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RESEARCH ARTICLE

KT-CDULF: Knowledge Transfer in Context-Aware Cross-Domain Recommender Systems via Latent User Profiling

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ABSTRACT Recommender systems are crucial in today's digital world, by enhancing user engagement experience in digital ecosystems. Internet of things (IoT) have huge potential to generate dynamic and real time data. The data generated through IoT are being utilized to extract dynamic context of the user. Integrating recommender systems with context-aware (IoT data) and cross-domain (Knowledge Transfer) capabilities have the capacity to further enhance the accuracy and relevance of recommendation systems. However, recommender systems struggle with the cold start problem, where non-availability of data hinders to make effective recommendations for new users. Therefore, IoT-enabled Context-Aware Cross-Domain Recommender Systems may employ latent user profiling to provide personalized and exceedingly relevant recommendations across domains. The proposed system, named Knowledge Transfer Cross-Domain User Latent Factors (KT-CDULF), creates a user profile that spans multiple data domains, capturing a wide range of user behavior on all domains. The KT-CDULF captures the combined knowledge across domains to make recommendations even with limited user data, i.e. cold start problem. Domain-independent factors, and context can be used across domains to make relevant recommendations. The effectiveness of a recommender system depends on the density of the ratings in the data. To address this, KT-CDULF used two benchmark datasets to create user profiles and an item-rating matrix with additional context extracted from IoT generated dataset. KT-CDULF is evaluated and compared it with state-of-the-art models for recommender systems and achieves an accuracy of 98%, demonstrating the benefits of transferring knowledge containing context across data domains in recommender systems.

INDEX TERMS Cold start problem, context-aware systems (CARS), cross-domain recommender systems (CDRS), data sparsity, internet of things (IoT), knowledge transfer (KT), latent user profiling, matrix tri-factorization (MF).

I. INTRODUCTION

The abundance of digital content over the past few decades [1], fueled by the advent of modern applications, radically changed individuals access and interaction with

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information. Information Retrieval (IR) systems have traditionally played a crucial role in managing this data deluge. As an extension of IR systems; Recommender Systems (RS), which are systems designed to suggest items of interest to users based on their preferences and behavior. Unfortunately, recommender systems face the challenge of suggesting items of interest to users when there is insufficient data on user preferences or item ratings [2], the cold start problem [3], and not having a diversity of recommendations [4], even though they are widely used in e-commerce, health [5], media and entertainment [6], and other fields. The exposure of RS to the cold start problem is critically important as the user behavior is either non-existent or not sufficiently available at the early stages [2]. Moreover, consumer preferences always alter and diverge due to environment, location, time of day, etc. [2]. Context-aware recommender systems (CARS) that use contextual information such as time, location, or user behavior to make more appropriate recommendations [7]. Furthermore, cross-domain recommender systems (CDRS), which utilize the knowledge from one domain to inform actions or decisions in another domain, were developed to mitigate the potential cold start problem [8]. By integrating the advantages of cross-domain and context-aware recommender systems, cross-domain context-aware recommender systems (CD-CARS) may provide users with recommendations that are not only diverse but also highly personalized. These recommendations would be predicated on the dynamic preferences and circumstances of users across various domains [8]. To capture the dynamic context, personalized devices of the user, i.e., the Internet of Things (IoT), come to an aid. The data generated from IoT has the potential to extract dynamic context of the user. Dynamic context helps in recommendation process by generated relevant recommendations according to the current context of the user.

CD-CARS utilizes data across domains and contextual aspects, making it an extensive area of research that aims to improve the recommendation process. This interdisciplinary field combines insights from recommender systems, machine learning, and data mining to provide more accurate and personalized recommendations across domains (e.g., movies, books, restaurants) by understanding the context of user preferences and behaviors [9]. CD-CARS research looks into a number of different approaches to deal with the issue of sparse data and knowledge transfer across domains. These include collaborative filtering (CF) [10], [11], content-based filtering (CBF) [12], and hybrid approaches [13].

This research study aims to broaden the existing framework by exploring the potential of integrating IoT data into CD-CARS to enhance recommendation quality. KT-CDULF proposes an innovative recommendation model that leverages the advantages of cross-domain data combined with context, adding significant value to typical CD-CARS. The key contributions of this research work are as follows:

1) This study proposes the design of a framework for context-aware cross-domain recommender systems that are enabled with IoT use cases for better recommendations.
2) This study contributes to the formulation of a unique method of user profiling across different domains of data for efficient knowledge representation.
3) Using the matrix tri-factorization decomposition method, the study suggests a way to find the trainable latent factors so that the model fits better. The decomposition method helps the model achieve robust performance with minimal cost, as demonstrated in the results.
4) In order to more effectively address the cold start problem in recommendation workflow, this research develops novel knowledge transfer mechanism for domain-independent user latent factors. As an innovation to this paradigm, the knowledge transfer method accumulates user preferences across all data domains, including the context derived from IoT.
5) This study demonstrates the efficacy of the proposed model with different density levels of user interactions for robust evaluations. For each domain of data, the study presents three granularity levels for model testing and evaluation in a thorough and detailed manner.

The rest of the document is organized as follows: The essential core concepts of recommender system paradigm will be discussed in the upcoming section as literature review section. Section III discusses problem formulation and methods, then Section IV discusses experiment setup and execution. The last section, Section V, offers a thorough comparative analysis, a conclusion, and future directions.

II. LITERATURE REVIEW

IoT-enabled CD-CARS are a rapidly developing discipline that has seen a lot of academic activity recently. The goal of this review of the literature is to examine the numerous studies and discoveries that have made a substantial impact on our comprehension of this intriguing but challenging field. In summary, Table 1 presents the comparative analysis of prominent RS algorithms of various features. The following sections present the studies attempting to provide solutions in the proposed domain.

The role of context in novel and scalable recommendations has been meticulously observed in the study [14]. It is possible to make recommendation systems better by using IoT devices to get contextual information. This can help with issues like data sparsity and domain sensitivity, leading to more accurate recommendation in music [6], e-commerce [15] smart cities [16] and smart healthcare [5]. Figure 1 elaborates the detailed taxonomy of IoT enabled Cross-Domain Recommender systems as per their techniques, context types, and applications.

User profile is a crucial aspect of recommendation systems, as it enables the personalization of information and enhances the user experience. Natural Language Processing (NLP) methods are efficient for assessing user-generated content [17], such as reviews and social media posts. These

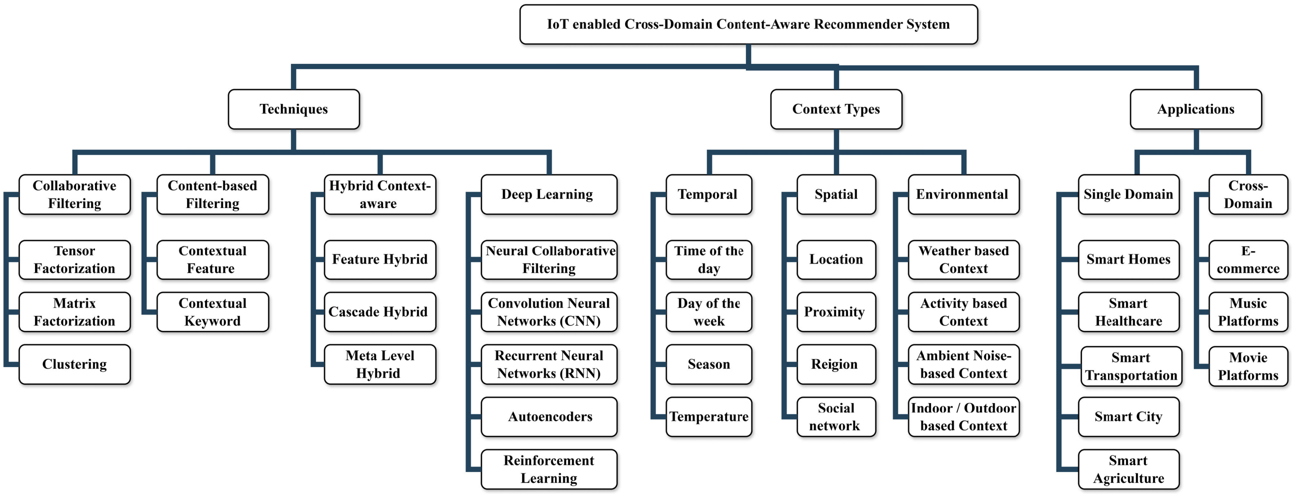


FIGURE 1. Detailed Taxonomy of IoT-enabled Cross-Domain Recommender Systems.

approaches demonstrate the capabilities of creating detailed and adaptable user profiles for cross-domain recommender systems. An alternative method for user profiling in literature involves using a hybrid recommender system that overcomes rating-based feedback by integrating sentiment ratings [18] gathered from user reviews. This technique highlights the significance of utilizing sentiment analysis to enhance the accuracy and comprehensiveness of user profiling in cross-domain recommender systems. Differentiating Users' Preferences and Items' Attractiveness (DUPIA) [19] is a hybrid framework based on probabilistic matrix factorization (PMF) that uses latent variables that are unique to each user and item to tell the difference between user preferences and item attractiveness. This system utilizes a stacked denoising autoencoder to extract latent features that are specific to the user, and an attention-based Convolutional Neural Network (CNN) to represent latent characteristics that are specific to the item.

Contextual information in Content-Based Recommender Systems refers to the modification of the formula used to calculate the similarity between the user and item based on the available context. Heuristic-based approaches are used in Memory-Based RSs, while tensor factorization and appropriately integrated matrix factorization techniques [26] are utilized in Model-Based RSs in Collaborative Filtering. The study conducted by [27] centers on the personalized recommendation of online shopping products. The approach utilized online fast learning through a latent factor model, with a particular emphasis on cross-domain recommendation. Singular Value Decomposition (SVD) [20] employs the concept of decomposing the rating matrix into a low-rank approximation using singular values, which facilitates fast data processing and recommendation generation. Probabilistic Matrix Factorization [21] is a method that, like SVD, uses a probabilistic Gaussian distribution to include the average and variability of user and latent data. This approach creates a probabilistic framework for understanding how users and items interact with each other. Non-negative Matrix Factorization (NMF) [28] is distinct because it exclusively considers non-negative feature values for both users and items. This guarantees that the resulting factors are easily understandable and consistent with real-world limitations. Moreover, Recommendation Systems using SVD++ [13] expands upon the SVD method by including implicit characteristics alongside explicit rating information, hence improving the model's capacity to consider both observable and unobservable user preferences. User and item similarity is maximized in a shared semantic space using Deep Structured Semantic Models (DSSM) [29], improving recommendation accuracy. To learn features of products across domains authors extended the DSSM model with the Multi-View Deep Neural Network (MV-DNN) by using rich user features, eliminating cold start issues, and improving user representation across domains. Moreover, [3] introduced a comprehensive deep learning framework that caters to both cross-domain and cross-system recommendation scenarios. The authors integrated deep neural network and matrix factorization models to facilitate the acquisition and transference of knowledge from the source domain to the target domain in a cross-domain recommendation system. The authors in [30] presented a novel technique called Tag Cross Domain Collaborative Filtering (TagCDCF) which integrates intra and inter-domain correlations to matrix factorization, thereby enhancing the efficacy of recommender systems in the target domain. The matrix factorization process was aided by utilizing user similarities that were extracted from shared tags. Another novel approach to transfer learning, that leverages neural networks as the underlying model for cross-domain recommendation [31], highlights the effectiveness of transfer learning to resolve the issue of data scarcity in a particular domain in recommender systems.

TABLE 1. Comparative analysis of prominent recommender system algorithms, detailing their underlying Mechanisms, Strengths, Limitations, and typical applications.

Algorithm	Type	Dataset	Scalability	Cold Start	Diversity
Collaborative Filtering (User-based) [10]	Memory-based	User-item matrix	Moderate	Poor	Moderate
Collaborative Filtering (Item-based) [11]	Memory-based	User-item matrix	Moderate	Poor	Moderate
Matrix Factorization (SVD) [20]	Model-based	User-item matrix	High	Poor	Moderate
Probabilistic Matrix Factorization (PMF) [21]	Model-based	User-item matrix	High	Poor	Moderate
Alternating Least Squares (ALS) [22]	Model-based	User-item matrix	High	Poor	Moderate
K-Nearest Neighbors (KNN) [23]	Hybrid	User-item matrix, content data	Moderate	Moderate	High
Content-Based Filtering [12]	Content-based	Item features, user profiles	Moderate	Good	High
Deep Learning (Neural Collaborative Filtering) [24]	Model-based	User-item matrix	High	Poor	Moderate
Bayesian Personalized Ranking (BPR) [25]	Model-based	User-item matrix	High	Poor	Moderate

A study on a recommender system that operates across several domains and uses kernel-induced knowledge transfer [32] to handle overlapping elements. The concept of Collaborative cross Networks (CoNet) [31] as a means of implementing collaborative techniques emphasized the utilization of cross-connection units as a means to facilitate precise and infrequent transmission of knowledge. Furthermore, a revised matrix approximation methodology for recommender systems that leverages context information and transfer learning by leveraging contextual information to partition the user-item interaction matrix into smaller sub-matrices and facilitate transfer learning within the confines of a single domain [33]. Another study explores enhancing IoT recommender systems by introducing a many-objective optimization model that incorporates six metrics: F1 measure, recommendation novelty, coverage, customer satisfaction, landmark similarity, and overfitting. A new optimization algorithm, Large-Scale Many-Objective Optimization Algorithm (LSMaOA) [34], is proposed to improve matrix factorization models.

Additional discovery techniques, particularly those in the field of artificial intelligence such as deep and transfer learning, are now being investigated to analyze the resemblances between user inquiries and products in the database. The ultimate aim is to offer more appropriate, contextualized, personalized and cross domain recommendations.

III. MATERIALS AND METHODS

In order to put together the data for the suggested framework, KT-CDULF (Knowledge Transfer for Context-Dependent User Latent Factor), the study employed datasets from four different domains on Amazon: Movies, Digital Music, CDs, and Books. The datasets were further partitioned into subgroups with proportions of 100%, 75%, and 50% to thoroughly evaluate the performance of the model.

In order to enhance the rating datasets with user and regional context, gender information was added to each user ID and merged additional contexts from the FitRec dataset. The weather attributes were incorporated into the rating tuples by utilizing timestamp and location data. In the matrix tri-factorization decomposition procedure, all missing values were replaced with zeros in order to prevent biases.

The objective of this technique was to acquire hidden characteristics of users and products, allowing for recommendations across different domains using IoT data while being unaffected by specific domains. This study concentrates on users who had a significant number of interactions (more than fifteen ratings) across all domains. This data is then used to generate a user-item matrix. The FitRec data includes further information such as timezone, hemisphere data, and categorized heart rates (elevated, normal, and low) to classify people into distinct physical and psychological groups. The recommender system's performance was assessed using the Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) metrics. The experiments were performed using hardware that was equipped with a GPU to accelerate the training process. The results were meticulously documented to ensure reproducibility and transparency.

A. PROBLEM FORMULATION

For the proposed model dataset of four domains is collected as $D \in \{d_1, d_2, d_3, d_4\}$ i.e. books, movies, music, and CDs respectively. Each domain D_i has a user set $U \in \{u_1, u_2, u_3, \ldots, u_j\}$, an item set $I \in \{i_1, i_2, i_3, \ldots, i_m\}$, and a context set $C \in \{c_1, c_2, c_3, \ldots, c_n\}$. Each context category c_i is associated with a set of values. Each value is a representation of contextual situation $S \in \{s_1, s_2, s_3, \ldots, s_k\}$ where k is the total population of each context. User profile block for each domain D_i is represented as $V = U_j$ x I_m x C_n. The overlapping users are defined between the domains D_j as $\widehat{U} \in \{U_1 \cap U_2 \cap U_3 \cap U_4\}$, however, it is pertinent to note that in all domains the data of rating against users and items are sparse. The proposed system goal is to predict and fill out the missing values of ratings for each block V_i by using the contextual similarities of each rating.

B. KNOWLEDGE REPRESENTATION

Cross-domain recommendation systems primarily use two-dimensional data, in the form of User $\times$ Items ratings, to generate the recommendation over the auxiliary and target domains. However, KT-CDULF defines cross-domain RS with three-dimensional data, by adding context as a third dimension with users and items dimensions by leveraging the foundations presented in study [35]. Based on the stages of context integration in the recommendation process, KT-CDULF defines domains explicitly requiring

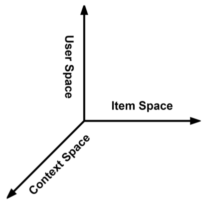


FIGURE 2. **Modelling of users, items, and contextual information in three-dimensional (IR^3) space.**

cohesive modeling of contextual information. Cross-domain knowledge transfer for recommendations typically assumes source domain to target domain scenarios, e.g. movies as the source domain and music as the target domain. This limitation raises questions about the limited utility of cross-domain recommender systems. This limitation directly leads to adverse effects on commercial objectives.

Furthermore, handling the time-drifting impact and evolving behavior of contextual attributes is another objective of this research. It is observed that user preferences in CARS must be able to generate domain independent recommendations. As motivation to resolve above-mentioned limitations of CD-CARS, the KT-CDULF framework identifies and applies the relevant context adaptively to the recommendation process. The pertinent advantage to introduce the KT-CDULF framework is to make it applicable for generalized utility considering commercial applications. Figure 2 represents the users' rating, and context in IR^3 space.

C. DECOMPOSITION OF LATENT FEATURES

To decompose the three-dimensional user latent rating matrix IR^3, Matrix Factorization (MF) is considered as a way-to-go approach. The proposed multilayer nonlinear semi-nonnegative matrix factorization method discovers latent factors for user and item representations using explicit ratings and a linear combination of non-linear item features. The approach is contrasted to deep-learning algorithms such as Restricted Boltzmann Machine and cutting-edge Deep Matrix factorization techniques in order to establish its efficacy in enhancing system performance. The proposed system uses the formulation represented in Equation 1 for embedding-based recommendations. Where W represents the latent feature vector associated with Item j and γ works as regularization parameter for feature vectors.

$$\begin{aligned} L = \min \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{n} I_{ij}(r_{ij} - U_i^T I_j - W_j^T X_j)^2 \\ + \frac{\gamma_u}{2} \|U\|_F^2 + \frac{\gamma_w}{2} \|W\|_F^2 \end{aligned} \tag{1}$$

However, to update the randomly initialized latent weights, authors have employed stochastic gradient descent represented in Equation 2.

$$\begin{aligned} W_j &\leftarrow W_j + \gamma_3(\Delta_{ij} X_j - \gamma_W W_j) \\ U_i &\leftarrow U_i + \gamma_1(\Delta_{ij} I_j - \gamma_U U_i) \\ I_j &\leftarrow I_j + \gamma_2(\Delta_{ij} U_i - \gamma_I I_j) \end{aligned} \tag{2}$$

The proposed framework incorporates user evaluations for specific interacting items such as class labels that the system must forecast, using a customized objective function, Equation 3, to maximize the suggestions.

$$\widehat{y(x)} = w_0 + \sum_{i=1}^{n} w_i x_i + \sum_{j=1}^{n} \sum_{k=j+1}^{n} v_j v_k^T x_j x_k \tag{3}$$

where $x \in \{0, 1\}^d$ is the feature vector in IR^d, d represents the total number of the users and items whereas $v \in IR^{n*m}$ is the latent factor matrix. Further the algorithm breaks down the underlying features into smaller matrices, which allows for a comprehensive representation of user, item, and domain-specific attributes. Hence, the loss function, in Equation 4, is specifically created to enhance the performance of the recommender system to accurately capture the underlying latent factors.

$$E^n = \min \phi(\theta^n | R^n + \Omega(\theta^n)) \tag{4}$$

where R^n is an input (training data) rating matrix and θ is a set of output parameters used to construct a model. ϕ is an error function, whereas Ω is a regularization function that addresses the overfitting issue. However, on leveraging the same idea, this study approaches this mapping in a different way such that the unnecessary cost of model computation and convergence can be achieved with a larger volume of data due to the coexistence of contextual information with the user-item rating.

$$\begin{aligned} \widehat{R^s} &\sim U^s C^s I^{s^T} \\ \widehat{R^t} &\sim U^t C^t I^{t^T} \end{aligned} \tag{5}$$

$$\begin{aligned} E^s &= \min_{U^s, C^s, I^s} \frac{1}{2} \left\| R^s - U^s C^s I^{s^T} \right\|_f^2 + \frac{\gamma_u}{2} \left\| U^s \right\|_f^2 \\ &\quad + \frac{\gamma_c}{2} \left\| C^s \right\|_f^2 + \frac{\gamma_i}{2} \left\| I^s \right\|_f^2 \\ E^t &= \min_{U^t, C^t, I^t} \frac{1}{2} \left\| R^t - U^t C^t I^{t^T} \right\|_f^2 + \frac{\gamma_u}{2} \left\| U^t \right\|_f^2 \\ &\quad + \frac{\gamma_c}{2} \left\| C^t \right\|_f^2 + \frac{\gamma_i}{2} \left\| I^t \right\|_f^2 \end{aligned} \tag{6}$$

where $U \in IR^{m*f}$, $B \in IR^{m*f}$, and $I \in IR^{f*f}$. The proposed model KT-CDULF, augmented the knowledge of each user across all the domains in a single user profile. This user profile represents each user in each domain for interaction with different items of different domains along with contextual information. Subsequently, matrix tri-factorization is utilized to break down the data into three separate matrices: a user domain-independent latent matrix, a domain-dependent latent matrix, and a domain-specific latent feature matrix. This decomposition allows the model to successfully capture both general and specific user preferences across several domains. The decomposition approximation for both target R^t and source domain R^s is represented in simpler form in Equation 5 with loss function of each domain as Equation 6.

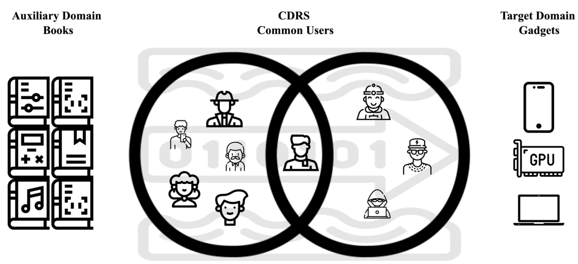


FIGURE 3. Transfer of Knowledge from Auxiliary Domain to Target Domain Cross-Domain Recommender System.

D. KNOWLEDGE TRANSFER

Knowledge transfer refers to the process of applying information gained from one domain to another domain. In the context of cross-domain recommender systems, it involves leveraging data and insights from a source domain to improve recommendations in a target domain [33], [36] rather than relying on a single domain, thereby addressing challenges such as the cold start problem. The choice of transfer learning method is contingent upon the type of data to be transferred and the manner in which data is shared across domains [37]. The key to ensuring that only pertinent knowledge is transferred [36] is to develop reliable and concrete domain correlations. Figure 3 shows a pictorial representation of transferring knowledge from one domain to another.

To establish domain independence in knowledge transfer KT-CDULF approach overcomes these challenges by learning the latent features of users across all domains with matrix tri-factorization to formulate and solve the problem in a simple and effective way.

$$\frac{\delta E}{\delta \theta} = \begin{cases} -(r^t_{u,i} - U_u C^t I^{tT}_i) I^t_i C^{tT}_i + \alpha_u U^t_u & \text{for } \dfrac{\delta E}{\delta U^t_u} \\ \alpha[-(r^t_{u,i} - U_u C^a I^{aT}_i) I^a_i C^{aT}_i + \alpha_u U^a_u] & \text{for } \dfrac{\delta E}{\delta U^a_u} \\ -(r^t_{u,i} - U_u C^t I^{tT}_i) U^t_u I^t + \alpha_i I^t_i & \text{for } \dfrac{\delta E}{\delta I^t_i} \\ \alpha[-(r^s_{u,i} - U_u C^s I^{sT}_i) U^s_u I^s + \alpha_i I^s_i] & \text{for } \dfrac{\delta E}{\delta I^s_i} \end{cases} \tag{7}$$

$$\frac{\delta F}{\delta \omega} = \begin{cases} -(r^t_{u,i} - w^{tT} * x_{ui}) x_{ui} + \alpha_c w^t & \text{for } \dfrac{\delta M}{\delta w_t} \\ \alpha[-(r^s_{u,i} - w^{sT} * x_{ui}) x_{ui} + \alpha_c w^s] & \text{for } \dfrac{\delta M}{\delta w_s} \end{cases} \tag{8}$$

As apart from [36], the KT-CDULF approach employed user overlap across domains for transferring knowledge. This method leverages different intuitions associated with latent matrix tri-factorization to enhance the recommendation process. The knowledge transfer employs the transfer in Collective Knowledge Transfer (CKT) where users in all domains are overlapping. The latent matrix of user-item rating is decomposed into three sub-matrices to capture the latent features of the user, item, and domain-specific knowledge $R \sim UCI^T$. These captured latent matrices would enhance the accuracy of the overall recommendations due to low-level features for each user, item, and context that exist in the data.

Algorithm 1 Proposed KT-CDULF Algorithm

Input : Rating Matrix of auxiliary domain R^a with user latent matrix U^α, item latent matrix I^α, and latent matrix C^α, rating matrix of target domain R^t and hyperparameters $(\alpha_u, \alpha_c, \alpha_i, \theta, \gamma)$

Output: Domain dependent interaction matrix C^t, item latent matrix I^t, user latent matrix $U \in [U^a, U^t]$

Randomly assign the U^a, C^a, I^a, C^t, I^t

Randomly shuffle the example set x

while *Converge* **do**

  foreach *Sample of example set* x_i **do**

    $\frac{\delta E}{\delta U^t_u} = -(r^t_{u,i} - U_u C^t I^{tT}_i) I^t_i C^{tT}_i + \alpha_u U^t_u$

    $\frac{\delta E}{\delta U^a_u} = \alpha[-(r^t_{u,i} - U_u C^a I^{aT}_i) I^a_i C^{aT}_i + \alpha_u U^a_u]$

    $\frac{\delta E}{\delta I^t_i} = -(r^t_{u,i} - U_u C^t I^{tT}_i) U^t_u I^t + \alpha_i I^t_i$

    $\frac{\delta E}{\delta I^s_i} = \alpha[-(r^s_{u,i} - U_u C^s I^{sT}_i) U^s_u I^s + \alpha_i I^s_i]$

    $\frac{\delta M}{\delta w_t} = -(r^t_{u,i} - w^{tT} * x_{ui}) x_{ui} + \alpha_c w^t$

    $\frac{\delta M}{\delta w_s} = \alpha[-(r^s_{u,i} - w^{sT} * x_{ui}) x_{ui} + \alpha_c w^s]$

    Update all parameters using γ as learning rate with $\theta = \theta - \gamma * \frac{\delta E}{\delta \theta}$

  end

end

$R^t = U^s * C^t * I^{tT}$

return R^t

After the decomposition of the latent matrix, the matrix U from the user profile is transferred to the target domain for the prediction of the missing ratings. The user profile matrix weights are updated in accordance with all the domains, thus having the most relevant knowledge. This user latent matrix is then transferred to the target domain where the item latent matrix and domain context are used with the upcoming user latent matrix to regenerate the rating matrix. The decomposition of the matrix is done separately and the weight of each matrix is updated as shown in Equation 7. The gradients of the latent factor matrix are calculated as shown in Equation 8. This process is cumulatively shown in Algorithm 1 until the convergence and prediction for the target domain are generated using the latent matrix of the user and item from the source domain along with domain knowledge of the target domain.

IV. EXPERIMENTAL SETUP AND IMPLEMENTATION

In the section for experiments and results, a detailed overview of dataset formation, data fusion, and implementation setup is discussed.

TABLE 2. A comparative overview of datasets in recommender systems literature, Highlighting key characteristics, and specifications.

Dataset	Size	Domain	Values	Context	Sparsity	IoT	Timestamp	Demographics
MovieLens	100k-20M	Movies	Ratings	Time, User Preferences	Medium	-	✓	✓
Netflix Prize	100M	Movies	Ratings	Time, User Preferences	Medium	-	✓	-
Jester	4.1M	Jokes	Ratings	N	Low	-	-	-
Last.fm	Varies	Music	Events, tags	Time, User Preferences	Medium	-	✓	-
Book-crossing	1M	Books	Ratings, Reviews	-	High	-	-	✓
CiteULike	16,800	Research papers	Likes	-	High	-	-	-
Amazon Reviews	Varies	Various products	Reviews	-	Medium	-	✓	-
Amazon Ratings	Varies	Various products	Ratings	-	Medium	-	✓	-
Foursquare	Varies	Locations	Check-ins	Time, Location	Medium	-	✓	-
UCI HAR	10,299	Human Activities	Values	Time, Sensor Data	Low	Wearable	✓	-
PAMAP2	385,050	Physical Activities	Values	Time, Sensor Data	Low	Wearable	✓	-
Goodreads	Varies	Books	Ratings, Reviews	-	Medium	-	✓	-
Epinions	Varies	Various products	Ratings, Reviews	-	Medium	-	-	-
Yelp	Varies	Businesses	Ratings, Reviews	Time, Location	Medium	-	✓	-
TripAdvisor	Varies	Travel & Tourism	Ratings, Reviews	Time, Location	Medium	-	✓	-
InCar	Varies	In-car HMI	Values	Driving behavior, voice commands	Varies	Sensors	✓	✓
Frappe	26,000	Mobile app usage	Activity	App usage	Medium	Smartphone	✓	✓

A. DATASET

This section emphasizes on existing datasets used for recommender systems along with IoT based datasets as shown in Table 2. Furthermore, a brief discussion on the fusion of Amazon and FitRec datasets used in KT-CDULF is presented.

1) EXISTING DATASETS

There are numerous available datasets for recommender systems that serve as valuable resources for the development and evaluation of recommendation algorithms. The MovieLens dataset [38], which contains users' movie ratings, is quite popular and available in 100K, 1M, and 20M versions, allowing researchers to work with varying sizes of data. The Netflix Prize dataset [39], which contains millions of Netflix user ratings, and e-commerce datasets such as Amazon product reviews [40] that contains information regarding user ratings and product metadata, along with social media platforms such as Twitter [41], Yelp [42], and StackOverFlow [43] provide datasets containing user feedback and interactions. The Endomondo fitness tracker dataset (FitRec) [44] is comprised of fitness tracking data taken from a varied group of 1,500 individuals and includes a wide variety of activities. This dataset offers a variety of elements, some of which are user demographics (such as age and gender), different sorts of sports, geographical coordinates (such as longitude and latitude), heart rate, distance covered, and more contextual information.

Recommendations can be dynamically altered based on users' present context, environment, and behaviors by integrating IoT devices. IoT gadgets have gained widespread acceptance, permeating many facets of our lives. They include a wide range of networked gadgets, including smartphones, wearable fitness trackers, smart home appliances, and others [45]. Using data from IoT devices, recommender systems can construct a highly granular user profile that encompasses various aspects of a user's life.

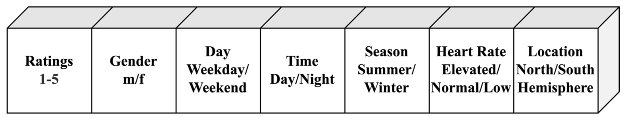


FIGURE 4. Pictorial representation of content vector of rating matrix.

TABLE 3. Statistical distribution of the amazon rating data domains with % of sparsity.

Domain	Users (#)	Items (#)	Ratings (#)	Sparsity (%)
Movies	691	32,426	73,694	99.67
Digital Music	691	21,073	25,463	99.82
CDs	691	78,319	126,388	99.76
Books	691	82,211	98,852	99.82

2) DATA FUSION

For this research the data of The Amazon rating dataset and FitRec dataset fuse to explore and establish the importance of IoT devices data in the recommender systems being used. The ratings from the Amazon dataset were randomly correlated with user actions from the FitRec dataset. This resulted in the production of extensive context feature vectors, which facilitated the generation of context-aware suggestions. After that, these vectors were incorporated into a three-dimensional rating tensor, which included the dimensions of the user, the item, and the context to produce a comprehensive contextual representation for the recommendation model.

B. IMPLEMENTATION SETUP

To prepare data for KT-CDULF individuals with similar ratings across Amazon domains are identified. In addition, as part of the data cleansing process, all duplicate, missing, and anomalous records are eliminated. The statistical distribution of the trimmed dataset is shown in Table 3.

The dataset was divided into subsets with proportions 100%, 75%, and 50%, respectively, to test the model's performance in a more exhaustive and rigorous way. The application of sophisticated imputation procedures successfully managed the missing ratings inside the three-dimensional tensor in order to transform the dataset into tidy data. Amazon ratings data set and FitRec are openly accessible to the public for the purpose of research. To integrate the user and geographic context within rating datasets, gender information is appended to each userID. Furthermore, additional FitRec contexts are added based on time and location to improve the contextual understanding of our recommender system, such as season, heart rate, and day, as shown in Figure 4.

The following sections discuss these transformations in more detail. In the creation and implementation of the suggested matrix factorization algorithm, the missing values were filled with 0s to avoid biases during this process. The recommender system's performance was assessed using the Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) metrics. The trials were carried out using hardware outfitted with a GPU for rapid training, and the results were analyzed and compared to current matrix factorization techniques. To ensure the research's reproducibility and transparency, thorough documentation was kept in the implementation phase.

1) DATA WRANGLING AND TRANSFORMATION

KT-CDULF aims to learn the latent features of users and items in collaborative filtering recommender systems. The goal is to enable domain independence for cross-domain suggestions using IoT data. In studies of Cross-Domain Recommender Systems, multiple dimensions have been identified, such as user overlap, item overlap, and no overlap. User overlap refers to common users across all domains. To improve the density of rating matrix users with more than fifteen ratings in each domain are identified and kept. Missing ratings with 0s are imputed for the matrix tri-factorization to capture the latent factors, these imputed ratings then become the main goal for the model to predict the rating with suitable cost. Similarly, for the context of these ratings, the FitRec data is aggregated by calculating the timezone, hemisphere, and heart rate categories. The intuition behind transforming the heart rate to fall into one of the following categories: i) elevated, ii) normal, and, iii) low is to classify the users into different physical and psychological groups to distinguish between the recommendations further. These transformed factors are then stacked together to represent the knowledge for the model to test and evaluate.

2) TIDY SUBSETS

In order to test the model for the different densities of the ratings in the data, KT-CDULF utilizes multiple variations of fused dataset and tidy subsets. Three possible subsets: 100:0, 75:25, and 50:50 are created to validate and construct recommendations by KT-CDULF in order to offer a robust evaluation. The 100:0 split represents that 100% of the data was used to capture the latent factors for users, items, and latent features. Similarly, the 75:25 split divided the data into 75% of the overall population and was selected randomly after shuffling it for the same process. Numerous splits are created to investigate the effect of different training set sizes on recommender system performance. This is to assess the system's capacity to generalize across various data proportions.

Furthermore, it is also pertinent to note that the role of context, particularly the IoT information should also be investigated w.r.t recommendation relevance. To demonstrate the KT-CDULF performance three case scenarios are designed within the usage of contextual information to test the proposed KT-CDULF with i) Whole Context (WC), ii) Partial IoT Context (PC) where just IoT information is brought to the rating matrix, and, iii) No Context (NC). Using constructed dataset subsets and scenarios for testing in our research offers distinct advantages encompassing robustness through the capture of variability, the capability to evaluate the recommender system's ability to perform well in various scenarios, and the establishment of consistency and dependability in the results by comparing consistent trends and patterns across all subsets. Figure 5 illustrates the comprehensive methodology of the KT-CDULF framework for cross-domain recommender systems, leveraging user latent factors, demonstrated in Algorithm 1. The process begins with data preprocessing and fusion, where rating data from multiple domains (Amazon and FitRec) are fused based on users and timestamps. This data is then structured into multi-dimensional rating matrices for each domain, which are horizontally padded. From these matrices, latent features are extracted, encompassing contextual information, user-specific behaviors. These extracted features are then utilized in a knowledge transfer process, combining context and user latent features to create a unified latent factor model. This model predicts ratings for items that users have not yet rated, resulting in a predicted rating matrix. This predicted matrix enhances recommendation accuracy by integrating knowledge from various domains and contextual data, providing more personalized and relevant recommendations for users.

V. RESULTS AND DISCUSSION

In this section the comparison results and evaluation metrics will be discussed.

A. EVALUATION METRICS

RMSE and MAE are major evaluation metrics in recommender systems. The average squared difference between anticipated and actual ratings is captured by RMSE, whereas the average absolute difference is measured by MAE [43]. By looking at these metrics at different levels of sparsity and density, researchers can test how well and how accurately matrix tri-factorization models work. This gives them a better idea of how they would work in real-life recommendation situations.

1) ROOT MEAN SQUARE ERROR (RMSE)

The RMSE is a commonly used evaluation statistic that quantifies the average squared difference between expected and actual ratings. RMSE is calculated mathematically as

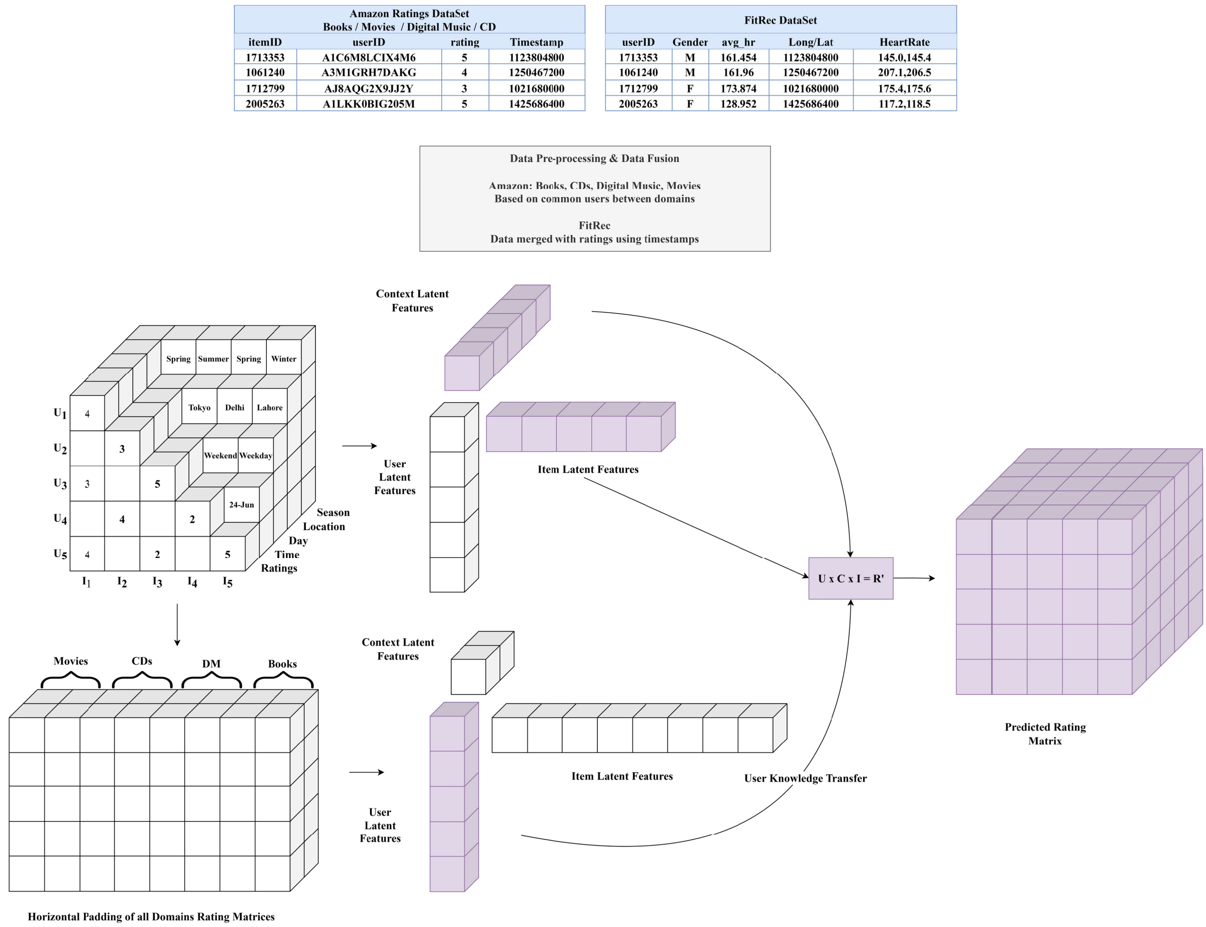


FIGURE 5. Complete pipeline of proposed methodology for knowledge transfer cross domain user latent factor recommender systems (KT-CDULF).

represented in Equation 9.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \|(y_i - \widehat{y}_i)\|^2}{N}} \tag{9}$$

where N is the total number of ratings, the predicted rating $\widehat{y}$ is the rating estimated by the matrix tri-factorization algorithm, and the actual rating y is the user supplied ground truth rating. RMSE increases the impact of greater errors by squaring the differences, making it susceptible to outliers.

2) MEAN ABSOLUTE ERROR (MAE)

In contrast to RMSE, MAE considers the average absolute difference between projected and actual scores. MAE is calculated mathematically as represented in Equation 10.

$$MAE = \frac{1}{N} \sum_{i=1}^{N} \|(y_i - \widehat{y}_i)\| \tag{10}$$

Lower MAE values, like lower RMSE values, indicate greater model performance. MAE calculates the average magnitude of errors, regardless of their direction and provides insight into the average variance between the model's predictions and the ground truth ratings by considering the absolute disparities between predicted and actual ratings. In recommender systems, MAE analysis supplements the data that RMSE provides.

B. COMPARATIVE ANALYSIS OF RESULTS

We use the RMSE and MAE errors between the predicted tensor and the original rating tensor that was made after the data was gathered and transformed to judge how well the proposed KT-CDULF works. The investigation process shows how accuracy varies by category (RMSE and MAE), by subset of training and testing size (100:0, 75:25, 50:50), and how well the system fared with all four domains (movies, CDs, digital music, books) available in the data. Discussion on accuracy measures in detail is provided in the below sections. For each scenario, the results for both tri-matrix factorization and knowledge transfer are demonstrated.

1) DECOMPOSITION FOR IOT ENABLED CONTEXT

In this section, comparison for Matrix Tri-Factorization (MF) our first case scenario where the performance of KT-CDULF is evaluated for whole contextual (WC) data,

TABLE 4. MAE & RMSE values for latent decomposition of IoT enabled contextual data in all domains where subset = 100%, 75%, 50%.

Dataset	Split Ratio	RMSE	MAE
Movies	100:0	1.28541 ± 0.15	0.74309 ± 0.15
	75:25	1.19394 ± 0.09	0.76106 ± 0.11
	50:50	1.19783 ± 0.25	0.74179 ± 0.15
CDs	100:0	0.95925 ± 0.12	0.58359 ± 0.09
	75:25	1.22423 ± 0.09	0.73290 ± 0.05
	50:50	1.05322 ± 0.16	0.64142 ± 0.11
Digital Music	100:0	1.15109 ± 0.10	0.73585 ± 0.05
	75:25	1.04943 ± 0.24	0.65203 ± 0.17
	50:50	1.02305 ± 0.21	0.69875 ± 0.06
Books	100:0	0.97327 ± 0.06	0.57239 ± 0.04
	75:25	1.06518 ± 0.13	0.67106 ± 0.06
	50:50	1.04534 ± 0.12	0.74602 ± 0.08
Cumulative	100:0	1.16000 ± 0.09	0.70281 ± 0.08
	75:25	1.03501 ± 0.20	0.67701 ± 0.14
	50:50	1.01087 ± 0.06	0.75961 ± 0.23

is discussed. The WC scenario revealed a moderate level of variability in both the RMSE and MAE across all data subsets. The RMSE values for the Movies, CDs, Digital Music, and Books domain datasets at a subset level of 100% were 1.28541, 0.95925, 1.15109, and 0.97327, respectively. The values represented in Table 4 suggest a comparatively elevated degree of prediction inaccuracy in relation to the other two models. The CD dataset exhibited the lowest RMSE, signifying that the proposed KT-CDULF yielded the most precise recommendations for this subset when the data capacity was complete. Additionally, for the subsets 75% and 50%, a slight increase in RMSE was observed for each. This implies that the performance of KT-CDULF may be contingent on the size of the available dataset. The MAE exhibited a comparable pattern to that of the RMSE, indicating coherence in the evaluation criteria of the model, as shown in Table 4.

In comparison to the other scenarios, the performance of KT-CDULF was comparatively inferior. In both scenarios, partial IoT-enabled context (PC) data given in Table 6 and no IoT-enabled context (NC) data given in Table 8, the proposed model exhibited reduced prediction errors in terms of RMSE and MAE for identical datasets and subsets. The reliance of WC on the magnitude of the dataset for optimal performance could potentially pose a constraint, particularly in situations where complete datasets are not readily accessible or employable.

2) KNOWLEDGE TRANSFER FOR IOT ENABLED CONTEXT

In this section, the comparison for knowledge transfer (KT) in the first case scenario where the performance of KT-CDULF is evaluated for whole IoT-enabled context (WC) data is represented. Table 5 demonstrates that this methodology yields the greatest RMSE and MAE values across all domains, suggesting less accurate recommendations in comparison to the PC and NC scenarios. In line with other methodologies, the WC exhibits a diminishing pattern in RMSE and MAE metrics as the subset size decreases from 100% to 50% as shown in Table 5. Although the WC approach exhibits higher error rates, its incorporation of contextual factors may offer more tailored and pertinent recommendations, ultimately enhancing user satisfaction and involvement. This attribute presents a prospective benefit in comparison to alternative approaches and warrants contemplation when selecting a context-sensitive recommendation technique.

TABLE 5. MAE & RMSE for knowledge transfer in IoT enabled contextual data in all domains where subset = 100%, 75%, 50%.

Dataset	Split Ratio	RMSE	MAE
Movies	100:0	1.12981 ± 0.17	0.69202 ± 0.12
	75:25	1.49080 ± 0.17	0.97408 ± 0.10
	50:50	1.08117 ± 0.4	0.80698 ± 0.13
CDs	100:0	1.21157 ± 0.21	0.76691 ± 0.15
	75:25	1.15305 ± 0.10	0.71507 ± 0.05
	50:50	1.18903 ± 0.26	0.76036 ± 0.18
Digital Music	100:0	1.12814 ± 0.22	0.69491 ± 0.10
	75:25	0.88797 ± 0.14	0.82342 ± 0.07
	50:50	1.30291 ± 0.11	0.87397 ± 0.10
Books	100:0	1.20672 ± 0.18	0.76413 ± 0.13
	75:25	1.55781 ± 0.27	0.98257 ± 0.15
	50:50	1.48656 ± 0.14	0.95954 ± 0.05

Despite the higher error rates, the WC methodology offers the potential benefit of delivering more individualized recommendations by integrating context. Hence, the perceived substandard performance in relation to elevated RMSE and MAE metrics could be compensated by the supplementary benefit of customized recommendations, which have the potential to be more captivating.

3) DECOMPOSITION FOR IOT ENABLED PARTIAL CONTEXT

In the second scenario, the partial IoT-enabled context (PC) subset, which includes contextual features such as day, time, and season, yielded an initial RMSE of 1.31504 for the Movies domain when subjected to a 100% subset. This value was observed to be greater than that obtained from the WC for the decomposition case. As the subset decreases to 75% and 50%, this results in a decrease in the RMSE values to 0.96144 and 0.92014, respectively. This observation suggests that the model in the PC scenario may exhibit greater robustness to variations in the dataset size compared to the WC for decomposition. The aforementioned observation was reinforced by the analogous patterns detected in the CDs and Digital Music domains shown in Table 6. The dataset pertaining to the domain of the book exhibited a comparable pattern, regardless of relatively subdued magnitude. Table 6 demonstrates that a decrease in subset ratio resulted in a consistent reduction of error measured by MAE suggesting that the PC for the decomposition, model may possess robustness in scenarios where data availability is restricted.

In comparison, the proposed model exhibited a noteworthy enhancement in contrast to the WC for the decomposition case, specifically in terms of its robustness towards decreases in the size of the dataset.

4) KNOWLEDGE TRANSFER FOR IOT ENABLED PARTIAL CONTEXT

In PC for knowledge transfer (TF), the model enhances the precision of recommendations across various domains and

TABLE 6. MAE & RMSE for latent decomposition with partial IoT enabled contextual data in all domains where subset = 100%, 75%, 50%.

Dataset	Split Ratio	RMSE	MAE
Movies	100:0	1.31504 ± 0.10	0.86518 ± 0.06
	75:25	0.96144 ± 0.03	0.61691 ± 0.04
	50:50	0.92014 ± 0.12	0.57182 ± 0.04
CDs	100:0	1.15634 ± 0.03	0.74233 ± 0.04
	75:25	1.02868 ± 0.04	0.68521 ± 0.05
	50:50	0.85857 ± 0.08	0.53251 ± 0.00
Digital Music	100:0	1.15135 ± 0.02	0.79032 ± 0.01
	75:25	1.04508 ± 0.14	0.65406 ± 0.10
	50:50	0.84556 ± 0.09	0.55738 ± 0.07
Books	100:0	1.18615 ± 0.10	0.74871 ± 0.00
	75:25	0.96005 ± 0.01	0.62647 ± 0.01
	50:50	0.89652 ± 0.13	0.59985 ± 0.07
Cumulative	100:0	0.99961 ± 0.14	0.62518 ± 0.12
	75:25	1.14473 ± 0.12	0.79878 ± 0.10
	50:50	1.13893 ± 0.05	0.76715 ± 0.06

TABLE 7. MAE & RMSE for knowledge transfer in IoT enabled partial contextual data in all domains where subset = 100%, 75%, 50%.

Dataset	Split Ratio	RMSE	MAE
Movies	100:0	1.23905 ± 0.05	0.73146 ± 0.03
	75:25	1.06037 ± 0.07	0.66275 ± 0.03
	50:50	0.83143 ± 0.11	0.50304 ± 0.03
CDs	100:0	1.12766 ± 0.12	0.70472 ± 0.10
	75:25	1.10797 ± 0.04	0.67175 ± 0.01
	50:50	0.95467 ± 0.03	0.57177 ± 0.04
Digital Music	100:0	1.34171 ± 0.03	0.79619 ± 0.01
	75:25	1.08390 ± 0.04	0.67768 ± 0.02
	50:50	0.76823 ± 0.05	0.46375 ± 0.01
Books	100:0	1.20332 ± 0.03	0.72103 ± 0.06
	75:25	0.93149 ± 0.09	0.55942 ± 0.09
	50:50	0.75707 ± 0.12	0.46869 ± 0.06

split ratios, as evidenced by the significantly reduced RMSE and MAE metrics. In the domain of movies, the RMSE and MAE values obtained for a complete data split of 100% are 0.66297 and 0.28074, respectively. These values are notably lower in comparison to the WC for the KT scenario.

An interesting finding from Table 7 can be noted that PC for KT analysis, the error rates exhibit minimal variance irrespective of the ratio at which the data is partitioned. The findings indicate that the cold start problem is efficiently addressed, even in situations where limited data is available, as evidenced by the consistently low error rates observed across all domains. The empirical findings indicate that the employment of a 50% subset ratio consistently yields the lowest RMSE and MAE across all domains, thus highlighting the resilience of the PC for the KT case. The results obtained from PC for KT from Table 7 demonstrate its potential for cross-domain recommendation by utilizing partial contextual information, as it outperforms WC for KT by a significant margin.

5) DECOMPOSITION FOR NO CONTEXT

The no IoT-enabled context (NC) for decomposition, the model exhibited remarkable performance by demonstrating the lowest RMSE values across all datasets and subset ratios, thereby signifying its superior accuracy compared to other cases. It is noteworthy that a decrease in subset ratio resulted in a decrease in RMSE values, which was observed consistently across all datasets as shown in Table 8. The aforementioned pattern, related to the PC for decomposition, suggests that NC for decomposition exhibits outstanding performance even under conditions of limited data availability as shown in Table 8.

TABLE 8. MAE & RMSE for latent decomposition with no contextual data in all domains where subset = 100%, 75%, 50%.

Dataset	Split Ratio	RMSE	MAE
Movies	100:0	0.68618 ± 0.00	0.28881 ± 0.00
	75:25	0.62929 ± 0.00	0.25750 ± 0.00
	50:50	0.55557 ± 0.01	0.22510 ± 0.01
CDs	100:0	0.67135 ± 0.01	0.27705 ± 0.00
	75:25	0.64640 ± 0.01	0.27062 ± 0.01
	50:50	0.61025 ± 0.02	0.25161 ± 0.01
Digital Music	100:0	0.67829 ± 0.00	0.28605 ± 0.00
	75:25	0.62258 ± 0.01	0.26826 ± 0.00
	50:50	0.60870 ± 0.00	0.25078 ± 0.00
Books	100:0	0.67078 ± 0.02	0.27955 ± 0.01
	75:25	0.63764 ± 0.00	0.26921 ± 0.01
	50:50	0.58728 ± 0.00	0.24366 ± 0.01
Cumulative	100:0	0.70419 ± 0.01	0.30777 ± 0.00
	75:25	0.65851 ± 0.00	0.27818 ± 0.00
	50:50	0.62221 ± 0.01	0.26347 ± 0.01

TABLE 9. MAE & RMSE for knowledge transfer with no contextual data in all domains where subset = 100%, 75%, 50%.

Dataset	Split Ratio	RMSE	MAE
Movies	100:0	0.66297 ± 0	0.28074 ± 0
	75:25	0.64914 ± 0	0.27866 ± 0
	50:50	0.58623 ± 0	0.24309 ± 0
CDs	100:0	0.66273 ± 0	0.2796 ± 0
	75:25	0.64059 ± 0	0.2647 ± 0
	50:50	0.62165 ± 0	0.26502 ± 0
Digital Music	100:0	0.68601 ± 0.01	0.29567 ± 0
	75:25	0.65111 ± 0	0.25841 ± 0
	50:50	0.63264 ± 0	0.26911 ± 0
Books	100:0	0.64241 ± 0	0.26315 ± 0
	75:25	0.60582 ± 0.01	0.22871 ± 0
	50:50	0.58635 ± 0	0.22294 ± 0

6) KNOWLEDGE TRANSFER FOR NO CONTEXT

The NC for the KT case involves the exclusion of contextual data during the process of generating recommendations. Table 9 demonstrates that the lack of context results in comparatively reduced RMSE and MAE values in all domains. Comparable to the PC for the KT case, the NC for the KT case similarly exhibits a declining pattern in RMSE and MAE metrics as the subset ratio diminishes which is shown in Table 9. The reason for this is the use of a 2D matrix table for prediction instead of a 3D tensor, which is caused by the inclusion of context as shown in Figure 2. The results obtained from the NC for the KT approach demonstrate a noteworthy reduction in both RMSE and MAE values when compared to the PC for the KT case scenario.

7) COMPARATIVE ANALYSIS WITH NON-CONTEXT AWARE BASELINES

To compare the KT-CDULF with other benchmark studies such as traditional AF, MF [46], MF-CDRS [47],

TABLE 10. MAE Performance Comparison of proposed KT-CDULF with State-of-the-Art algorithms.

Algorithms	50:50	75:25	100:0
AF	0.8867 ± 0.00	0.8845 ± 0.00	0.8830 ± 0.00
kNN-CF	0.8346 ± 0.00	0.8294 ± 0.00	0.8225 ± 0.00
MF	0.7924 ± 0.00	0.7903 ± 0.00	0.7712 ± 0.00
AF-CDRSs	0.8671 ± 0.01	0.8817 ± 0.01	0.8726 ± 0.01
kNN-CDRSs	0.8250 ± 0.01	0.8172 ± 0.01	0.8280 ± 0.01
MF-CDRSs	0.7922 ± 0.00	0.7914 ± 0.00	0.7919 ± 0.00
FM-CDRSs	0.7826 ± 0.01	0.7783 ± 0.01	0.7712 ± 0.01
NL-EMCDR	0.7874 ± 0.01	0.7853 ± 0.01	0.7682 ± 0.00
KT-DiULF	0.7816 ± 0.00	0.7678 ± 0.01	0.7505 ± 0.01
KT-CDULF	$\mathbf{0.2796 \pm 0.00}$	$\mathbf{0.2647 \pm 0.00}$	$\mathbf{0.2650 \pm 0.00}$

TABLE 11. RMSE Performance Comparison of proposed KT-CDULF on Dataset with State-of-the-Art Algorithms.

Algorithms	50:50	75:25	100:00
AF	1.1635 ± 0.00	1.1603 ± 0.00	1.1588 ± 0.01
kNN-CF	1.1025 ± 0.00	1.0978 ± 0.00	1.0871 ± 0.01
MF	1.0809 ± 0.01	1.0741 ± 0.01	1.0701 ± 0.01
AF-CDRSs	1.1623 ± 0.01	1.1067 ± 0.01	1.1066 ± 0.01
kNN-CDRSs	1.1151 ± 0.01	1.1033 ± 0.00	1.0949 ± 0.00
MF-CDRSs	1.0804 ± 0.00	1.0829 ± 0.01	1.0847 ± 0.00
FM-CDRSs	1.0821 ± 0.01	1.0745 ± 0.01	1.0723 ± 0.01
NL-EMCDR	1.0877 ± 0.01	1.0711 ± 0.01	1.0701 ± 0.00
KT-DiULF	1.0801 ± 0.00	1.0718 ± 0.00	1.0649 ± 0.01
KT-CDULF	$\mathbf{0.6627 \pm 0.00}$	$\mathbf{0.6405 \pm 0.00}$	$\mathbf{0.6216 \pm 0.00}$

FM-CDRS [48], kNN-CF and kNN-CDRS [49], NL-EMCR [50], and KT-DiULF [36], a thorough investigation is conducted based on MAE and RMSE errors w.r.t to context-aware and non-context-aware studies. After conducting an analysis, it is observed that the proposed model, KT-CDULF, exhibited noteworthy enhancements in performance when compared to the other non-context-aware studies in evaluation throughout the subsets of all domains. The KT-CDULF exhibits exceptional performance as compared to other models represented in Table 10, consistently demonstrating superior results across all subsets. The proposed model exhibits superior performance as evidenced by its MAE values of 0.2796, 0.2647, and 0.2650, which are significantly lower than the corresponding values of 0.7924, 0.7903, and 0.7712. The algorithm's superior predictive accuracy and higher efficiency are indicated by its robust performance.

When compared to other models such as AF and kNN-CF, the MF model demonstrates a relatively strong performance to other methods. However, it is outperformed by the KT-CDULF model in carried experiments. Despite its stability, the AF model exhibits a relatively elevated MAE. Despite exhibiting consistent performance, the kNN-CF model demonstrates an elevated MAE, indicating sub-optimal prediction accuracy. The performance of various CDRS variations, including AF-CDRSs, kNN-CDRSs, MF-CDRSs, and FM-CDRSs, exhibit varying levels of performance. However, none of these models demonstrate comparable efficiency to that of the KT-CDULF model.

Similarly for RMSE, it is determined that KT-CDULF proposed model exhibits superior performance in comparison to other studies. This holds true across all three subsets. Superior model performance is indicated by a lower RMSE value, and it is apparent that the RMSE value for KT-CDULF is significantly lower than that of alternative models consistently across each domain. The model shows superior performance compared to other models as shown in Figure 6 evidenced by its RMSE values of 0.66273, 0.64059, and 0.62165, which are significantly lower than the corresponding RMSE values of 1.0809, 1.0741, and 1.0701. When comparing with AF, kNN-CF, and MF models, it can be observed that the AF model, despite its stability, presents relatively elevated RMSE values. The kNN-CF model exhibits a degree of stability, however, it is comparatively deficient in terms of predictive accuracy when compared with the proposed model.

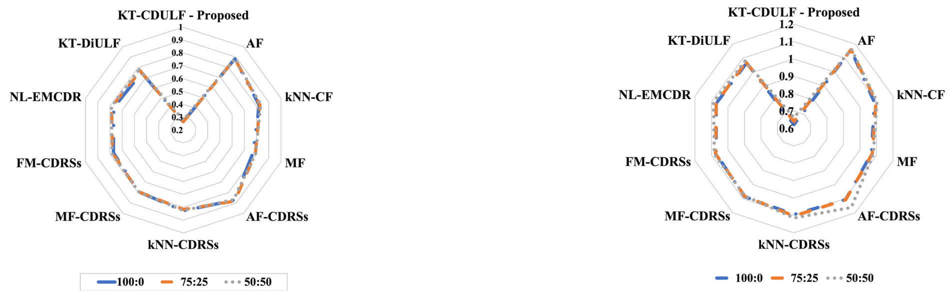
8) COMPARATIVE ANALYSIS WITH CONTEXT-AWARE BASELINES

In a similar fashion, we have carried the experiments to test the proposed model with context-aware benchmark studies such as CDRec [14], CD-CARS [9], and CD-SPM [51]. Based on the MAE performance of baseline models in comparison to the KT-CDULF outperforms demonstrating the efficacy of knowledge transfer techniques in enhancing the accuracy of recommendations.

Analyzing the MAE values across all subsets, it can be observed that traditional CF algorithms, such as kNN-CF and MF, produce recommendations with moderate accuracy. However, the proposed KT-CDULF model consistently outperformed these methods, indicating its ability to capture and transfer knowledge from related domains more effectively.

By combining collaborative filtering with knowledge transfer techniques, KT-CDULF is able to pass the limitations of conventional methods and provide more precise and personalized recommendations. The substantial reduction in MAE values attained by KT-CDULF suggests that leveraging existing knowledge can mitigate data sparsity issues and improve the overall user experience.

These results highlight the significance of knowledge transfer in recommender systems. By utilizing knowledge from related domains, recommender systems can access a broader range of data and enhance recommendation accuracy by leveraging the existing knowledge of similar domains. The accuracy of recommendations is directly associated with the quality of user experience. KT-CDULF shows a significant improvement in the current comparison by attaining a remarkable accuracy of 98.50% as shown in the Table 12. Through the use of Collaborative Filtering Contextual Matrix Tri-Factorization, and cumulative Knowledge Transfer this outcome not only indicates more accurate recommendations but also points to an effective handling of contextual data. In contrast, the CD-CARS algorithm, which utilizes both Contextual Prefiltering and Collaborative Filtering techniques, has demonstrated a noteworthy accuracy rate of 87.02%. However, an apparent disparity in performance exists between CD-CARS and KT-CDULF. The tangible



(a) MAE (b) RMSE

FIGURE 6. MAE & RMSE for Performance Comparison of proposed KT-CDULF on Dataset with State-of-the-Art Algorithms.

TABLE 12. Accuracy comparison of proposed KT-CDULF with State-of-the-Art algorithms.

Algorithms	Technique Used	Avg. Accuracy
CDRec-CAS (SRM)	Contextual Prefiltering, CF, and SRM	95.23%
CD-CARS	Contextual Prefiltering, and CF	87.02%
CD-SPM	CF, SPM, and SRM	86.59%
KT-CDULF - Proposed	**Contextual Matrix Tri-Factorization, and CF**	**98.50%**

impact of integrating contextual information to enhance accuracy is visible.

VI. CONCLUSION AND FUTURE DIRECTION

This study explores the potential of incorporating the Internet of Things (IoT) context into recommendation systems to improve their accuracy and personalization, reflecting the increased interaction of users with IoT devices. The primary goal is to leverage the knowledge transfer paradigm to address the classical cold start problem. To enhance model efficiency and provide a cost-effective solution, the proposed system utilizes the latent decomposition of three-dimensional rating data. The MAE and RMSE values were higher for prediction of rating using full context, due to the added complexity of predicting a three-dimensional matrix with an additional dimension of context, compared to the traditional two-dimensional user-item matrix. This reflects the challenge of integrating context-aware data, highlighting the model's ability to handle more sophisticated data structures even though it results in higher error rates.

Future research should focus on refining methods for integrating IoT data, considering the challenges and complexities of its complete aggregation. Advanced data processing techniques, such as feature engineering and outlier detection, can be applied to the chaotic and complex nature of IoT data to extract meaningful insights. Developing specialized algorithms and models that effectively leverage IoT data can further enhance the precision and personalization of recommendations. Moreover, the controlled and structured design and collection of IoT data are crucial. The random infusion of IoT data, as demonstrated, have shown the potential to capture the necessary contextual factors and user dynamics for accurate recommendations. A more sophisticated and systematic approach to accumulating and integrating IoT data, tailored to specific domains and user preferences, could lead to a deeper understanding of user behavior and preferences.

In conclusion, while the integration of IoT data in the recommender systems showed limited benefits, this study paves the way for future research to address the challenges and limitations. Recommender systems can get the most out of IoT data to make highly accurate and personalized suggestions across many domains by improving techniques for combining data, researching more advanced algorithms, and collecting IoT data in a controlled way.

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