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A global user profile framework for effective recommender systems

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Abstract
Modern Recommender Systems (RSs) compete to maintain rich user profiles that can accurately reflect user behavior, interests, and service contexts. While benefiting from an online service supported by an RS, user preferences and interests may rapidly change over time. To keep up with the changes from the user perspective, an RS should maintain the making of effective personalization as supported by robust profile construction methods. Building an effective user profile database requires exhaustive data and behavior analysis over extended periods. In this paper, we delve into traditional RS architectures to identify limitations, gaps, and opportunities for improvements in existing user profile mechanisms. To that end, a Global User Profile Framework (GUPF) is proposed towards achieving increased effectiveness. Furthermore, the adoption of the developed framework is exemplified by presenting different potential scenarios. The presented work concludes with the identification of important venues and research directions that are enabled by the proposed GUPF.

Keywords Global user profile · Profile ownership · Profile construction · Recommender systems

1 Introduction

With the development of web and mobile online industries, Recommender Systems (RSs) have become an essential technique to attract more income. RSs help users be efficiently directed towards items that best meet their needs and preferences [1, 2]. An important part of

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building an RS is constructing user profiles. From sparse data types, it is a challenge to formulate well-structured information about users and their preferences, especially since there are multiple types of users' profiles depending on available data [3, 4]. There are various techniques to follow to accommodate user preferences and generate valuable recommendations [4], such as, collaborative filtering [1, 5, 6], content-based filtering, knowledge-based, and context-based techniques [7]. Moreover, there are various methods to construct user profiles from different sources, like rating information, attributes of items, and user information and behavior [8].

Rethinking the traditional practice of improving the effectiveness of user profiling within the boundary of a single autonomous RS is a direction that may promise significant improvements. Specifically, a collaborative and global setup, among already deployed RSs, can lead to multiple desirable features. The idea of allowing RSs to promote careful user profile sharing, flexible customization, and improved distribution is a game-changer where reusability, accuracy, performance, and user's Quality of Experience (QoE) can be significantly elevated. Furthermore, such globalization promises better RS scalability, immunity from failure, control over cold starts, and significant time savings in effectively constructing user profiles. Throughout the surveyed literature, limited or no investigations were presented to address the aforementioned aspects of a Global User Profile Framework (GUPF). Accordingly, the research objectives of this article are as follows:

- Explore traditional RS Architectures as they relate to the user profile.
- Identify limitations and gaps in existing user profile mechanisms.
- Propose a GUPF that can address the limitations and close the gaps towards a more effective RS deployment and use.
- Exemplify the proposed framework by presenting different potential scenarios.
- Present the benefits of the framework.
- Identify the important venues and research directions that will be made open by the proposed GUPF.

The methodology of this article development is as follows:

1. Develop the search protocol for related work.
2. Search in recent outstanding published articles from the literature.
3. Develop classifications of related work.
4. Identify patterns in existing user-profile mechanisms in RSs.
5. Develop the generic GUPF.
6. Present recommendations on various important aspects.
7. Identify and propose future work.

This paper is organized so that Section 2 surveys the literature for similar work. In Section 3, the developed GUPF is presented along with the authorization, recommendation computation, feedback collection, and profile update processes. Section 4 presents a thorough discussion that comprises potential deployment scenarios and an analysis of the proposed framework. In Section 5, the paper is concluded.

2 Related work

The volume and variety of online data are increasing exponentially, making finding information and providing recommendations a significant hurdle that negatively affects smooth user experience. The use of different RSs, by service providers, results in various user experiences for the same requests, such as searching online for an item. In addition to the possible variation in RS techniques, each service provider stores different information and constructs different profiles for the same user.

In modern internet applications, user profiling offers the possibility to capture user-specific information, which then can be used to design personalized user experiences [9, 10]. User information is available from various online sources, like social media applications, professional/social networking sites, location-based service providers, and web pages. The format of user data is sparse, heterogeneous in type and structure, high in volume, and might change over time [11]. Collecting user data from separate sources to create complete and accurate user profiles is challenging [8, 12]. Thus, it is essential to dynamically build a structured user profile that considers the temporal nature of users' behaviors, take into account all data changes in the short and long term, and consider the types of user profile construction (See Table 1) [3, 4]. Natural language processing techniques, machine learning, and many more techniques can be employed to implement profiling [11]. It is very important to support the representation of generated user profiles so that RSs consume them to provide personalized services [13]. In [11], the authors presented a solution called "3D User Profile," where profiles are created from multiple sources. Such a multiplication of sources enriches the constructed profiles and enables personalization with high accuracy. Moreover, the same profile can be used across different applications to provide multiple services that are tailored for the needs of a specific user.

Table 2 presents the highlights, personalization approach, and suggested open issues of modern investigations on RSs with a focus on user profiles. The presented investigations varied across applications to include travel [15], heterogeneous information networks [8], e-learning [4], news [22], and movies RSs [23]. A variety of personalizations were presented, including techniques based on user preference across different domains [14, 17, 20], user activities and behavior [3, 11, 15, 21], besides a variety of other approaches based on user reviews, experience, interests, to name but a few.

From the investigated literature, several limitations and gaps were identified, including negative transfer in CDR systems [14], low effectiveness, accuracy, and decision-making [15], limited exploration of review age and review usefulness [16], lack of real-time online mode within a dynamic environment, poor explainability of user profiling, the cold start problem [8], targeting a single domain [17], limited investigation of the impact of time on user interests [18], lack of user dislike profile [19], limited interoperability [20], poor exploitation of short-term and long-term user preferences [21], lack of a framework to model user interests and track changes [22], in addition to data sparsity [25].

In the surveyed investigations, different open issues related to profile were also identified, including efficiency (time, throughput, and complexity) [3, 15, 18], effectiveness (accuracy, embedding users and items) [8, 14, 15, 17], usefulness [22], convenience [13], security [3], scalability [20], robustness [20], testing [23], interoperability [20], and integration of Artificial Intelligence (AI) & Machine Learning (ML) techniques and improving their learning process [4, 8, 15, 16, 20].

CDR has been proposed to leverage the relatively richer information (e.g., user/item information, thumbs-up, tags, review, and observed ratings) from a richer domain to improve the recommendation performance in a sparser domain [14]. CDR has received considerable attention from researchers in the last decade and has been extensively studied to address data sparsity and cold start problems. Heitmann et al. [26] proposed fully portable profile data through Semantic Web technologies (Friend of a Friend (FOAF), WebIDs[1], and the Web Access Control vocabulary). Using this method, profile data can be shared between services

[1] A way to uniquely identify a person, organization, or other entity using a Uniform Resource Identifier (URI)

Table 1 User profile construction types and their description

User Profile Construction Type	Description
Explicit	Includes gathering profile information through direct involvement of the user [4].
Implicit	Includes gathering information of the user through their indirect interaction with the system, like scrolling [4].
Hybrid	Includes both implicit and explicit types.

Table 2 State-of-the-art RS investigations, adopted architecture or framework, personalization approach, and suggested open issues with a focus on user profiles

Ref., Year	Title	Highlights	Personalization	Profile-related Open Issues
Zhu et al. [14], 2021	Cross-Domain Recommendation: Challenges, Progress, and Prospects	Presented different scenarios: Single-target Cross-Domain Recommendation (CDR), dual-target CDR, multi-target CDR, multi-domain recommendation.	Based on user preferences sharing across different domains	Improving accuracy; Optimizing the embedding of users and items; Avoiding negative transfer
Anjali et al. [15], 2021	User Profiling in Travel Recommender System using Hybridization and Collaborative Method	User profiling module: collection of information, constructing profile; Collaborative data: similarities between users and products, profile collection; Location information; User feedback: ratings and reviews; Data storage; Data processing; Hybridization recommendation method; Recommended products	Based on activities and behavior of active users and similar users in travel domains; Personalization includes a history of prior visits, suggestions, friend’s activity, reviews, ratings, user interests, and behavior analysis using location-based online services.	Improving effectiveness, accuracy, and decision making; Integrating machine learning techniques
Hernandez-Bocanegra and Ziegler [13], 2020	Explaining Review-Based Recommendations: Effects of Profile Transparency, Presentation Style and User Characteristics	An RS with personalized explanations and presentation styles.	Based on user reviews; Recommendations are explained to increase users’ perception of transparency or effectiveness; The effect of different display styles (bar chart and table) on the perception of review-based explanations is studied.	Testing the difficulty of understanding the improved explanatory part of user profile and its usefulness; Exploring the convenience of using reviews as the primary source for modeling user preferences in review-based explanatory methods.
Bilal et al. [16], 2020	Profiling Users’ Behavior, and Identifying Important Features of Review “Helpfulness"	A framework for modeling reviews helpfulness: Data collection and pre-processing; Profiling/feature engineering; Data analysis and statistical modeling	Based on the business choice, rating behavior, popularity, and experience.	Targeting multi-platform reviews and business domains; Analyze datasets of short-term reviews; Further explore review age and the review usefulness; Use machine learning algorithms to predict the usefulness of online reviews.

Table 2 continued

Ref., Year	Title	Highlights	Personalization	Profile-related Open Issues
Liang [8], 2020	DRprofiling: Deep Reinforcement User Profiling for Recommendations in Heterogeneous Information Networks	Graph environment: users and items; Intelligent agent environment based on deep reinforcement learning	Based on defining user profiling as the process of learning decision making for users in heterogeneous information networks.	Improving the learning process using training and testing using a real-time online mode within a dynamic environment; Consider explicit rating; Further improve the explainability of user profiling agent; Explore item-based reinforcement learning approach; Explore reinforcement learning approaches for the cold-start problem.
Sahu and Dwivedi [17], 2019	User Profile as a Bridge in Cross-Domain Recommender Systems for Sparsity Reduction	Source domain; Target domain; User profiles; Similarity computations; Graphical model building; Prediction	Based on similar profiles from different domains	Target different domains; Effectiveness of transfer learning
Kulkarni et al. [4], 2019	User Profiling Based Recommendation System For E-Learning	Flow: user keyword search, dynamic scrapping, hybrid filtering, user profile update, recommendation	Based on using a web crawler using keyword search	Integrating machine learning techniques
Eke et al. [3], 2019	A Survey of User Profiling: State-of-the-Art, Challenges, and Solutions	User profiling process: construction, collection methods, and updating; Profiling techniques: neighborhood, machine learning, ontology, or statistics-based.	Based on user interests, characteristics, behaviors, and preferences	Addressing domain dependence; Security; Trust; Efficiency; Cold-start problem; Multilingual profiles; Folksonomy; Computational complexity; Need for large datasets
Stakhiyevich and Huang [18], 2019	An experimental study of building user profiles for movie recommender system	Using cosine similarity between users and items to find the top recommendations	Based on aggregating all features of movies rated by the user	Studying the impact of time on user interests
Stakhiyevich and Huang [19], 2019	Building user profiles based on user interests and preferences for recommender systems	Using similarity between users and items to find the top recommendations	Based on the general descriptions attributes of items reviewed by the user	Investigating negative user reviews and building a user dislikes profile
Zang et al. [20], 2018	A Survey on Cross-domain Recommendation: Taxonomies, Methods, and Future Directions	CDR: Combinations of different user and item overlapping (non-overlap, partial overlap, and full overlap)	Based on user's interactions in different domains.	Adopting latest advances in Deep Learning; Exploring robustness of recommendation; Scalability; Interoperability

Table 2 continued

Ref., Year	Title	Highlights	Personalization	Profile-related Open Issues
Zhu et al. [21], 2018	A Dynamic Personalized News Recommendation System Based on BAP User Profiling Method	News collection and processing; Profile of user and construction; Short-term and long-term user preferences are considered in order to generate personalized news recommendations using BAP method	Based on user behavior and news popularity	Exploring providing a dynamic method for news recommendation in which both short-term and long-term user preferences are considered
He et al. [22], 2018	UP-TreeRec: Building Dynamic User Profiles Tree for News Recommendation	Using a decision tree with a dynamically changeable structure to construct a user interest profile	Based on dynamic user feedback	Modeling user interests and track changes
Uyangodage et al. [23], 2018	User Profile Feature-Based Approach to Address the Cold Start Problem in Collaborative Filtering for Personalized Movie Recommendation	Main data inputs; Feature score calculation; User profile creation; User profiles similarity calculation; Rating predictions generation; Predicted rating	Based on users' past interactions with movies	Testing the system with different datasets
Li et al. [24], 2018	Leveraging Reconstructive Profiles of Users and Items for Tag-Aware Recommendation	A Generative Adversarial Network is used to create profiles of users and items for tag-aware recommendations; Relevance scores are calculated as the similarity between the user and item represented by outputs of the disentangling network	Based on the top relevance scores attained by a set of items	Exploring simultaneously generating item recommendations and interesting tags for users.
Chen et al. [25], 2017	Modeling User-Item Profiles with Neural Networks for Rating Prediction	Usage of Neural Networks	Based on generating improved personalized recommendations through solving data sparsity-related issues	Addressing data sparsity
Krishnan and Kamath [11], 2017	Dynamic And Temporal User Profiling For Personalized Recommenders Using Heterogeneous Data Sources	Data collection from online sources; Application Programming Interfaces; User profile	Based on static, dynamic, and activities data	Improving personalization by having one user profile to all online services; Dynamically build a structured user profile that captures the dynamic user behavior

of an ecosystem, and the users can decide the parts of their profiles to be shared with each provider. The user's privacy is protected by allowing multiple data providers to only host a partial view of the user's profile. A formal statement of the CDR is formulated in [27].

A comprehensive review of existing CDR approaches has been included in [20]. As users are using different domains (e.g., books, movies, music), there is a need to consider how to transfer knowledge among domains which leads to two main issues: 1) what to transfer by mining useful knowledge in each domain and 2) how to transfer by linking between domains and transferring the knowledge. The survey proposes a two-level taxonomy of cross-domain recommendation, which identifies nine recommendation scenarios based on the overlap of user/item sets and four recommendation tasks based on whether the recommended items and the user belong to the same domain and whether the number of target domains is single or multiple. Many methods have emerged and have been used to address these issues such as extracting cluster-level rating patterns, capturing tag correlations, applying active learning, collective matrix factorization, embedding and mapping, graph neural network-based approaches, tensor factorization, and deep dual knowledge transfer [28, 29]. User profile as a bridge in CDR for transferring knowledge between domains is proposed in [17]. A user profile is built using demographic information of a user, explicit ratings, and content information, and the probabilistic graphical model is used to learn latent factors of users and items by maximizing posterior probability.

The authors in [30] presented a thorough review of a substantial amount of research on psychology-informed RSs along with three categories: cognition-inspired, personality-aware, and affect-aware RSs. These systems leverage psychological constructs and theories to model and predict user behavior and improve the recommendation process. The most commonly used model in the context of recommender systems research to describe human personality traits is the Five Factor Model (FFM) [31]. The FFM model describes personality along the following five dimensions:

1. Openness to experience (conventional vs. creative thinking).
2. Conscientiousness (disorganized vs. organized behavior).
3. Extroversion (engagement with the external world).
4. Agreeableness (need for social harmony).
5. Neuroticism (emotional stability).

A user study with over 1,800 subjects in [32] found that personality traits of users can infer the users' preferences for recommendation diversity, popularity, and serendipity, and that user satisfaction increases when personality traits are incorporated into the recommendation process. This correlation between user preferences and personality traits is also investigated in [33]. In their work, a study of 1840 users of the MovieLens recommender system using the FFM of personality types [31] is conducted. Personality traits correlate significantly with behaviors and preferences such as newcomer retention, the intensity of engagement, activity types, item categories, consumption versus contribution, and rating patterns.

3 Global user profile framework

In this section, we will describe the Local User Profile Manager (LUPM) which is currently in use in all RSs, followed by the target features and the design considerations for an enhanced User Profile Manager (UPM). The new Global User Profile Manager (GUPM) is proposed, and a description of the involved processes (e.g., authorization, recommendation computation, and profile update) is also included.

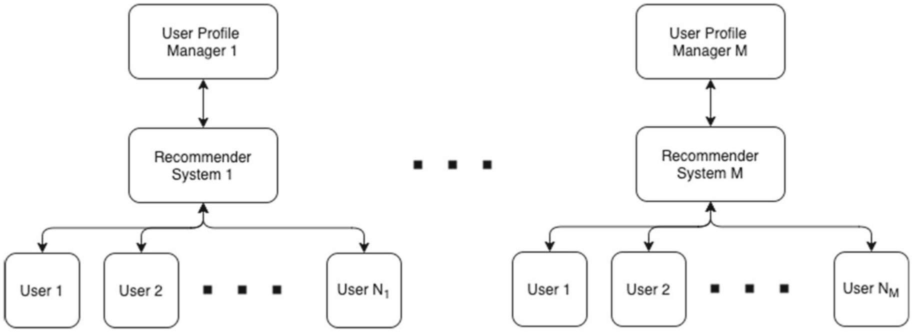

Fig. 1 Local user profile management

3.1 Local user profile management

In the typical Local User Profile (LUP) management, a recommender system is composed of an application that provides users with recommendations based on a local UPM as shown in Fig. 1. The UPM maintains a collection of users' profiles, and the recommendation module is used to generate recommendations for users.

Figure 2 shows the sequence diagram for a typical traditional LUP management. Two important processes are described: recommendation computation and feedback collection.

3.1.1 Recommendation computation

- **Recommend (1a):** For the recommendation process to start, a recommend event is generated to trigger the recommendation process. This triggering can happen every specified time when a significant amount of user data becomes available or upon user request or activity, for example, when the user interacts with an item.
- **Get Data (1b):** The application engine sends a request to retrieve the users' profiles.
- **Data (1c):** In addition to the other collected users' profiles, the user profile will be sent for the recommendation computation. A logically centralized server is usually used to store these collected users' data.

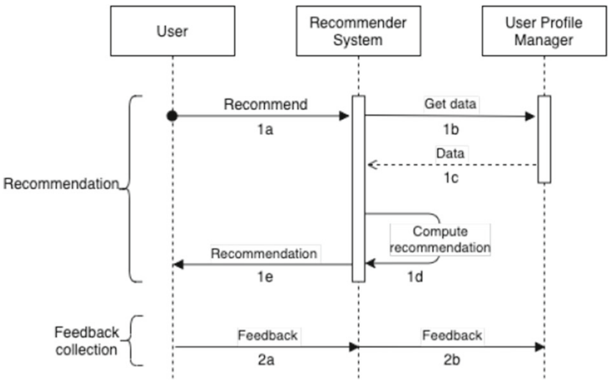

Fig. 2 The sequence diagram for the local user profile management

- **Compute Recommendation (1d):** The computation of the recommendations will be performed by taking into account the user profile to generate recommendations according to their interests.
- **Recommendation (1e):** The generated recommendations will be forwarded to the user.

3.1.2 Feedback collection

- **Feedback Submission (2a):** The data collection process begins by receiving data from users. Explicit feedback such as ratings can be submitted by users of a specific application via their user interface. Implicit feedback based on user activity may also be collected from the users.
- **Feedback Storage (2b):** The application receives user feedback and updates the user's profile accordingly.

3.2 Target features

Having a local profile for every application or service provider has several limitations. It takes a long time to build a user profile with a service provider to obtain valuable recommendations. To update his profile, the user has to make several purchases/views/downloads. This profile construction is repeated for the same user for each application. Once users move from one application to another, this valuable information regarding users' likes/dislikes and preferences is no longer available. In addition, each service provider has a limited view of the user's preferences, resulting in a fragmented user profile. The local profile of a user within an application is not updated when this user interacts with another application. Therefore, the application may use a stalled user profile, resulting in poor recommendations. Furthermore, the user has no control over his own local profile in terms of added or updated data. Also, fragmented user profiles limit innovation in terms of designing more efficient recommender systems due to the lack of relevant information as a result of cold start and data sparsity.

In this paper, we propose to take advantage of this profile and make it shareable for better recommendations. Sharing the user profile helps provide new insights into the user likes and dislikes and better understand user preferences from different dimensions/angles and make more relevant recommendations accordingly.

The following is a list of motivation points for a unified user profile:

- Persistence: Having a unified profile prevents the loss of crucial historical user data if the service provider is unavailable, either temporarily due to connectivity loss or location-based censorship or permanently due to the cease of activity.
- Completeness: Instead of having a fragmented profile with user preferences scattered across different service providers, a unified profile will allow the user to have a complete representation of their preferences spanning the various areas of interest and including various aspects (preferred/detested movies, books, music, hotels, restaurants, food).
- Freshness: A unified profile will allow the user to have an always up-to-date representation of their preferences. Having multiple partial profiles, as is the case currently, will ultimately lead to the staleness of the data.
- Control: The user will control who has access to which part of their profile. They should be able to grant read or write access to specific profile components. For example, a user can give Amazon read and write access to book preferences but can deny or give only read access to hotel preferences. If needed, the user can also control the frequency and sources of updates to their profile. This is not dissimilar to the idea of the Open Researcher

and Contributor IDentifier (ORCID) [34], where the researcher profile can be updated regularly from different sources with user approval. The user will also control which part of their profile will be available to which service provider. Like the concept of views in databases, the user can control which part of their profile gets taken into account by the recommendation algorithm.

- Relevancy: Possibility of new and more relevant recommendation algorithms thanks to:
  - Data fusion: New recommender systems can take advantage of the different parts of the user profile by fusing relevant essential data. For example, a customer's book preferences may affect their movie preferences and can be used for movies' recommendations.
  - Context-awareness: A unified profile will allow a better assessment of the customer context, which will allow more relevant recommendations.
- Mitigation: Potential to provide a solution to the *cold start* and the *data sparsity* problem that most RS suffer from. Applications with no information on a new user can use the existing profile to make accurate recommendations. For example, the books read by a user (e.g., from Amazon) can help in recommending some movies (e.g., from Netflix), some videos (e.g., from YouTube), and some music (e.g., from Apple Music or Spotify).

3.3 Global user profile management

In this proposed framework, the recommender system is composed of an application that provides users with recommendations by using three entities, as shown in Fig. 3.

These entities are the following:

- The GUMP is responsible for collecting and storing user data for the applications.
- The recommender system uses a recommendation module responsible for computing the predictions and generating the recommendations.
- The private UPM manages its own users' profiles and uses this collective intelligence to produce personalized recommendations. This UPM is the LUMP for each system.

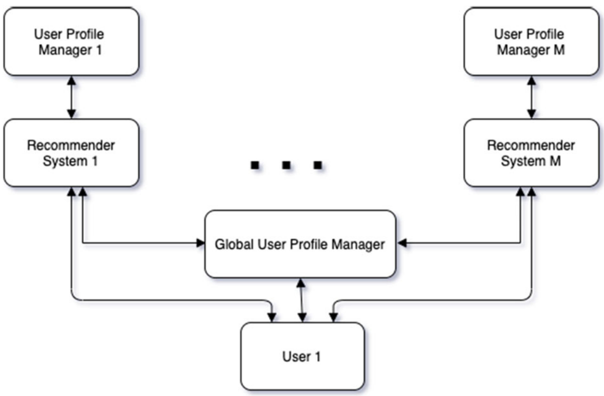

Fig. 3 The architecture of the global user profile framework

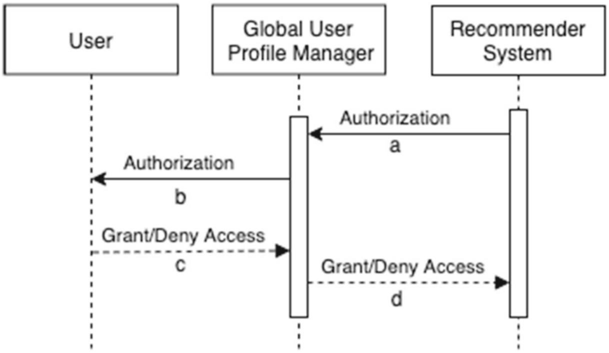

Fig. 4 Authorization Phase.c

3.3.1 Authorization

After authenticating the user, the recommender system asks the user for authorization to access their profile. This is a mechanism to allow the user to retain full control over their profile, a target feature of GUPF. The authorization module is typically not used in the local user profile scenario, as the user has no control over his profile, and the updates are performed at the discretion of the service provider. The authorization process goes through the GUMP. Access can be to the whole or a portion of the profile as specified by the user. The user can also limit the access to specify one-time or a specific period access. These choices are retained and managed by the GUMP. An RS with expired access has to go through the authorization phase to restore its access. Figure 4 shows a typical sequence diagram for the authorization phase.

Figure 5 shows the sequence diagram for the two important processes: recommendation computation, and feedback collection and storage.

3.3.2 Recommendation computation

- **Recommend (1a):** For the recommendation process to start, a recommend event is generated to trigger the recommendation process.

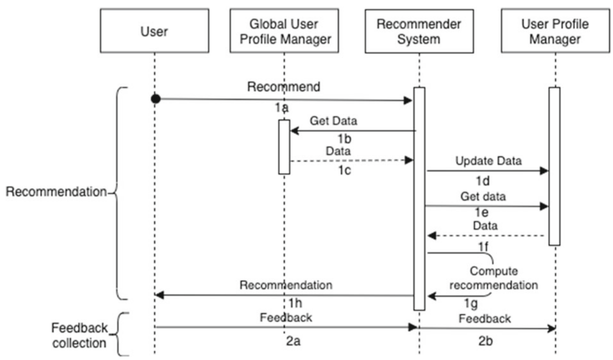

Fig. 5 Recommendation and feedback collection phases

- **Get Data (1b):** The application engine sends a request to the GUMP for the retrieval of the user's profile. This entity is accessible by the recommender systems. It provides a shareable platform for the user's profile.
- **Data (1c):** The user profile will be sent to be used in the recommendation computation.
- **Update Data (1d):** The application engine sends a request to its UPM to update the user's profile based on the received user data.
- **Get Data (1e):** The application requests the collected users' data from its UPM.
- **Data (1f):** The UPM sends the collected users' data for the recommendation process.
- **Compute Recommendation (1g):** The computation of the recommendations will be performed by taking into account the user profile to generate recommendations according to their interests. At this stage, computations can be performed according to the fixed and chosen recommendation method.
- **Recommendation (1h):** the generated recommendations will be finally forwarded to the user.

While the recommendation computation in the LUP scenario involves two entities: the RS, and the UPM of the service provider, the same process in the GUPF involves an additional entity, GUPM, responsible for managing the Global User Profile (GUP). The service provider takes advantage of this request for recommendation to update its local profile for this user from the GUMP. Another difference with the LUP scenario, is that the recommendation computation can involve elaborate mechanisms like data fusion, thanks to the rich user profiles it has access to.

3.3.3 Feedback collection

- **Feedback Submission (2a):** The data collection process begins by receiving data from users. The user can submit explicit feedback such as ratings, and it is handled by the RS.
- **Feedback Storage (2b):** The application receives user feedback and updates the user's profile accordingly.

3.3.4 Profile update

The global profile's updates are under the user's control. The user gets notified of the available updates and can control which updates will go to their profile. For trusted RSs, the user can opt for automatic updates, while the user can approve the updates individually for the less-trusted ones. Figure 6 depicts a typical update phase.

The feedback collection processes in the LUP and GUP scenarios are similar. In both cases, the user sends his feedback to the local UPM of the service provider. The main difference lies in how the global user profile is updated. While in both scenarios the local UPM of the service provider can update the local user profile, in the GUPF, the global user profile update needs the user's approval. This is enforced by the GUPM before allowing any update to the global profile of any user.

3.3.5 Hybrid feedback

The user profile is based on the submitted feedback (e.g., explicit ratings). Temporal and spatial information related to items/services, along with relevant keywords and descriptions, can also be collected and added to the GUP to increase the recommendations' accuracy. Data

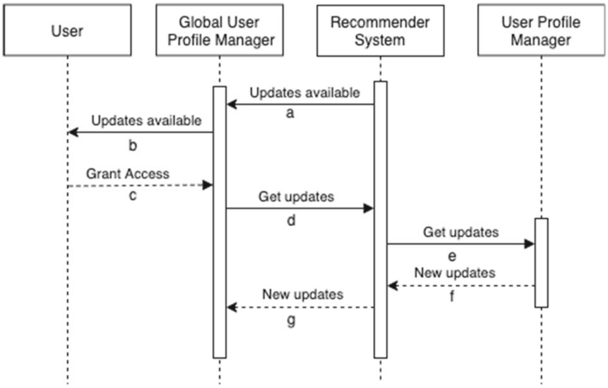

Fig. 6 Profile update phase

can also be collected implicitly from user activity (e.g., the number of clicks, percentage scrolled of a webpage, browsing history). User's activity can create valuable data that can be mined to generate efficient recommendations.

Two possible scenarios can be considered. In the first scenario, the service provider can collect and keep the implicit feedback as private information. This collected information is internal, private, and can be managed by its local UPM. This implicit information can be used as a competitive edge to differentiate among the generated recommendations by different service providers. In the second scenario, the Service Provider (SP) can collect this implicit information, update its local UPM and also the GUPM for the users. Providing hybrid feedback by combining explicit and implicit feedback will add their advantages and power. This can significantly improve the effectiveness of the recommendation process.

4 Discussion

We present in this section potential scenarios of the proposed framework. We also describe the compelling features of the GUPF such as transparency, persistence, and accuracy. In addition, we discuss issues related to user data models in the context of RS, the corresponding advantages and challenges, and customization within the proposed framework.

4.1 Potential scenarios

The GUP is similar in concept to ORCID [34]. ORCID provides a unique, persistent digital identifier (i.e., an ORCID) that a researcher owns and controls forever. This is how a researcher is distinguished to avoid any confusion or ambiguity. This ORCID can connect the researcher with their professional information, grants, publications, and much more. It can also be shared with other platforms to receive credit for their contribution.

Figure 7 presents an overview of the recommendation process in typical GUPFs and highlights some of their important aspects. The figure attempts to confirm the fact that RSs are critical and integral subsystems of mainstream online service providers, such as Netflix, Amazon, and Facebook. The RS communicates with users to input queries, ratings, tracked behavior, human and social attributes, and possibly their QoE, and outputs personalized

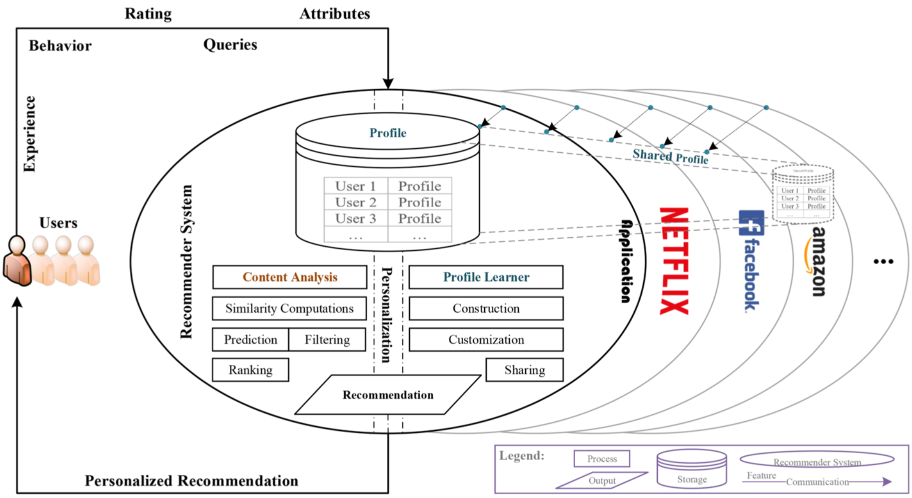

Fig. 7 An overview of the recommendation process in a GUPF

recommendations. A typical GUPF enables constructing profiles based on information amalgamated from different service providers. Processes within a GUPF may comprise content analysis, filtering, similarity computations, profile learning, prediction, ranking, customization, and finally, generating personalized recommendations.

The following scenario describes how different service providers can adopt the proposed framework:

A user showed some interest in Business books. He recently bought a book from Amazon entitled "Starting a Business QuickStart Guide: The Simplified Beginner's Guide to Launching a Successful Small Business, Turning Your Vision into Reality, and Achieving Your Entrepreneurial Dream.". The user has submitted an excellent rating on different business books. Based on the feedback submitted to Amazon in the GUPF, this user will receive some videos from YouTube on how to start and run a small business explaining a step-by-step basics guide. Rating positively some of the videos shows that the user is eager to run a business successfully. Based on the stored feedback in the GUP from both Amazon and YouTube, this user will also receive some recommendations on movies based on real-life from Netflix such as "Joy" and "The Pursuit of Happyness." These movies are interesting, helpful, and inspiring masterpieces for entrepreneurs. CDR is also possible, and Amazon can recommend some electronics and stationery for the new startup. Benefiting from the collective intelligence of RSs users and harnessing their wisdom in making the appropriate choices in addition to the detailed user profile in the GUP, empower these systems in generating valuable and tailored recommendations.

4.2 Relationship with cross-domain recommendation systems

CDR has been proposed to use the information available in a richer domain to improve the performance of the recommendation in a sparse domain. Indeed, knowledge learned in one source domain could be transferred and exploited in another target domain.

GUPF allows for the creation, maintenance, update, and management of user profiles for recommendation systems. This global profile is updated based on the interactions and behavior of the user within different domains. CDR can be used to interpolate user preferences in a domain not yet available in the user's global profile. GUPF hence allows for CDR in the case of new user profiles, but also allows for recommender systems based on data fusion in the case of more rich user profiles. Furthermore, traditional CDR systems often have only a partial overlap of users and items. By design, the GUPF is based on combining different domains. Because it contains different ratings for various service providers for the same users, it provides complete overlap of users in the context of CDR, allowing full benefits from these systems. Additional benefits of the proposed framework are listed in Section 4.4.

4.3 User data model

According to [35], a user profile is defined as an instance of a user model that is an explicit representation of the properties of a user, including needs, preferences, and physical, cognitive, and behavioral characteristics. The user profile is used to express users' preferences or future behavior. Integrating user profiles within a service/application, or transferring profiles from one service/application to another is challenging due to the heterogeneity of users' profiles among different contexts. In [36], the World Wide Web Consortium developed the Composite Capabilities (CC)/Preference Profiles (PP) framework. In this work, CC/PP allows defining user and device profiles for an appropriate adaptation of resources in terms of content and presentation for internet services. It is stated that e-commerce and e-learning are the major sources for the development of user models and several user modeling tools were created to adapt content to users' preferences.

In [37], the authors describe personalization and profile management activities at European Telecommunications Standards Institute Technical Committee Human Factors and other European research projects. One way to reduce the inconsistency among different devices/services is to set a consistent set of parameters having value ranges producing the same effects for different devices/services of the same type.

Similar works have also been realized to develop Universal Electronic Medical Records for the patients in e-health systems [38]. In the context of recommendations, a unified user profile can also be realized to accommodate different users' preferences according to various service providers.

4.4 Analysis

4.4.1 Data quality

Several metrics have been proposed to measure the quality of the data [39]. The proposed GUPF presents the following features as related to data quality:

- **Transparency:** The users manage ratings as they own their profiles. The process of profile management is transparent to the users and it is not hidden as is the case in LUMP.
- **Persistence:** The historical user data is managed by the GUMP. All the submitted ratings are saved.
- **Accuracy:** The user profile contains the ratings as submitted by the user, hence, the data is accurate.
- **Profile Ownership:** The user owns his profile and can permit different views according to his needs.

- **Privacy:** Preserving user privacy is important as the data used in recommendation computation may be sensitive. This issue is alleviated as the user privacy is preserved, and only a partial view of the data may be shared with the user's permission.
- **Control:** The user controls who has access to which part of their profile. It is accessible to authorized service providers, upon permission from the user.
- **Availability:** The availability of the user's profile does not depend on the availability of any service provider.
- **Completeness:** The user profile is complete as it includes all the submitted ratings for the different recommender systems, including the temporal, spatial, and social information.
- **Current:** Users' interests change over time, and their ratings of items may evolve with time. The user profile is constantly updated, and hence, it reflects the user's preferences, including the new trends and the recent preferences' changes. The latest changes in preferences are captured in the user's profile by adding temporal information.
- **Integrity:** Users' profiles are owned and managed by the users, increasing the content's integrity. The data is protected from being modified or misused by an unauthorized party. Hence, ensuring the trustworthiness of data.
- **Confidentiality:** Users' profiles are managed by their owners to protect the information from being exposed to unauthorized parties.
- **Consistency:** The submitted ratings by users for different SPs are compatible and congruous. A user who does not like action movies will probably not read action books. This consistency can help in exploring the hidden relationships between the different items.
- **Uniqueness:** As the user is discovering and exploring new products and services from different service providers, their profile is enriched by various experiences reflecting their interests, preferences, and up-to-date trends. Only the shareable user profile stores all the submitted ratings for different items. Capturing the user's choices over time makes their profile unique as it summarizes their online experience.
- **Timeliness:** This metric refers to the time expectation for availability and accessibility of information. Once the users submit their ratings, their profiles get updated and are ready to be used by service providers for recommendations.

4.4.2 Customization

While providing explainability to the users on the output of recommendations may increase the users' trust, explaining the concepts of the used techniques (e.g., content-based, collaborative filtering, hybrid) may not be easy for the users to understand. Therefore, providing the users with metrics to choose from (e.g., novelty, diversity, and serendipity) may produce better results in achieving customization [40–42].

A customization feature can be integrated into the GUPF to choose which metrics are essential to the users. Customization features and the user profile can be forwarded to the application to receive personalized recommendations. The recommender system will choose the function or method to be used when computing item scores accordingly.

For example, a user who is interested in receiving new and diverse suggestions in books (i.e., the user prefers novelty and diversity), is also interested in acquiring new and diverse movies recommendations. Looking for novelty, diversity, or serendipity is a characteristic of the user and can be incorporated in their profile in the proposed framework.

In fact, the FFM model can be included in the user profile to generate personalized recommendations. Each personality dimension is described along a given multi-point rating scale, e.g., between 1 and 5, and therefore, each user can be characterized by five values. In [30], an approach that resembles memory-based collaborative filtering where similarities are computed over personality trait vectors rather than rating vectors is adopted to calculate users' similarity. Service providers may adopt the appropriate technique based on users' personality traits.

Another innovative technique that can also be incorporated into the proposed framework is using human affect. Affect plays a crucial role in human life, and it is commonly categorized into mood and emotion [30]. While mood is an affective experience that lasts from minutes to hours, emotion is an affective response to a particular stimulus that lasts from seconds to minutes. Personality traits, mood, and emotion can be integrated into the user profile to produce appropriate recommendations correspondingly.

The GUP represents the online version of the user summarizing their demographic information, online transactions, activities, ratings, and content information of rated items (e.g., keywords, temporal and spatial information). Personality traits, mood, and emotion play a crucial role in users' preferences and decision-making. Capturing and integrating these characteristics in the GUPF provides relevant information on the person behind making these choices and decisions.

4.4.3 Benefits

Although traditional user profiles are easy to use and manage since all the information related to users' preferences is stored at the service provider, the GUPF provides the following benefits:

- **Reducing the cold start problem:** The problem results from the lack of ratings of new users to a SP, and hence, their interests and preferences are not yet known to the SP to produce sound recommendations. The proposed approach reduces the cold start problem by making the existing GUP available to new service providers.
- **Reducing the data sparsity problem:** This problem occurs when only a few ratings are available. Since the GUP has contributions from different SP for the same items, the data sparsity problem is reduced.
- **Better user experience:** Thanks to the cross-domain nature of the GUP that reflects real users' interests and preferences, RSs can filter out irrelevant recommendations, saving time and effort for users and increasing the recommendations' accuracy, the user's satisfaction, and enhancing the overall user experience.
- **Joint recommendations across different domains:** The GUP can be used to generate joint recommendations of a line of items in multiple domains. For example, recommending a movie, the original novel, the film soundtrack, movie merchandise, and much more. By recommending different items across different domains, users get nudged and persuaded to get more items, increasing profits and revenues from the service provider's side. The users on the other hand will be offered novel, diverse and serendipitous products, and services.
- **Reducing the user elicitation effort:** The detailed user profile contains all the ratings for accurate user profiling. Users do not need to continuously submit explicit feedback after some time unless to express a shift in interests or integrate their evolving requirements.

5 Conclusion

The effective construction and proper adoption of user profile frameworks enable wide opportunities to improve the operation and performance of modern RSs. In this paper, we propose a GUPF that promotes accuracy, completeness, user ownership, and many more appealing features through a global integration of user profiles. The paper presents a description of the local and global user profile management, focusing on recommendation computation, and feedback collection. The expected primary outcomes of adopting the proposed GUPF include reducing the cold start problem, reducing data sparsity, improving user experience, improving quality of recommendation, and enabling joint recommendations across domains. Challenges to the proposed framework include creating a data model for the GUPF, its implementation, and promoting its adoption. Future work includes the practical realization and embedding of the proposed GUPF in modern RSs and applications.

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