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Research paper

Scope of context awareness in cross domain recommender system – a brief review

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Abstract

Cross Domain Recommender Systems (CDRS) and Context Aware Recommender systems (CARS) are the major emerging and fast growing research topics in the active research field of Recommender Systems. For personalized recommendation, CARS utilizes different contexts in a particular domain along with user ratings, whereas CDRS utilizes data from one or more domains to make predictions to the users either one of the domains by using utilizing the context similarity among those domains. These research areas are still new and largely unexplored. Here we are surveying different researches happened in each field of Recommender System(RS) separately and thus tries to find out the scope of combining them to solve the state of the art problems in RS research and the possibilities of improving the efficiency and accuracy of RS. CDRS is emphasized mainly only the historical data of both source and target domains only, but the thing is that users choice may change according to different temporal contexts such as time, location etc. Both can complement each other for the betterment of recommendation tasks. As a result of this survey, an outline of the framework is proposed for Cross Domain-Context Aware Recommender System (CDCARS).

Keywords: *Cross Domain Recommender Systems; Context Aware Recommender Systems; Cross Domain-Context Aware Recommender System (CDCARS); Multi Domain RS; Contextual Modeling; Evaluation Metrics.*

1. Introduction

The large and ever increasing quantity, complexity of heterogeneous data in information processing area increases the scope of recommender systems because human processing capability is overwhelmed. Recommender Systems (RS) is a full-fledged area in information processing and these are utilized in number of e-commerce and entertainment websites like Flipcart Netflix, Amazon, Youtube, iTunes, etc for the personalized recommendation of their items for their users.
RS is emerged based on the basic concepts from the areas of information retrieval, consumer choice modeling, Approximation theory, cognitive science, and knowledge management, Data engineering and forecast theories [1]. In the mid of 1990, RS emerged as a separate and independent research area based on rating mechanism. The RS is used for estimating the unknown ratings for the new items, which have not even seen by the user, based on the previous ratings of other items given by the same user. After estimating the ratings, the items with most estimated ratings are recommending to the user.
Basically the recommender systems are of 3 categories, regarded to how the recommendations are made [2]:
Content-based recommendation System [2]: "The user will be recommended items similar to the ones the user preferred in the past".
Collaborative recommendation System [2]: "The user will be recommended items that people with similar tastes and preferences liked in the past"
Hybrid recommendation system [3]: "Combination of collaborative and content-based methods".
Apart from these three basic strategies, many advanced techniques are raised in the area of recommender systems by assimilating the basic categories [3]. They include:
Context-Aware Recommender System (CARS) [3]: "A recommender system that provides a target user within a specific context with a list of items that is most relevant to the target user in the specific context".
Cross-Domain Recommender System (CDRS) [3]: "A recommender system that provides a target user with a list of items in the target domain that are most relevant to the target user by exploiting knowledge from the source domain that shares resources with the target domain".
Group Recommender System (GRS) [3]: "A recommender system that provides a group of users as a whole with a shared list of items that are most relevant to the users in the group".
Multi-Criteria Recommender System (MCRS) [3]: "A recommender system that provides a target user with a list of items that are most relevant to the target user by using the relevance ratings of items in multiple criteria that are provided by the users".
This survey is focusing on the two emerging recommendation areas: Cross-Domain and context aware recommender systems. By surveying the related papers we are trying find out the scope of integrating both of the techniques for assuring most accurate and personalized recommendations.
For this survey, we analyze, compare, and classify a subset of both CDRS and CARS papers over the last decade (2001-2018). Survey is focused on the major research solutions proposed in both the fields separately.
In the case of CDRS, this survey is focused on the study and scrutinization of the techniques used (Clustering, Semantics, Graph based, Probability distributions, Factorization), evaluation metrics (MAE, RMSE, Recall, Precision, F-Measure, nDGC, MRR, etc.),

problems addressed (Accuracy, Scalability, Trust, Sparsity, Cold-Start, New user, new item, etc.) and various datasets(MovieLens, EachMovies, NetFlix, Epinions, DBPEDIA, MovieLens, Book-Crossing, Librarythings, Douban,Weibo) used in each selected papers.

In the area of CARS, this survey aims to find the application domains(Multimedia, e-Commerce, Health Care, Distributed Networks, Travel and Tourism, Social Networks, Mobiles); contexts incorporated in each domain(users mood, age , gender, Time and Space, Social data, location , occupation, etc.); data extraction Methods(Implicit, Explicit, Machine Learning, Explicit and Implicit); modeling approaches(ontology, graph, vector, markup and logic); contexts filtering approach(pre-filtering, post-filtering and contextual modeling) and evaluation metrics(MAE, RMSE, Recall, Precision, F-Measure, nDGC, MRR, etc) from the selected papers.

It is found that CDRS itself can improve the quality of the recommendations for items by incorporating information from different domains. But it utilizes only user, items and rating information from those domains. If it can effectively consider and integrates contexts of those domains through CARS techniques, the recommendations become more personalized specific to those contexts. That will be more effective with today's most complex data and knowledge engineering processes for different application domains. CDRS is emphasized mainly only the historical data of both source and target domains only, but the thing is that users choice may change according to different temporal contexts such as time, location etc. Both can complement each other for the betterment of recommendation tasks. Focusing on this idea, an outline of the framework is proposed for CDCARS at the section V of this paper.

This paper is organized into 6 sections as follows: Section II deals with Cross-Domain Recommender System, Which contains its definition, and techniques used, datasets and evaluation techniques. Section III contains definition, techniques used, datasets and evaluation techniques found in Context Aware Recommender Systems. Section IV discusses the common evaluation techniques found in both CDRS and CARS. Section V explains the scope of integrating CARS and CDRS and Section VI concludes review work with future directions.

2. Cross-domain recommender system

CDRS emerged in-order to solve the problems in single domain RS and thus improve the quality and accuracy of the personalized recommendation. A domain is a recommender ecosystem which consists of users' items, and the rating matrix. In single domain, items are recommended related to the same domain itself where users have expressed interest through ratings, where as cross-domain recommender systems utilizes the knowledge acquired in a single or multiple source domain to enhance the recommendations of the target domain. Thus they combine multiple domains for better accuracy, diversity, new item and new user problems instead of treating each and every domain separately as in single domain recommender system.

2.1. Definition

Ignacio Fernandez et al.[4] formally defines Cross-Domain RS for two domains A and B as follows.

"let U_A, U_B be the sets of users and , I_A, I_B be the sets of items with "characteristics" (user preferences and item attributes) in the domains A and B respectively". They defined two cross-domain recommendation tasks:

- "Exploit knowledge about users and items in the source domain A for improving the quality of the recommendations for items in the target domain B".
- "Making joint recommendations for items belonging to different domains, i.e., suggesting items $I_A U I_B$ in to users in $U_A U U_B$ ".

There is no clear definition and separation of domains can be found in the literature for CDRS. Cantador et al.[15] defines Domains for CDRS as 4 levels as shown in Table 1.

Table 1: Domain Definition Levels

Domain definition Levels	Domain similarity	Distinct domain consideration	Domain example	Example of Datasets
Attribute Level	Items may be of same type with same attributes.	Items have difference in the value of certain attribute are considered as distinct domains.	Comedy Movies and Thriller Movies	EachMovie and MovieLens
Type Level	Items may be of same type with some common attributes.	Items with different attribute subset are considered as distinct domains	Movies and TV series	Amazon
Item Level	Items are of different types with most different attributes	Different items considered as different domains	Movies and Books	BookCrossing and MovieLens/Each Movie
System Level	Items may be of same type with same attributes	Items belongs to different systems are considered as different domains	Theatre Movie and TV Movie	MovieLens and Movie Pilot Douban and Netflix

2.2. Techniques used in CDRS

CDRS tries to overcome the problems of conventional recommender system by utilizing knowledge from multiple domains instead of focusing single domain. The CDRSs are based on the algorithms such as

1) Clustering

Clustering based CDRS tries to cluster the ratings based on the users and items have the same rating pattern [CD1-CD11] and thus recommend the items that follow of the same cluster similarity pattern.

2) Semantics

Ontology and Knowledge engineering has made their own path in Recommender systems. By using these techniques, information from the source domain is mapped, by using this knowledge map, and

thus the target domain is classified[CD12-CD15].

3) Graph-based approaches

Graph- based approaches aims to generate the connection between the user and items in the target domain by identify the same in the source domain [CD16-CD21].

4) Probability distribution

In this recommendation score is calculated from the probability of each item with respect to all users of the source domain and then it is transferred to the target domain for recommendation [CD22-CD25]

5) Factorization

Through factorization the rating matrix is factorized to feature matrices in the source domain and then transferred to the target domain by combing it with target domain feature matrix for finding the missing ratings. Most of the CDRS is based on matrix factorization [CD26-CD43].

6) Tag-based association

In this grouping of source users and items with respect to the assigned tag is performed first. Then the associated tags in both

source and target domain is identified thus a rating pattern is generated for recommendation [CD44-CD50]
The most researched problems of conventional recommender systems, which have been effectively solved so far in CDRS and the criteria for evaluating those recommender systems, are listed in Table 1 There are mainly 7 algorithms or methods are used in CDRS for their effective implementation. The algorithms and corresponding evaluation metrics, problems addressed and datasets which are used, they are also listed in Table 2.

Table 2: Algorithms, Evaluation Metrics, Problems Addressed and Datasets Used in CDRS

Paper	Techniques used	Evaluation Metrics	Problems Addressed	Data Set
[CD1]		Hit ratio	Accuracy, scalability, trust	MovieLens and LibraryThing
[CD2]		RMSE	Accuracy,	MovieLens
[CD3]		MAE	Sparsity	Netflix, GameLoad, Jester, MusicLoad
[CD4]		MAE	Sparsity	MovieLens
[CD5]	Clustering	MAE	Sparsity, Confidence	MovieLens, EachMovies
[CD6]		MAE	Sparsity	MovieLens, EachMovies
[CD7]		RMSE	UI Modelling	NetFlix
[CD8]		MAE	Accuracy	
[CD9]		MAE	Accuracy	MovieLens
[CD10]		MAE, RMSE	Sparsity	Self Generated
[CD11]		Recall	Confidence	Epinions
[CD12]		Recall, Precision, F-Measure		DBPEDIA
[CD13]	Semantic	Recall, Precision, F-Measure,	UI Modeling	MovieLens, BookCrossing
[CD14]		Hit Ratio		Librarythings
[CD15]		Recall, Precision	Scalability	Douban
[CD16]		Recall, Precision, F-Measure, MAE, Kendal	Cold-Start	Weibo
[CD17]		Precision	Accuracy	MovieLens
[CD18]	Graph- based	Recall, Precision, MAE	Accuracy	Facebook
[CD19]		Precision	Cold-Start	GameLoad, Music Load
[CD20]		Precision	Accuracy	Self generated
[CD21]		MAE	Diversity	Listenjapan
[CD22]		ROC	Robustness	Internetradio
[CD23]	Probability Distribution	MAE		Movielens, BookCrossing, EachMovies
[CD24]		RMSE	Accuracy	Netflix,Douban,Wikipedia, IMDB
[CD25]		Recall, Precision	Privacy	Movielens IMDB
[CD26]		Recall, MAP	Confidence	Internetradio
[CD27]		Recall	Confidence	Amazon
[CD28]		Precision, ARP,AUC, nDGC, MRR	Confidence	MovieLens, Netflix
[CD29]		MAE	Sparsity	Movielens
[CD30]		MAE	Accuracy, UI Modeling, Confidence, Cold start	Amazon, KDDCUP
[CD31]		MAE, RMSE	Accuracy	Douban, DianPing
[CD32]		MAE,RMSE	Accuracy	Amazon
[CD33]		MAE	Accuracy	MovieLens, LibraryThings
[CD34]	Factorisation	MAE, RMSE	Sparsity	MovieLens, Netflix
[CD35]		MAE, RMSE	Sparsity	MovieLens
[CD36]		MAE, RMSE	Accuracy	MovieLens, Netflix
[CD37]		MAE, RMSE	Sparsity	MovieLens, epinions
[CD38]		MAE	Accuracy	MovieLens, Netflix
[CD39]		RMSE	UI Modeling	Netflix, Douban
[CD40]		RMSE	UI Modeling, Confidence	Douban, Netflix
[CD41]		RMSE	Sparsity	Movielens
[CD42]		RMSE	Sparsity	Movielens, Netflix, BookCrossing, EachMovie
[CD43]		RMSE	Accuracy, Sparsity	Flixter, Movielense
[CD44]		Recall, Precision, F-Measure		Facebook
[CD45]		Recall, Precision, F-Measure		Douban, Weibo
[CD46]		Precision, MAP, nDGC	Sparsity	Douban, Weibo
[CD47]	Tag Based Association	Precision	UI Modeling	Douban
[CD48]		MAE, RMSE	UI Modeling, Confidence	Douban
[CD49]		MAE	Utility	LibraryThings
[CD50]		Correlation	Cold-Start	Facebook

In each paper authors have tried to solve few problems found in traditional RS such as cold start, sparcity, accuracy, privacy etc in an effective way, which also listed in the Table 1 along with other details. CDRS models can be categorized into adaptive models and collective models. Adaptive models utilize knowledge from one or more source domain to make recommendations to a target domain directly where as collective models can exploit information from multiple domains jointly and thus attain the potential to make recommendations for any one of those domains [5]. Thus CDRS can combine two or more domains effectively.

3. Context-aware recommender system

The traditional conceptual recommender system only deals with two entities that are users and items. CARS extends traditional RS paradigm which considers the two dimensions (user and items), by adding more dimensions(contexts) in which recommendations are made. This contextual information can be attained, explicitly by manual input from the user or implicitly from the environment or by analyzing user interactions.

3.1. Definition of context

Dey et al. [4] defines context as "any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves." Schilit et al. [6] divided context in 3 categories such as user context, computing context, and physical context. User contexts include the details of the user profiles such as social situation, location, people nearby, etc. Computing context includes communication costs and bandwidth, network connectivity, and nearby resources such as displays, printers, and workstations. Physical contexts include traffic, noise, and lighting and temperature conditions of the environment of the user. Chen and Kotz [7] added time as next category of contexts in RS. Schmidt et al. [8] added another context category as tasks. They also define the dimensions for tasks such as the social environment of the user, location of the tasks, time of the tasks, infrastructure and physical conditions of the tasks. Zimmermann et al. [9] categorizes contexts fundamentally as individuality, location, activity, time, and relations. From all the definitions of contexts and its categories shows that the dimensions of context is based on who (user), what (object), how (activities), where (location), and when (time) the RS used.

3.2. Techniques for modelling CARS

CARS have been applied in every domain such as multimedia, ecommerce healthcare, tourism etc., where traditional recommender systems are worked for better personalized recommendations. The success of CARS depends on the extraction of appropriate contexts, in which the recommendation has to be based. Contextual information can be extracted implicitly [CA1-CA20], explicitly [CA21-CA23] or by using machine learning [CA24] approaches. In explicit extraction process users are required to provide the information which are relating to the contexts, where as in implicit mode of extraction, contexts are identified from the user profiles in the environment itself. Machine learning techniques utilize data mining or statistical learning techniques for automatically identifying the contexts by monitoring user activities.

Modeling approaches are concerning with the design of a structure corresponds to all users and their preferences to improve the prediction of recommendations. The modeling approaches found in papers are vector space, graph, ontology, mark up and logic. Among this ontology and vector is mostly used. Those are used along with both implicit and explicit data extraction methods. In a vector space user profile is represented using multidimensional vectors. Items scores according to the contexts are deducted by using probabilistic algorithms [CA5-CA17, CA23, CA24, CA37-CA44]. Ontology uses the concept of class hierarchy for representing user profiles. Each hierarchy denotes the users interested knowledge area [CA1-CA4, CA21, CA22, CA28-CA36]. In Graph approach, a graph is generated according to the context and a random walk is performed for finding the most suitable recommendation choices [CA18-CA20, CA25-CA27]. Mark up is another approach for contextual modeling. In this mark up tags along with attributes are used to infer the probability of recommending items [CA45]. In logic approach contexts are represented as a set of conditions in which concluding expressions for recommendation are derived from [CA46]. Table 3 contains all the details scrutinized regarding CARS.

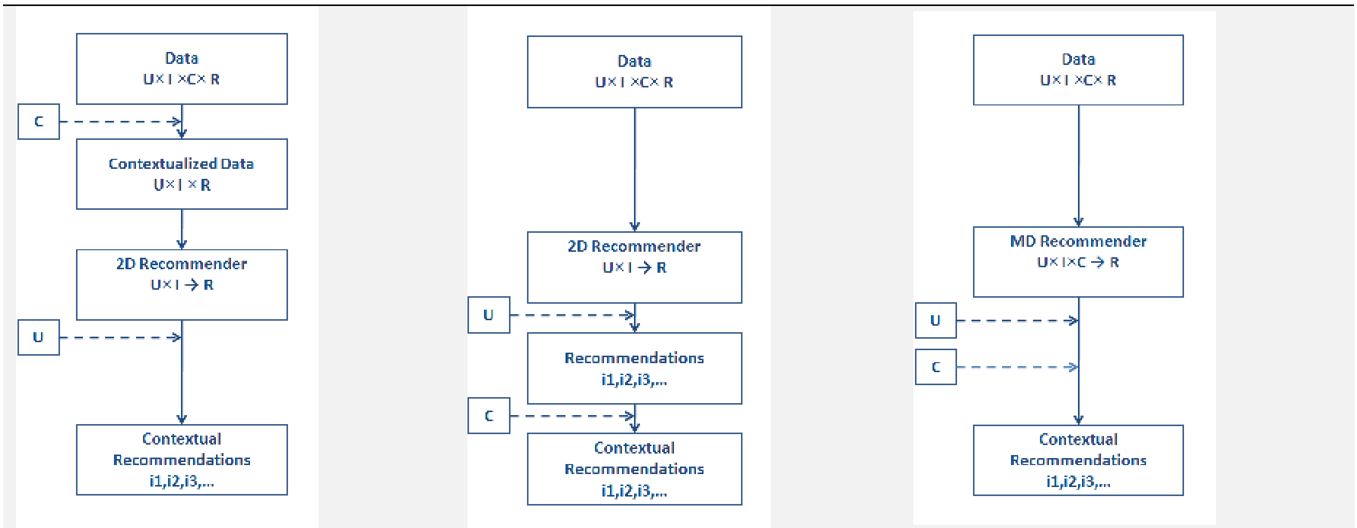
Table 3: Modeling and Filtering Approaches Along with Incorporated Contexts and Evaluation Techniques in CARS Application Domain

	Application Domain	Contexts incorporated	Data Extraction Method	Modeling Approach	Filtering Approach	Evaluation Technique
[CA1]	e-Commerce	Current budget , State of mind			Post-filtering	CTR, PR
[CA2]	Multimedia	Previous logs		ontology	Pre-filtering	
[CA3]	e-Commerce	Volume, Valance			Post-filtering	Recall, MRR
[CA4]	Health Care	Location			Pre-filtering	NA
[CA5]	Multimedia	Reviews, abstracts, or synopses			Contextual Modeling	RMSE
[CA6]	Multimedia	Health and emotions			Pre-filtering	Precision
[CA7]	Places	textual, geographical, Social and popularity information			Contextual Modeling	Precision, Recall,RMSE
[CA8]	Places	Personal Descriptions			Post-filtering	Precision, Recall, MAE,RMSE
[CA9]	Multimedia	users mood			Pre-filtering	RMSE
[CA10]	Multimedia	Users mood, age , gender			Post-filtering	MAE, RMSE
[CA11]	e-Commerce	Time and Space	Implicit	Vector	Contextual Modeling	Recall, MRR
[CA12]	Mobiles	Social data, location time			Contextual Modeling	Recall
[CA13	Mobiles	Social data, location time			Pre-filtering	Recall
[CA14]	General	Gender, Age, Occupation, Location			Pre-filtering	MAE, RMSE
[CA15]	Social Networks	tags, time,Companions			Pre-filtering	MAE, RMSE
[CA16]	Social Networks	tags, time,Companions			Pre-filtering	Precision, Recall, MAP
[CA17]	Distributed Networks	Location,time,user profile			Post-filtering	Precision, Recall, F-measure, RMSE
[CA18]	Travel and Tourism	Social relations, Personal Preferences, current location		Graph	Pre-filtering	Precision, Recall, F-measure
[CA19]	Social Net-	Friend of friends, location,			Pre-filtering	Precision, Recall

	works	profession				
[CA20]	Mobiles	Contact Profiles and other mobile data			Pre-filtering	MAE, RMSE
[CA21]	Multimedia	tag, duration, location, mood		Ontology	Pre-filtering	Precision, Recall, F-measure
[CA22]	Social Net-works	tags, time,Companions	Explicit		Pre-filtering	Precision, Recall, F-measure
[CA23]	General	mood, location,landscape, age, gender		Vector	Pre-filtering	Precision, Ndcg
[CA24]	Mobiles	logs	Machine Learning	Vector	Pre-filtering	MAE, RMSE
[CA25]	Multimedia	when,who, what, where			Pre-filtering	Precision, Recall
[CA26]	e-Documents	Time and topic		Graph	Pre-filtering	Precision, Recall
[CA27]	e-Commerce	Time and choice			Pre-filtering	Precision, MAE, RMSE, nDCG
[CA28]	e-Documents	Mobile model, screen size, speed etc			pre-filtering	Precision, Recall
[CA29]	Places	external and physical con-text			Contextual Mod-eling	Precision
[CA30]	Travel and Tourism	Social relations, Personal Preferences, current loca-tion			Post-filtering	Precision, Recall, F-measure
[CA31]	e-Documents	Subject, Document Type, Degree, Repository		Ontology	Pre-filtering	Nil
[CA32]	e-Documents	Subject, Location			Pre-filtering	nDCG
[CA33]	Social Net-works	Attitude towards tags			Pre-filtering	CTR
[CA34]	General	role			Pre-filtering	
[CA35]	Social Net-works	Mood, location	Explicit and Implicit		Pre-filtering	Precision, Re-call,RMSE
[CA36]	Multimedia	companion, day of the week			Contextual Mod-eling	Precision, Recall, RMSE,MAE
[CA37]	Multimedia	Mood, day of the week			Pre-filtering	Precision, Recall, F-measure, MAP
[CA38]	Multimedia	detecting contexts accord-ing to Applications			Pre-filtering	Precision
[CA39]	Multimedia	time			Pre-filtering	Precision, Recall
[CA40]	Places	Landscape, location		Vector	Pre-filtering	F-measure,MAE
[CA41]	Places	Location,time			Pre-filtering	Precision, Recall
[CA42]	Multimedia	tag informtion, rating dura-tion			Contextual Mod-eling	Precision,MAE,RMSE
[CA43]	e-Documents	time			Pre-filtering	Nil
[CA44]	Social Net-works	social relations, Personal Preferences			Contextual Mod-eling	MAE
[CA45]	Multimedia	Pattern of music		Markup	Post-filtering	Precision, Recall
[CA46]	Travel and Tourism	Detecting contexts accord-ing to Applications		Logic	Pre-filtering	Precision

Table 4: Techniques for Information Filtering

Contextual Pre-filtering	Contextual Post-filtering	Contextual-modeling
Here recommendation system input is contextu-alized and performs traditional 2D recommended system process on filtered data set. [CA2, CA4, CA6, CA9, CA13-CA16, CA18-CA28, CA31-CA35, CA37-CA41, CA43, CA46]	Here recommender system output is contextual-ized. First performs traditional 2D recommenda-tion and then contextualization is performed on the selected data set. [CA1, CA3, CA8, CA10, CA17, CA30 CA45]	Here contextualization is performed on the rec-ommendation function itself. As part of the esti-mation of rating, contextual information is direct-ly applied in the recommender system models. [CA5, CA7, CA11, CA12, CA29, CA36, CA42, CA44].



Another major focus of CARS is how and when to incorporate the contexts in to the recommendation process. There are mainly three filtering approaches found in literatures each have their own role in CARS. In pre-filtering the irrelevant scores to the context are filtered out before computing the final recommendations [CA2, CA4, CA6, CA9, CA13-CA16, CA18-CA28, CA31-CA35, CA37-CA41, CA43, CA46], where as in post-filtering the irrelevant scores to the current contexts are filtered out after the final recommendations[CA1, CA3, CA8, CA10, CA17, CA30 CA45]. The third approach is contextual modeling, in which the contexts are used along with the traditional recommendation-generation algorithms [CA5, CA7, CA11, CA12, CA29, CA36, CA42, CA44].
In CARS contextual information are also added along with the input data for traditional recommender systems (user, item, and rating). The input to CARS consists of user, item, context, and rating. we start with the data having the form U ×I ×C×R, where C is additional contextual dimension and end up with a list of contextual recommendations i1, i2, i3 . . .There are three methods of incorporating contexts in recommender systems depends on the time of incorporating contextual information with traditional recommender systems. They are shown in Table 4.

4. Evaluation of metrics found in CDRS and CARS

The evaluation techniques for CDRS and CARS are same as that of Traditional Recommender Systems. The most relevant measure of recommender system evaluation is accuracy. The metric for evaluating the accuracy of recommender system can be classified into classification metrics, prediction metric and ranking metrics. The metrics commonly used under categories are shown in Table 5.

Table 5: Evaluation Metrics

Category	Metric	Formulae	Explanation
Classification Metrics	Recall(R)	$P = \frac{TP}{TP+FN}$ TP- True Positive FP- False Negative	It is the fraction of all relevant items that were recommended.
	Precision(P)	$P = \frac{TP}{TP+FP}$ TP- True Positive FP- False Positive	It is the fraction of all recommended items that are relevant.
	F-Measure(F1)	$F1 = \frac{2.P.R}{P+R}$	It is the Harmonic mean measure of precision and recall
Prediction Metrics	Mean Absolute Error	MAE= $\frac{1}{\lvert Q \rvert}\sum_{(u,i)\in Q}\lvert r_{u,i} - \hat{r}_{u,i}\rvert$ Q - Testing Data Set $r_{u,i}$ - True Ratings $\hat{r}_{u,i}$ - Predicted Rating	MAE is the simplest, but it does not take into account the direction of the error (positive error or negative error)
	Mean Squared Error	MSE = $\frac{1}{\lvert Q \rvert}\sum_{(u,i)\in Q}(r_{u,i} - \hat{r}_{u,i})^2$	MSE has a larger penalty on large errors and the squared error does not have an intuitive meaning.
	Root Mean Squared Error	RMSE= $\sqrt{MSE}$	RMSE is more widely used in computing the prediction accuracy of the recommender system
Ranking Metrics	Mean Average Precision(MAP)	$MAP = \frac{\sum_{q=1}^{Q} avep(q)}{Q}$ Q- No. of Recommendations	MAP is the average of multiple recommendation precision
	Receiver Operating Characteristic(ROC) Curve		The ROC curve is a two-dimensional coordinate graph, the X-axis is the false positive rate (FPR) and the Y-axis is the true positive rate (TPR). The ROC curve shows the correspondence between FPR and TPR
	Area Under Curve		The performance of different recommender

		systems can also be compared by the Area Under the ROC curve.
Mean Reciprocal Rank	$MRR = \frac{\sum_{q=1}^{Q} \frac{1}{rank_i}}{Q}$ $rank_i$- are the user's favorite items in the list of recommendation rankings.	It can measure whether the recommender system places the user's favorite items in the front
Normalized Discounted Cumulative Gain(nDCG)	$nDCG = \frac{DCG(r)}{DCG(r_{perfect})}$ $DCG(r)$=disc(r(i).u(i)) disc(r(i)) - a discount function based on the ranking u(i) - the utility of the items in the recommendation list DCG($r_{perfect}$ represents a perfect ranking of discounted cumulative gain	It can measure the quality of ranking in terms of its relevance.

5. Scope of context-awareness in cross domain recommender system

Recommender systems suffer from cold start and data sparsity problems invasively. Researchers have proposed various solutions to this problem, in which CDRS is an effective approach. CDRS utilizes user data from multiple domains to generate prediction for the target user. The focus of existing researches in the area of Recommender System is in Cross Domain and Context aware recommender systems (CDCARS). From the study we found that both areas are complementing each other for the betterment of recommendation tasks. One challenge exists in CDRS is that the emphasize mainly only the historical data of both source and target domains only, but the thing is that users choice may change according to different temporal contexts such as time, location etc. Now the researchers are focusing on the context aware cross domain recommender system for the most personalized recommendations. Contexts can be used in CDRS in two ways. Firstly different contexts can be treated as different domains and secondly it can act as a bridge between different domains. The synergy between cross domain and contextual recommendations still is not fully explored. In CDRS context can be treated as a bridge between various domains.

Joshy et al. [10] emphasize the role of the time context in CDRS. They proposed a cross domain model for both movie and novel domain, which focus on the current interest of the user. Yuan et al [12] propose a structural context-aware feature selection framework for cross media recommendation. In [13] recommend a frame work, which is evaluated for recommending music suited to place of interest. They use semantic concepts to link several domains and contextual information (location and time). In [D] they propose a CDRS for cosmetics related to skin care issues. They use ontology to implement context awareness.
The above three CDRS is only applicable to the specific domain only, which means that making use of their algorithm to other domain would be difficult and ineffective. Later Veras et al. [11] investigate the adoption of both pre-filtering and post filtering context aware techniques in CDRS in order to improve its predictive performance and accuracy. They found pre-filtering is more accurate for adopting contexts in CDRS and their models can be applicable to all domains.
Schedl et al [14] surveyed Music Recommender System for finding the scope of future directions. They suggests the incorporation of contexts such as psychology, culture and situation in RSs, which will leads to CDRS for getting all these contexts. Only 4 papers has been found related to context aware cross domain Recommender Systems, which means the area is still unexplored and researchers has to focus on it to improve the accuracy of CDRS.

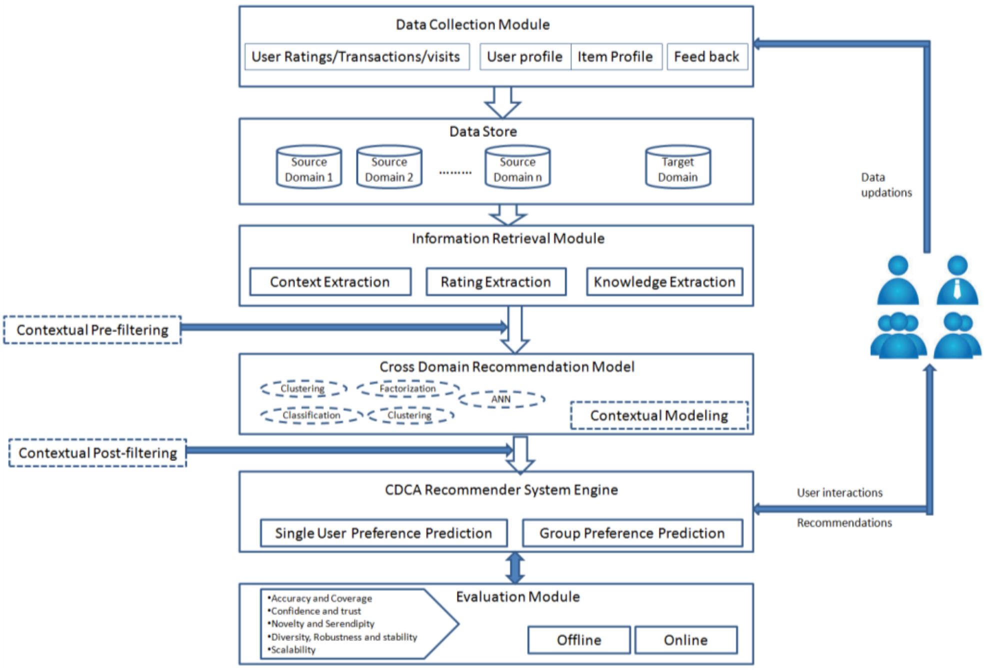


Fig. 1: Module Configuration for CDCARS.

Fig.1. shows a proposed module configuration for Cross Domain Context Aware (CDCA) Recommender System framework. It consists of 6 modules; they are Data Collection Module, Data Store, Information retrieval module, Cross Domain Recommendation Model, CDCA Recommender Engine and evaluation module. The Data Collection Module collects the data from the users which include user, item, and ratings/transaction details. Updating of dynamic feedback to data stores is also has to do by that module. Data store contains the information collected from different Domains, both source and target domains. Information retrieval module extracts new knowledge about contexts for bridging different domains, ratings and other necessary information from the available data in the data store. Next is the main part of the framework in which recommender system modeling has to take place. Contexts incorporation is revolving around this module. As shown in the Fig. 1. contexts can be filtered prior to this module, along with CDRS modeling and after this module. The selection of context filtering is based on the domain of application and the nature of the contexts. In next phase recommender system is implemented for single user recommendation and for group recommendation and then it is evaluated by using various evaluation techniques. By interacting with the user feedback data is collected and updated in the data store. A framework that integrates modules like this can easily develop a CDCA Recommender System for both single and group of users.

6. Conclusion and Future work

This paper presents a report on the survey performed in the area of CDRS and CARS separately as well as it investigates the scope of context awareness in the CDRS. CDRS is found to be an effective solution for Cold start, New user and New item problem in a RS. Increasing accuracy and diversity is also the aim of CDRS. It is found that in the near future researchers have to focus on the effective use of different contexts in CDRS for the better accuracy and more personalized recommendations. Contexts can be used in CDRS in two ways. Firstly different contexts can be treated as different domains and secondly it can act as a bridge between different domains. Both of these are not yet explored by the researchers.

There is no framework exists for cross domain context aware recommender systems by utilizing various machine learning techniques which will help to reduce the model elicitation without explicitly collecting the contexts. The most evaluation metric used along with CDRS as well as CARS is only used for measuring the accuracy only. In the case of CDRS it has to give more emphasize on diversity and novelty for getting higher utility and satisfaction. As a result of our study it is clear that Context Aware Cross Domain Recommender System is the near future of the Recommender system research.

References

[1] Gediminas Adomavicius and Alexander Tuzhilin. Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. IEEE Trans. on Knowl. and Data Eng., 17(6):734–749, 2005 https://doi.org/10.1109/TKDE.2005.99.

[2] M. Balabanovic and Y. Shoham, "Fab: Content-Based, Collaborative Recommendation," Comm. ACM, vol. 40, no. 3, pp. 66-72, 1997 https://doi.org/10.1145/245108.245124.

[3] Park, Young. "Advanced Recommender Systems." Encyclopedia of Information Science and Technology, Fourth Edition. IGI Global, 2018. 1735-1745. Web. 21 May. 2018. https://doi.org/10.4018/978-1-5225-2255-3.ch151.

[4] A. Dey, G. Abowd, and D. Salber, "A Conceptual Framework and a Toolkit for Supporting the Rapid Prototyping of Context-Aware Applications," HumAN-Computer Interaction, vol. 16, pp. 97-166, Dec. 2001 https://doi.org/10.1207/S15327051HCI16234_02.

[5] I. Fernández-Tobías, I. Cantador, M. Kaminskas and F. Ricci, "Crossdomain recommendr sysems: A servey of the State of the Art", Escuela Politécnica Superior, Universidad Autónoma de Madrid, 28049 Madrid, Spain and Faculty of Computer Science,Free University of BozenBolzano, 39100 Bolzano, Italy, 2012

[6] B. Schilit, N. Adams, and R. Want ―Context-Aware Computing Applications‖ In WMCSA '94: Proceedings of the 1994 First Workshop on Mobile Computing Systems and Applications, IEEE Computer Society, pp. 85–90, Washington, DC, USA, 1994.

[7] G. Chen and D. Kotz ―A Survey of Context-Aware Mobile Computing Research‖ Technical Report, Hanover, NH, USA, 2000.

[8] A. Schmidt, M. Beigl, and H.-W. Gellersen ―There is More to Context than Location‖, Computers & Graphics, 23(6):893 – 901, 1999 https://doi.org/10.1016/S0097-8493(99)00120-X.

[9] A. Zimmermann, A. Lorenz, and R. Oppermann ―An Operational Definition of Context‖ In Proceedings of the 6th International and Interdisciplinary Conference on Modeling and Using Context, CONTEXT'07, Springer-Verlag, Berlin, Heidelberg, pp. 558–571, 2007. https://doi.org/10.1007/978-3-540-74255-5_42.

[10] Swapna Joshi, Kashibai Navale and Manisha Patil -- Enhanced Cross Domain Recommender System using Contextual parameters in Temporal Domain, International Journal of Computer Applications Technology and Research Volume 6–Issue 8, 355-361, 2017, ISSN: -2319–8656

[11] Silva, Douglas Veras da, Ricardo B. C. Prudêncio, Carlos Ferraz, Alysson Bispo and Thiago Monteiro Prota. "Context-Aware Techniques for Cross-Domain Recommender Systems." 2015 Brazilian Conference on Intelligent Systems (BRACIS) (2015): 282-287.

[12] Yuan Z., Yu K., Zhang J., Pan H. (2012) Structural Context-Aware Cross Media Recommendation. In: Lin W. et al. (eds) Advances in Multimedia Information Processing – PCM 2012. PCM 2012. Lecture Notes in Computer Science, vol 7674. Springer, Berlin, Heidelberg https://doi.org/10.1007/978-3-642-34778-8_74.

[13] M. Kaminskas, I. Fernandez-Tob ´ ´ıas, I. Cantador, and F. Ricci, "Ontology-based identification of music for places," in 13th International Conference on Information and Communication Technologies in Tourism. Springer, 2013

[14] Schedl, Markus, Zamani, Hamed, Chen, Ching-Wei, Deldjoo, Yashar, and Elahi, Mehdi, Current Challenges and Visions in Music Recommender Systems Research, Information Retrieval, 2018, arXiv:1710.03208 [cs.IR]

[15] Ivan Cantador & Cremonesi, Paolo. (2014). Tutorial on cross-domain recommender systems. RecSys 2014 - Proceedings of the 8th ACM Conference on Recommender Systems. 401-402. 10.1145/2645710.2645777.

Selected PAPERS- CDRS

[CD1]. Wei Chen, Wynne Hsu, and Mong Li Lee. 2013. Making recommendations from multiple domains. In Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.ACM, 892–900

[CD2]. Meng Jiang, Peng Cui, Fei Wang, Qiang Yang, Wenwu Zhu, and Shiqiang Yang. 2012. Social recommendation across multiple relational domains. In Proceedings of the 21st ACM International Conference on Information and Knowledge Management. ACM, 1422–1431.

[CD3]. Orly Moreno, Bracha Shapira, Lior Rokach, and Guy Shani. 2012. Talmud: transfer learning for multiple domains. In Proceedings of the 21st ACM International Conference on Information and Knowledge Management. ACM, 425–434

[CD4]. Sheng Gao, Hao Luo, Da Chen, Shantao Li, Patrick Gallinari, Zhanyu Ma, and Jun Guo. 2013b. A crossdomain recommendation model for cyber-physical systems. IEEE Trans. Emerg. Top. Comput. 1, 2 (2013), 384–393.

[CD5]. Chang Yi, Ming-Sheng Shang, and Qian-Ming Zhang. 2015. Auxiliary domain selection in cross-domain collaborative filtering. Appl. Math 9, 3 (2015), 1375–1381.

[CD6]. Bin Li, Qiang Yang, and Xiangyang Xue. 2009. Can movies and books collaborate? cross-domain collaborative filtering for sparsity reduction. In IJCAI, Vol. 9. 2052–2057.

[CD7]. Bin Li, Xingquan Zhu, Ruijiang Li, Chengqi Zhang, Xiangyang Xue, and Xindong Wu. 2011. Cross-domain collaborative filtering over time. In Proceedings of the 22nd International Joint Conference on Artificial Intelligence-Volume Volume Three. AAAI Press, 2293–2298.

[CD8]. Shlomo Berkovsky, Tsvi Kuflik, and Francesco Ricci. 2007. Cross-domain mediation in collaborative filtering. In User Modeling 2007. Springer, 355–359.
[CD9]. Xiang Li, Ronglin Hu, Quanyin Zhu, and Haiyan Zhang. 2016. Recommendation algorithm based on Bispectral clustering and rating-matrix transfer learning. Journal of Computational and Theoretical Nanoscience 13, 3 (2016), 1971–1978.
[CD10]. Jiuhong Tang, Zhihong Zhao, Jia Bei, and Weiqing Wang. 2013. The application of transfer learning on e-commerce recommender systems. In Proceedings of the 2013 10th Web Information System and Application Conference (WISA'13). IEEE, 479–482.
[CD11]. Dimitrios Rafailidis and Fabio Crestani. 2016. Top-N recommendation via joint cross-domain user clustering and similarity learning. In Proceedings of the Joint European Conference on Machine Learning and Knowledge Discovery in Databases. Springer, 426–441.
[CD12]. Hla Hla Moe and Win Thanda Aung. 2014a. Building ontologies for cross-domain recommendation on facial skin problem and related cosmetics. In Proceedings of the International Journal of Information Technology and Computer Science (IJITCS'14) 6, 6 (2014), 33.
[CD13]. Ajit Kumar, Narendra Kumar, Mutawarra Hussain, Santanu Chaudhury, and Sankalp Agarwal. 2014b. Semantic clustering-based cross-domain recommendation. In Proceedings of the 2014 IEEE Symposium on Computational Intelligence and Data Mining (CIDM'14). IEEE, 137–141
[CD14]. Krishna Mohan P. D. Shrivastva, Shailendra Singh, et al. 2016. Cross domain recommendation using semantic similarity and tensor decomposition. Procedia Computer Science 85 (2016), 317–324.
[CD15]. Ali Mamdouh Elkahky, Yang Song, and Xiaodong He. 2015. A multi-view deep learning approach for cross domain user modeling in recommendation systems. In Proceedings of the 24th International Conference on World Wide Web. ACM, 278–288.
[CD16]. Meng Jiang, Peng Cui, Fei Wang, Qiang Yang, Wenwu Zhu, and Shiqiang Yang. 2012. Social recommendation across multiple relational domains. In Proceedings of the 21st ACM International Conference on Information and Knowledge Management. ACM, 1422–1431.
[CD17]. Tomoharu Iwata and Koh Takeuchi. 2015. Cross-domain recommendation without shared users or items by sharing latent vector distributions. In Proceedings of the 18th International Conference on Artificial Intelligence and Statistics. 379–387.
[CD18]. Bracha Shapira, Lior Rokach, and Shirley Freilikhman. 2013. Facebook single and cross domain data for recommendation systems. User Model. User-Adapt. Interact. 23, 2–3 (2013), 211–247.
[CD19]. Naseem Biadsy, Lior Rokach, and Armin Shmilovici. 2013. Transfer learning for content-based recommender systems using tree matching. In Availability, Reliability, and Security in Information Systems and HCI. Springer, 387–399.
[CD20]. Ying Guo and Xi Chen. 2014. Cross-domain scientific collaborations prediction with citation information. In Proceedings of the 2014 IEEE 38th International Computer Software and Applications Conference Workshops (COMPSACW'14). IEEE, 229–233.
[CD21]. Makoto Nakatsuji, Yasuhiro Fujiwara, Akimichi Tanaka, Tadasu Uchiyama, and Toru Ishida. 2010. Recommendations over domain specific user graphs. In ECAI. 607–612.
[CD22]. Natalie Aizenberg, Yehuda Koren, and Oren Somekh. 2012. Build your own music recommender by modeling internet radio streams. In Proceedings of the 21st International Conference on World Wide Web. ACM, 1–10
[CD23]. Siting Ren, Sheng Gao, Jianxin Liao, and Jun Guo. 2015. Improving cross-domain recommendation through probabilistic cluster-level latent factor model. In Proceedings of the 29th AAAI Conference on Artificial Intelligence
[CD24]. Xi Zhang, Jian Cheng, Ting Yuan, Biao Niu, andHanqing Lu. 2013. TopRec:Domain-specific recommendation through community topic mining in social network. In Proceedings of the 22nd International Conference on World Wide Web. International World Wide Web Conferences Steering Committee, 1501–1510.
[CD25]. Burcu Demirelli Okkalioglu, Mehmet Koc, and Huseyin Polat. 2016. Reconstructing rated items from perturbed data. Neurocomputing 207 (2016), 374–386.
[CD26]. Rohit Parimi and Doina Caragea. 2015. Cross-domain matrix factorization for multiple implicit-feedback domains. In Proceedings of the International Workshop on Machine Learning, Optimization and Big Data. Springer, 80–92
[CD27]. Nima Mirbakhsh and Charles X. Ling. 2015. Improving top-N recommendation for cold-start users via cross-domain information. ACM Transactions on Knowledge Discovery from Data (TKDD) 9, 4 (2015), 33.
[CD28]. Weike Pan, Hao Zhong, Congfu Xu, and Zhong Ming. 2015b. Adaptive bayesian personalized ranking for heterogeneous implicit feedbacks. Knowl.-Based Syst. 73 (2015), 173–180.
[CD29]. Yue Shi, Martha Larson, and Alan Hanjalic. 2011. Tags as bridges between domains: Improving recommendation with tag-induced cross-domain collaborative filtering. In User Modeling, Adaption and Personalization.Springer, 305–316
[CD30]. Liang Hu, Jian Cao, Guandong Xu, Longbing Cao, Zhiping Gu, and Can Zhu. 2013a. Personalized recommendation via cross-domain triadic factorization. In Proceedings of the 22nd International Conference on World Wide Web. International World Wide Web Conferences Steering Committee, 595–606.
[CD31]. Xin Xin, Zhirun Liu, and Heyan Huang. 2014. A nonlinear cross-site transfer learning approach for recommender systems. In Neural Information Processing. Springer, 495–502.
[CD32]. Babak Loni, Yue Shi, Martha Larson, and Alan Hanjalic. 2014. Cross-domain collaborative filtering with factorization machines. In Advances in Information Retrieval. Springer, 656–661.
[CD33]. Yue Shi, Martha Larson, and Alan Hanjalic. 2013a. Exploiting social tags for cross-domain collaborative filtering. ArXiv Preprint arXiv:1302.4888 (2013).
[CD34]. Weike Pan, Evan Wei Xiang, Nathan Nan Liu, and Qiang Yang. 2010. Transfer learning in collaborative filtering for sparsity reduction. In Proceedings of the 24th AAAI Conference on Artificial Intelligence, Vol. 10. 230–235
[CD35]. Weike Pan, EvanWei Xiang, and Qiang Yang. 2012. Transfer learning in collaborative filtering with uncertain ratings. In AAAI
[CD36]. Weike Pan and Qiang Yang. 2013. Transfer learning in heterogeneous collaborative filtering domains. Artif. Intell. 197 (2013), 39–55.
[CD37]. Jiangfeng Shi, Mingsheng Long, Qiang Liu, Guiguang Ding, and Jianmin Wang. 2013b. Twin bridge transfer learning for sparse collaborative filtering. In Advances in Knowledge Discovery and Data Mining. Springer, 496–507
[CD38]. Weike Pan and Zhong Ming. 2014. Interaction-rich transfer learning for collaborative filtering with heterogeneous user feedback. IEEE Intelligent System 29, 6 (2014), 48–54.
[CD39]. Yu-Jia Huang, Evan Wei Xiang, and Rong Pan. 2012. Constrained collective matrix factorization. In Proceedings of the Sixth ACM Conference on Recommender Systems. ACM, 237–240.
[CD40]. Zhongqi Lu,Weike Pan, EvanWei Xiang, Qiang Yang, Lili Zhao, and ErHeng Zhong. 2013. Selective transfer learning for cross domain recommendation. In SDM. SIAM, 641–649.
[CD41]. Yu Zhang, Bin Cao, and Dit-Yan Yeung. 2012. Multi-domain collaborative filtering. ArXiv Preprint ArXiv:1203.3535 (2012).
[CD42]. How Jing, An-Chun Liang, Shou-De Lin, and Yu Tsao. 2014. A transfer probabilistic collective factorization model to handle sparse data in collaborative filtering. In Proceedings of the 2014 IEEE International Conference on Data Mining (ICDM'14). IEEE, 250–259.
[CD43]. Weike Pan, Zhuode Liu, Zhong Ming, Hao Zhong, Xin Wang, and Congfu Xu. 2015a. Compressed knowledge transfer via factorization machine for heterogeneous collaborative recommendation. Knowledge-Based Systems (2015).
[CD44]. Makbule Gulcin Ozsoy, Faruk Polat, and Reda Alhajj. 2016. Making recommendations by integrating information from multiple social networks. Appl. Intell. 45, 4 (2016), 1047–1065
[CD45]. Mala Saraswat, Shampa Chakraverty, Namrta Mahajan, and Nikita Tokas. 2016. On using reviews and comments for cross domain recommendations and decision making. In Proceedings of the 2016 3rd International Conference on Computing for Sustainable Global Development (INDIACom'16). IEEE, 3656–3659.
[CD46]. Deqing Yang, Yanghua Xiao, Yangqiu Song, Junjun Zhang, Kezun Zhang, and Wei Wang. 2014. Tag propagation based recommendation across diverse social media. In Proceedings of the Companion Publication of the 23rd International Conference on World Wide Web Companion. International World Wide Web Conferences Steering Committee, 407–408
[CD47]. Ying Guo and Xi Chen. 2013b. A framework for cross-domain recommendation in folksonomies. J. Autom. Contr. Eng. 1, 4 (2013).
[CD48]. Zhenhua Dong and Qian Zhao. 2012. Experimental analysis on cross domain preferences association and rating prediction. In Proceedings of the 1st International Workshop on Cross Domain Knowledge Discovery in Web and Social Network Mining. ACM, 26–31
[CD49]. Hla Hla Moe andWin Thanda Aung. 2014b. Context aware cross-domain based recommendation. In Proceedings of the International Conference on Advances in Engineering and Technology. International Institute of Engineers, (2014).

[CD50]. Muhammad Murad Khan, Imran Ghani, Seung Ryul Jeong, Roliana Ibrahim, and Kashif Naseer Qureshi. 2016. Facebook's public social interaction utilization to assist recommendation accross system domain. J. Theoret. Appl. Inf. Technol. 88, 3 (2016), 392

Selected PAPERS- CARS

[CA1]. Shi, F.; Ghedira, C.; Marini, J.-L. Context Adaptation for Smart Recommender Systems. IT Prof. 2015, 17, 18–26.
[CA2]. Chen, Z.; Cao, J.; Song, Y.; Guo, J.; Zhang, Y.; Li, J. Context-oriented web video tag recommendation. In Proceedings of the 19th international conference on World wide web, Raleigh, NC, USA, 26–30 April 2010;pp. 1079–1080
[CA3]. Lin, Z. An empirical investigation of user and system recommendations in e-commerce. Decis. Support Syst.2014, 68, 111–124.
[CA4]. Jaouadi, I.; Djemaa, R.B.; Ben-Abdallah, H. A model-driven development approach for context-aware systems. Softw. Syst. Model. 2016, 1–27.
[CA5]. Kim, D.; Park, C.; Oh, J.; Lee, S.; Yu, H. Convolutional matrix factorization for document context-aware recommendation. In Proceedings of the 10th ACM Conference on Recommender Systems, Boston, MA, USA, 15–19 September 2016; pp. 233–240
[CA6]. Alhamid, M.F.; Rawashdeh, M.; al Osman, H.; Hossain, M.S.; el Saddik, A. Towards context-sensitive collaborative media recommender system. Multimed. Tools Appl. 2015, 74, 11399–11428.
[CA7]. Ren, X.; Song, M.; Haihong, E.; Song, J. Context-aware probabilistic matrix factorization modeling for point-of-interest recommendation. Neurocomputing 2017, 241, 38–55
[CA8]. Durán, J.I.; Laitakari, J.; Pakkala, D.; Perälä, J. A user metamodel for context-aware recommender systems. In Proceedings of the 1st InternationalWorkshop on Information Heterogeneity and Fusion in Recommender Systems, Barcelona, Spain, 26–30 September 2010; pp. 63–66.
[CA9]. Wu, W.; Zhao, J.; Zhang, C.; Meng, F.; Zhang, Z.; Zhang, Y.; Sun, Q. Improving performance of tensor-based context-aware recommenders using Bias Tensor Factorization with context feature auto-encoding. Knowl.-Based Syst. 2017, 128, 71–77.
[CA10]. Lutz, J.; Thönssen, B.; Witschel, H.F. Breaking free from your information prison. In Proceedings of the First International Conference on Enterprise Systems: ES 2013, Cape Town, South Africa, 7–8 November 2013.
[CA11]. Doryab, A.; Bellotti, V.; Yousfi, A.; Wu, S.; Carroll, J.M.; Dey, A.K. If It's Convenient: Leveraging Context in Peer-to-Peer Variable Service Transaction Recommendations. IMWUT 2017, 1, 48.
[CA12]. Bouneffouf, D.; Bouzeghoub, A.; Gancarski, A.L. Following the user's interests in mobile context-aware recommender systems: The hybrid-E-greedy algorithm. In Proceedings of the 26th International Conference on Advanced Information Networking and Applications Workshops (WAINA), Fukuoka, Japan, 26–29 March 2012; pp. 657–662.
[CA13]. Wang, J.; Zeng, C.; He, C.; Hong, L.; Zhou, L.; Wong, R.K.; Tian, J. Context-aware role mining for mobile service recommendation. In Proceedings of the 27th Annual ACM Symposium on Applied Computing,Riva (Trento), Italy, 26–30 March 2012; pp. 173–178
[CA14]. Wu, S.; Liu, Q.;Wang, L.; Tan, T. Contextual operation for recommender systems. IEEE Trans. Knowl. Data Eng. 2016, 28, 2000–2012
[CA15]. Alhamid, M.F.; Rawashdeh, M.; Hossain, M.A.; Alelaiwi, A.; el Saddik, A. Towards context-aware media recommendation based on social tagging. J. Intell. Inf. Syst. 2016, 46, 499–516.
[CA16]. Cui, L.; Huang, W.; Yan, Q.; Yu, F.R.; Wen, Z.; Lu, N. A novel context-aware recommendation algorithm with two-level SVD in social networks. Future Gener. Comput. Syst. 2017
[CA17]. Kim, S.; Lee, S.; Kim, J.; Yoon, Y.-I. MRTensorCube: Tensor factorization with data reduction for context-aware recommendations. J. Supercomput. 2017, 1–11.
[CA18]. Bagci, H.; Karagoz, P. Context-aware location recommendation by using a random walk-based approach. Knowl. Inf. Syst. 2016, 47, 241–260
[CA19]. Bagci, H.; Karagoz, P. Context-aware friend recommendation for location based social networks using random walk. In Proceedings of the 25th International Conference Companion on World Wide Web, Montreal, QC, Canada, 11–15 April 2016; pp. 531–536.
[CA20]. Han, J.; Schmidtke, H.R.; Xie, X.; Woo, W. Adaptive content recommendation for mobile users: Ordering recommendations using a hierarchical context model with granularity. Pervasive Mob. Comput. 2014, 13, 85–98.
[CA21]. Zheng, C.; Haihong, E.; Song, M.; Song, J. CMPTF: Contextual Modeling Probabilistic Tensor Factorizationfor Recommender Systems. Neurocomputing 2016, 205, 141–151.
[CA22]. Colombo-Mendoza, L.O.; Valencia-García, R.; Rodríguez-González, A.; Colomo-Palacios, R.; Alor-Hernández, G. Towards a knowledge-based probabilistic and context-aware social recommender system. J. Inf. Sci. 2017.