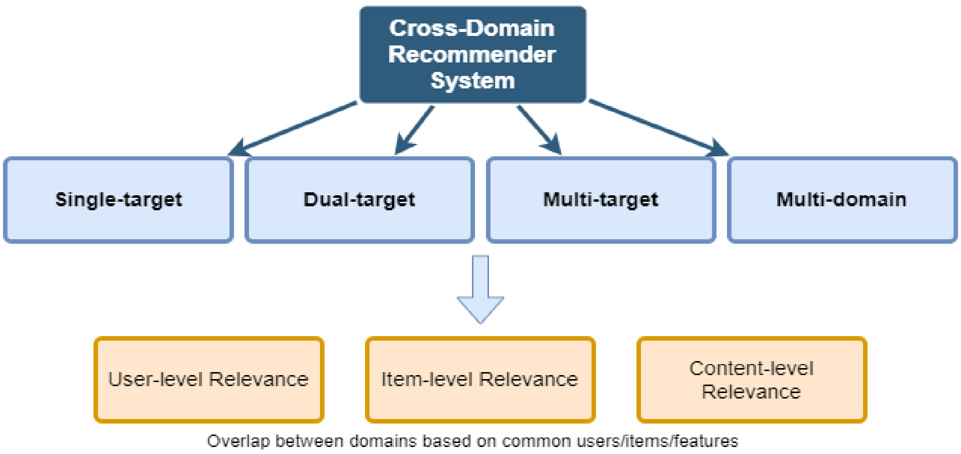

Figure 1. Type of cross-domain RS

2.4. Linked open data

LOD technology is the foundation for creating a knowledge graph that may be used in CDRS. The semantic web is a core. Hence, LOD technology is a part of the semantic web. LOD datasets create new difficulties and problems for complicated Web applications and next-generation RSs [55].

A massive, decentralized knowledge repository comprises linked resource description framework (RDF) statements [56]. Metadata is described and exchanged using RDF statements, allowing for a standardized data interchange based on relationships. Multiple sources of data are combined using RDF. In addition to political and geographic data, the LOD cloud includes structured data on various subjects, including biological sciences and media (books and movies). The most frequently used way to access these data is through DBpedia, which is Wikipedia's RDF mapping and is widely acknowledged as the epicenter of developing web of data [56]. Data mapping is crucial in CDRS, which uses LOD technology. A similar study made use of DBpedia and LOD. Pereira [57] took advantage of LOD in DBpedia to lower prediction errors in CF RS, and the work was presented in the master's thesis.

There is a lot of integration of LOD technology alone in individual RS, such as the empirical study by Natarajan *et al.* [7]. Some related studies on integrating LOD or semantic and cross-domain approaches in individual RS, such as the work by Zhang *et al.* [58]. However, we can find only one related study by Nawi *et al.* [25] on GRS with LOD technology to tackle the problems of GRS introducing the integration of LOD in GRS. However, the integration is without the application of a cross-domain approach.

3. LINKED OPEN DATA ON CROSS-DOMAIN RECOMMENDER SYSTEM

Section 3.1. will concentrate on the impacts of the CDRS model without LOD technology, while section 3.2. will focus on the impacts of the CDRS model using LOD technology. Section 3.1. examines thirteen articles on CDRS without applying LOD technology. We discover and review four papers concerning the CDRS model leveraging LOD technology in section 3.2. The two mentioned sections will be presented with a summarized table for comparative analysis. These sections attempt to collect existing research by identifying CDRS on the issue, the method applied, the outcome, and the domain. Various methods and algorithms can be applied to the cross-domain individual RS to improve its performance of user recommendations. We discovered that LOD technology is one of the methods that can enhance the performance of traditional RS. In this section, we discuss our findings on the existence of LOD in CDRS for individuals and compare the issue, the method applied, the outcome, and the domain of different studies.

3.1. Cross-domain individual recommender system without linked open data

As shown in Table 1, CDRS can implement a variety of unique techniques, such as "geometric deep learning (D-GDL) with discriminative basis" by Arthur *et al.* [59], "deep graph mutual learning (DGML)" by Wang *et al.* [60] and "cross-domain collaborative recommendation without overlapping entities based on domain adaptation (CCR-DA)" by Zhang *et al.* [61]. The other summaries can be found in Table 1.

Arthur *et al.* [59] introduction of D-GDL with discriminative basis" for CDRS demonstrates that it can provide accurate recommendations in a way to efficiently support recommending 3D objects, especially in the non-Euclidean domains (3D virtual objects). This study was conducted to properly manage user recommendations in single-domain and cross-domain scenarios in non-Euclidean domains and address cold-start and data sparsity concerns. The suggested D-GDL technique achieves the best dictionary while boosting the recommended systems' ability to discriminate. To successfully address cold-start and data sparsity concerns, this permits the implementation of geometric DL representation of the 3D non-linear features in both sparse and dense environments. According to experimental findings, incorporating geometric and kernel deep learning (DL) into the design of representative solutions for RS naturally enhances performance accuracy compared to other baseline DL techniques.

Due to prior approaches that primarily share and map user attributes among different domains to transfer knowledge, Wang *et al.* [60] aim to capture users' shared interests while overlooking domain-specific preferences. The authors use "mutual regularization" techniques to build the complete preference that learned from proposed parallel graph neural networks (GNN) recommendation models, which promote domain-specific features distinct across domains while staying close to the domain-shared feature to encode both common and specific user preferences among different domains. Extensive tests on the two real-world datasets listed in Table 1 show the effectiveness, interpretability, and significant improvements over state-of-the-art methods of the proposed framework for cross-domain recommendation utilizing DGML. According to experimental findings, the performance learned from domain-shared data is superior to the version learned from data from a single unique domain. Mutual regularization improves performance even more, illustrating the value of sharing and learning user preferences for recommendations across domains.

On the other hand, the development of "cross-domain collaborative recommendation without overlapping entities based on domain adaptation (CCR-DA)" by Zhang *et al.* [61] shows that the proposed method outperforms eight non-transfer learning and CDRS methods. This study guarantees consistency when transferring knowledge in cross-domain collaborative filtering RSs. In the proposed CCR-DA framework, the weighted collective matrix tri-factorization framework incorporates the maximum mean discrepancy (MMD) and graph regularization terms. Most existing cross-domain recommendation algorithms rely on the assumption that overlapping entities are shared to transfer information between domains, but not all instances support this statement [61]. Hence, they introduced the proposed method without overlapping entities.

There is an innovative technique for the medical domain by Chang *et al.* [62] introduction of "information transfer for medical diagnosis (ITMD)", a suggested cross-domain RS, that offers physicians personalized suggestions for illness risks. The ITMD outperforms four baselines and enhances the accuracy of disease risk recommendations in patients, to help doctors make a final medical diagnosis when there are not enough records, as demonstrated by experiments and a case study utilizing real-world data. When there are insufficient diagnostic record data to train a prediction model and provide recommendations, this is known as the "data sparsity problem". Uncertain representations in medical records and minimal feature space overlap are two problems in the development of CDRS for medical diagnostics. However, based on the results of this study, the proposed ITMD's performance in CDRS was improved, and the two common issues with CDRS for medical diagnostics development have been solved.

Table 1. A summary of cross-domain RSs without leveraging linked open data

Paper	Problem/purpose	Method	Domain/dataset
Arthur *et al.* [59]	To solve cold-start and data sparsity issues.	D-GDL with discriminative basis"	(1) Flixter (social network platform) (2) Netflix (3) CiteULike (citation management system)
Wang *et al.* [60]	To capture users' shared interests while overlooking domain-specific preferences.	DGML	(1) Dianping platform’s dataset (point of interest and feeds domains) (2) Amazon dataset (Cell Phones & Electronics domains)
Zhang *et al.* [61]	To ensure consistency when transferring knowledge in a collaborative filtering CDRS.	"Collaborative CDRS without overlapping entities based on domain adaptation (CCR-DA)"	(1) Netflix (2) Goodreads (3) AmazonBook (4) MovieLens20M (5) DoubanBook (6) Flixster
Chang *et al.* [62]	To address data sparsity, uncertain representations in medical records, and minor overlaps between feature spaces.	"Information transfer for medical diagnosis (ITMD)"	(1) Thyroid cancer dataset (2) Breast cancer dataset
Ogunseyi *et al.* [63]	To promote safe information exchange between various domains.	"MF- somewhat homomorphic encryption (SWHE)"	(1) MovieLens-Goodbooks (2) MovieLens-BookCrossing
Ouyang *et al.* [64]	To model interactions across domains to solve data sparsity in the target domain.	"Cross-graph knowledge transfer network"	(1) Books (2) Movies (3) CDs (4) TV (5) Vinyl
Wang *et al.* [65]	To solve cold-start issues in the e-commerce domain.	"deep neural network (DNN)"	(1) Ads domain (platform dataset) (2) Online shopping domain
Zhang *et al.* [9]	To solve the problem of data sparsity.	CDRS with multiple sources	(1) EachMovie (2) Movielens1M (3) LibraryThing (4) Amazon Book (5) YahooMusic
Zhang *et al.* [8]	To alleviate the data sparsity issue in the RS.	"Kernel-induced knowledge transfer, called KerKT"	(1) Movielens20M (2) Netflix (3) AmazonBook (4) Douban (Movie and Book)
Yu *et al.* [66]	Seek to solve the issue of information overload in mobile multimedia applications.	"Feature transfer and imbalanced classification (FTIC)"	(1) Book (2) Music CD (3) Video (4) DVD
Thendral and Valliyammai [67]	To reduce the RS's cold start and data sparsity issues.	"Clustering-based knowledge transfer between domains"	(1) Restaurant (2) Tourist Attraction
Veras *et al.* [68]	To address difficulties with single-domain RS and improve the accuracy of CDRS.	"Context-aware algorithms (pre-filtering and post-filtering)".	(1) Books (2) Television
Kumar *et al.* [69]	To reduce the data sparsity issue and accelerate prediction.	Distributed approaches based on sharing latent rating patterns using big data.	(1) MovieLens (2) Book-crossing

The development of a "privacy-preserving cross-domain RS" using a MF approach that utilized the "somewhat homomorphic encryption (SWHE)" by Ogunseyi *et al.* [63] reveals that it can always safeguard user privacy across different stages. In addition to being protected from any privacy leakage, experiments on actual and simulated datasets demonstrate how successful the technique is at safeguarding privacy in CDRS. In our opinion, RSs are essential to ensure the user's privacy and prevent data leakage while collecting the user's preferences and historical data. We can promote secure information transfer between different domains using this technique.

A novel model known as a "cross-graph knowledge transfer network" has been introduced by Ouyang *et al.* [64], and it demonstrates how it can use knowledge from a source domain to a target domain to deal with the problem of data sparsity. It can also explicitly describe cross-domain connections and consider the latent data underlying user-item interactions. The authors specifically modeled intra-domain and cross-domain interactions using the graph structure, which they used to transfer information from the source domains. The authors focused on product recommendations that frequently leverage Amazon 5-core product data. The outcomes demonstrate that the model outperforms five state-of-the-art techniques [64]. The effectiveness of recommendations has improved, and this knowledge graph method is the cornerstone of the CDRS with LOD.

Wang *et al.* [65] introduction of "DNN-based CDRS" demonstrates the effectiveness of the integration model in that it can make more precise product recommendations to customers of other domains through the distribution of ads, as well as the value of deep neural methods employing data from a different domain for the cold-start problem. Using Word2Vec, the authors transform textual data on users and items into latent vectors, which serve as their representations. Another proposed R-metapath2Vec method is improving user modeling to alleviate Word2Vec's inability to capture structural and semantic relationships between various users.

A CDRS with multiple sources, introduced by Zhang *et al.* [9] to improve recommendations in a sparse target domain by extracting group-level information from many source domains, can outperform six benchmarks and increase target domain recommendation accuracy. This approach can solve the problem of data sparsity by transferring knowledge from a source domain with dense data to a target domain with little data. Since there may be information in many other source domains, more than knowledge from just one source domain is needed [9].

Zhang *et al.* [8] introduction of CDRS based on "kernel-induced knowledge transfer (KerKT)" demonstrates that it can effectively transfer knowledge through overlapping entities, resolving the problem of data sparsity. Four data sets with three different sparsity ratios were used in tests, and KerKT's prediction accuracy was shown to be 1.13%-20% greater than that of six benchmarks [8]. The findings also show that knowledge transfer from the source domain to the target domain is feasible and advantageous with even minor overlaps. This technique uses overlapping entities as a link between the source and target domains. It can be used on e-commerce platforms like Amazon, where data on book ratings is abundant but lacking in other categories.

In terms of four separate assessment measures—mean absolute error (MAE), root mean square error (RMSE), precision, and recall—the development of "CDRS with feature transfer and unbalanced classification (FTIC)" by Yu *et al.* [66] demonstrates that it is superior. Item features are collected from Wikipedia, and additional user features are extracted with a funk-SVD model from use-side auxiliary domains. An imbalanced classification model (AdaBoost.NC) solves the resulting imbalanced classification problem. By inferring user preferences from user actions, such as rating matrices, the CDRS can utilize this novel approach to address the issue of information overload in mobile multimedia applications. However, because users are consistently reluctant to rate things, especially ones they dislike, rating matrices are very scarce and distorted. Previous recommendation algorithms cannot successfully handle the issues of sparsity and skewed distribution [66].

Thendral and Valliyammai [67] introduction of "clustering-based knowledge transfer" between the domains in CDRS supports the assertion that one transfer learning method, clustering, can effectively address the cold start and sparsity difficulties in RSs. User affinity discovered through clustering is effectively applied to transfer knowledge between closely related domains. As user affinity, the knowledge is transferred successfully and effectively [67].

According to Veras *et al.* [68], rare research has been done on CDRS' usage of contextual features. According to experimental evaluation using a real dataset, adopting context-aware collaborative filtering algorithms over cross-domain datasets by Veras *et al.* [68] is an excellent strategy to boost cross-domain recommendation accuracy compared to typical collaborative filtering algorithms over cross-domain datasets. In CDRS, this study employs two context-aware algorithms, pre-filtering, and post-filtering, that use diverse contextual variables [68]. This approach can improve CDRS accuracy and fix problems with single-domain RSs.

We examine the last paper in this section. According to Kumar *et al.* [69], constructing a distributed implementation of a CDRS based on latent rating pattern sharing using big data was more scalable than the sequential method. By accelerating prediction and utilizing information from other fields, this strategy can address the problem of data sparsity [69].

In a nutshell, CDRS outperformed conventional RS based on the facts above. According to Zhu *et al.* [41], there are specific challenges faced by each type of CDRS. In single-target CDRS, learning accurate mapping relations, generating accurate rating patterns, and building content-based links is challenging. On the other hand, it is challenging to design a feasible method or framework and optimize the users and items embedded in a dual-target CDRS, while multi-target CDRS is challenging to avoid negative transfer. However, we have seen the success of CDRS in improving the accuracy of recommendations. Yu *et al.* [4] designed a sophisticated framework to extract and fully expand user- and item-side features in single-target CDRS by utilizing the source domain's latent factor space and its information.

3.2. Cross-domain individual recommender system with linked open data

Compared to Table 1, which contains solely CDRS without LOD technology, the following discussion focuses on CDRS that leverages LOD technology. There are two semantic measures to explore the correlation between different LOD domains, which are similarity and relatedness. According to Table 2, CDRS with LOD is capable of several innovative strategies, including "cross-domain semantic relatedness-based matrix factorization model (CD-SemMF)" [26], "CDRS with LOD based on MF using cross-domain correlation" [70], "combining linked open data similarity and relatedness for cross online social networks (OSN) Recommendation" [71] and a "cross-domain recommender system based on common-sense knowledge bases" [72].

Table 2. A summary of cross-domain RSs with linked open data

Paper	Problem/purpose	Method	Domain/dataset
Natarajan *et al.* [26]	To address the user cold start problem in a collaborative filtering RS with LOD.	CD-SemMF	(1) Book (2) Music (3) Movies
Y. Wang *et al.* [70]	To study the empirical impact of semantic measures in CDRS in a user cold-start scenario.	MF-correlation (NeighborMF-PICSS and CentroidMF-PICSS)	(1) Movies (2) Books
Boubenia *et al.* [71]	Examine the feasibility of combining similarity and relatedness in LOD space and introduce a novel LOD-based similarity measure to deal with cold start issue.	Mixed approaches of relatedness, as LDSD and Resim, and the similarity of description, as LODS.	OSNs (1) Twitter-YouTube
Tsai *et al.* [72]	To retrieve technical phrases from various domains and recommend them.	CDRS based on common-sense knowledge bases	(1) ITRI knowledge base (2) ConceptNet (3) Wikipedia

According to the experimental study in the severe user cold start scenarios, Natarajan *et al.* [26] introduction of CD-SemMF provides accurate suggestions for new users in the target domain by utilizing item metadata based on the source and target domains involved in the recommendation process. It is a proposed method for recommendations that exploit the computed relatedness between items to link knowledge across different domains. Using this approach, the problem of user cold start in a collaborative filtering RS using LOD can be resolved easily with publicly available data.

According to research on the empirical effects of semantic measures in a CDRS in a user cold-start scenario by Wang *et al.* [70], relatedness measures can produce a wide range of recommendations through trials on a real-world dataset. In contrast, the user's existing interests can be precisely captured by similarity measures. The study also showed that even in the cold-start scenario, the cross-domain recommendation approach could provide consumers with pertinent and satisfying recommendations [70]. This study is a CDRS with LOD based on MF using cross-domain correlation.

According to Boubenia *et al.* [71], the mixed techniques of relatedness and similarity for cross-OSN significantly improve when similarity and relatedness are combined. The relatedness, as linked data semantic distance (LDSD) and resource similarity (Resim), which is a revised version of LDSD, are mixed in different combinations with the similarity, as LODS (a semantic similarity metric that makes use of more LOD features). According to the experimental outcomes, integrating LODS with the Resim offers the best accuracy and diversity trade-off. This integrated approach is a robust CDRS with LOD to solve the cold-start problem efficiently with publicly available data. The authors suggest that the mixed techniques of both relatedness and similarity measures produce a better performance of a CDRS, particularly the OSNs CDRS, compared to a single measure.

The last paper to be examined in this section is the CDRS based on common sense knowledge bases by Tsai *et al.* [72]. The system selects significant terms from provided documents based on user queries and then calculates the semantic cosine similarity between those terms. Consequently, network structures connect the queries to those extracted keywords by utilizing external common sense knowledge bases. According to the experimental research, employing the Wikipedia intermediary terms can improve search results for technical terms from the Industrial Technology Research Institute (ITRI) knowledge base. It is a basic and simple knowledge graph for transferring information from a source domain to a target domain. It can be more complex to fully exploit the benefits of the semantic web in the CDRS.

On balance, CDRS, by leveraging LOD technology, generally solved the problems of RS, particularly the cold-start issue. This is because LOD technology can extract and access publicly available data of users on a new platform that only has little or no information about the users. Moreover, LOD technology can be leveraged by extracting publicly available data, such as a user-item rating matrix, to alleviate data sparsity.

Although cross-domain and LOD can serve as an approach to alleviate data sparsity issues, generating a mapping relation between different domains using LOD technology might be challenging.

4. DISCUSSION

RS is crucial today for boosting a particular website's or online business's revenue [73]. As an illustration, consider an online bookstore that utilizes a RS to provide book recommendations to enhance the overall user experience and increase the chance of the transaction occurring [74]. According to Ma and Liu [75], rating prediction accuracy in a website that utilizes a RS influences the user experience and the company's profitability. A RS's cold-start and data sparsity issues must be addressed to guarantee rating prediction accuracy.

We understand that a CDRS is well-versed in solving the cold-start problem and alleviating data sparsity issues. However, the privacy and legal concerns of users prevent domains with enough ratings from sharing their users' ratings with other RS or domains [63]. Given the advantages of the CDRS model, secure users' privacy can avoid legal concerns and simultaneously ensure CDRS's performance. However, we require open-access data that can be utilized in CDRS. Fortunately, we discovered and examined the CDRS that uses LOD to alleviate data sparsity issues since LOD is a knowledge graph that can be accessed openly. In the meantime, we can ensure the high performance of the CDRS.

According to Veras *et al.* [68], the lack of publicly available data indicating the ratings of the same users on things categorized in several domains makes testing cross-domain RSs challenging. Hence, to tackle the lack of publicly available data, we can apply LOD in CDRS. It is easy to query, access, and integrate the data openly with the available knowledge graph on the semantic web. This study has examined the impacts of LOD in the performance of CDRS.

In some situations where providing recommendations to a group of users rather than an individual is prevalent and necessary, this also motivates us to examine existing methodologies that improve the performance and recommendation quality of GRS. While earlier studies have explored the impacts of LOD technology or cross-domain approach independently in GRS, they have not explicitly addressed the influence of integrating both LOD technology and cross-domain approaches in GRS. Hence, we discovered the gaps in previous research and the GRS's potential future direction.

4.1. Cross-domain on group recommender system

Unlike CDRS, a trend for individual RS, the idea of cross-domain has yet to be exploited to its full potential in GRS. According to Liang *et al.* [24], various cross-domain solutions are often developed for individual RS and cannot be applied directly into the context of GRS. We must consider the fundamental process of GRS while creating a new solution to solve its drawbacks, as discussed previously in section 1: Introduction. The existing studies involving CDRS for groups will be the main focus of the following discussion. In the published evidence, we found that the CDRS for groups is not frequently observed. In light of this, we have prepared a summary of three prior studies concerning the CDRS for groups, as shown in Table 3.

According to Richa and Bedi [23], the "cross domain group recommender system (CDGRS)" method, shown in Table 3, is superior to the traditional GRS. The authors introduce the cross-domain way and CDGRS to deal with the severe cold-start and data sparsity problems in the GRS target domain by utilizing the knowledge from the source domain. Delhi's restaurants, tourist attractions, shopping areas, and accommodations in Delhi are all included in four subdomains of the tourism dataset. "Zomato", "MakeMyTrip", "TripAdvisor", "Delhi Tourism", and "ShopKhojc" websites are used to collect information about restaurants, hotels, tourist destinations, and shopping locations. In this study, only the users with a good reputation and trustworthiness are influential and can contribute their opinions to the group recommendations. Traditional GRS served as a baseline method to compare with the proposed method and verify the effectiveness of CDGRS by using "F-measure", "mean absolute error ", "precision", and "recall". The proposed CDGRS outperforms traditional GRS.

Moreover, Liang *et al.* [32] support the results of CDGRS by Richa and Bedi [23]. The authors believe that using individual RS methods in GRS with pre-defined aggregation strategies is why GRS suffers from data sparsity issues. According to Liang *et al.* [32], the suggested CDGRS with a generalized aggregation strategy gives decision-makers more flexibility to choose the ideal aggregation technique based on practical decision scenarios. This is because the proposed CDGRS includes the average, maximum, and minimum strategies as aggregation strategies instead of the prior GRS's single aggregation strategy. The proposed CDGRS outperforms the other baseline methods that were chosen by the authors in the experiments using a real-world data set CAMRa2011, which is a movie rating record of group members based on two evaluation metrics - "MAE" and " RMSE".

Data sparsity in GRS is a well-known issue that Liang *et al.* [24] offered a novel approach to address this, called the "hierarchical attention neural-network-based cross-domain group recommendation method (HAN-CDGR)", as summarised in Table 3. The results of this proposed method outperform the other baseline methods chosen by the authors in the experiment. For instance, "Bayesian personalized ranking (BPR)" for individual and group recommendations [76], CDRS with item overlapping for group recommendation tasks [77] baseline methods. Effective knowledge transfer from a source domain to a target domain is accomplished through adversarial learning. The authors created a variant of HAN-CDGR, called HAN-GR, that excludes adversarial learning in the cross-domain knowledge transfer process to validate the hierarchical neural network's effectiveness. Comparing the results of HAN-CDGR and HAN-GR showed that the GRS, using the cross-domain method, dramatically enhances the performance of both user and group recommendations in the target domain. By transferring information from a source domain, HAN-CDGR can outperform the other eleven baseline methods, including HAN-GR. The authors validate the strength of cross-domain in GRS. In terms of the dataset, the Mafengwo dataset from the tourism website, the Yelp dataset from the restaurant domain, CAMRa2011, which is a movie rating record of group members, MovieLens1M, MovieLens25M, and MovieLens-Simi datasets are being used in the experiments.

Table 3. A summary of existing works regarding the cross-domain group RSs

Paper	Problem/purpose	Method	Domain/dataset
Richa and Bedi [23]	To solve cold start and data sparsity issues in GRS	CDGRS	(1) Restaurant (2) Hotel (3) Tourist Places (4) Shopping
Liang *et al.* [32]	To alleviate data sparsity in GRS	CDGRS with a generalized aggregation strategy	(1) Movie (user and group's ratings)
Liang *et al.* [24]	To solve data sparsity in GRS	HAN-CDGR	(1) Tourism (2) Restaurant (3) Movie

In RS and GRS, the data sparsity issue is severe. There are many ways to simultaneously reduce data sparsity and enhance the performance of RS and GRS. There are some findings on the impact of cross-domain and LOD on the performance of RS and GRS. We found that only CDRS for groups and CDRS with LOD technology for individual RS are implemented in current research, but not both. Since there are some empirical studies on the integration of LOD and cross-domain approach in the individual RS based on the literature review, this study suggests exploring the integration of LOD and cross-domain approach in GRS that has yet to be studied to increase the performance of group recommendations. This is because no related works on the cross-domain GRS with LOD technology are currently explored. Hence, our study identified the research gaps that need to be explored in future research.

We experimented with the combination of cross-domain and LOD approaches and verified the performance with better accuracy results in individual RS [78]. Our study demonstrated that this integration of methodologies was superior to other comparable results in that paper. However, further and in-depth analysis may be needed to confirm its performance in GRS instead of individual RS, especially regarding the alleviation of data sparsity issue. Future studies may explore to further alleviate data sparsity issue with feasible ways of integrating cross-domain and LOD approaches prior to group formation of a new group profile and verify its performance in GRS.

5. CONCLUSION AND FUTURE WORK

From the extensive literature review on cross-domain techniques, we can conclude that the CDRS is generally superior to the traditional RS for individuals and groups. Since LOD technology has recently gained popularity in individual RS to alleviate the RS problems, particularly the data sparsity, LOD technology should be fully exploited and implemented in CDRS for groups to alleviate the data sparsity issue.

This work emphasizes the apparent potential research gap on our discussed topic compared to existing studies. Besides that, we aim to identify the future directions for the research possibilities in GRS. In addition to contributing to the GRS, this work will facilitate group research on CDRS's future directions, emphasizing the use of linked open data. In a nutshell, based on the review and viewpoint analysis above, we believe that the CDRS, by leveraging LOD technology, ensures the performance of a complex RS that can give excellent and relevant recommendations to users using publicly available data through DBpedia, as an example. Hence, the combination of LOD and cross-domain approaches in GRS should be investigated in depth in future research. This is because the GRS is also pragmatic in some circumstances.

In the future study, with the goals and motivations to improve the performance of GRS to provide more accurate recommendations to a group of users in the use cases we discussed in introduction, the integration of both the cross-domain and LOD technology with vital mapping between data and domains using different algorithms can be further explored. The algorithms, such as the enhanced or integrated versions of DL, MF, graph-based machine learning techniques, and can be the area of focus on the algorithms in future empirical studies.

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