User Profile: Theoretical Background

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Abstract
The user profile is commonly used nowadays to support personalization, web search, adaptation and any other user-based features applications including recommendation systems. User profiles are a data structure that is used to store user's characteristics and preferences. Therefore, it has a significant impact on the recommendation accuracy. However, it contains more sensitive information about the user, such as demographic characteristics and physical location that reveal privacy.

There are different models for user profile representation in the literature. Each has its advantages and disadvantages. The most frequently used models are reviewed in this paper. Moreover, this paper investigates the most widely used approaches that handle privacy issues in the user profiling.

Keywords: *user profile, Level Of Interest, Privacy, Recommender System*

I. Introduction

User profiles are a data structure that is used to store user's characteristics and preferences. They are commonly used nowadays to support personalization, web search, adaptation and any other user-based features applications including recommendation systems. Such applications are automatically adapted according to the user's behavior and preference represented in the user profile. Especially, user profiles are considered a key component of most recommendation system (RS).

A user profile can incorporate static data as demographic information (e.g., age, gender and habits) [5] and dynamic data as online user's behavior (e.g., purchase basket placement and click-through) [2,3, 4]. User profile recently starts to incorporate contextual information such as time and user's physical location[40, 11,41]. The recent trend of all applications is to develop user profile that combines personal and contextual information. This enables them to decide what's relevant to the user in a particular situation depending on dynamic parts of profile and context [7].

User profile data can be collected from various data sources including online users' behavior extracted from log files, their own generated content, their social interactions data from the social network, or other user profiles using collaborative filtering techniques[8,9].

This paper is structured as follows: section 2 investigates different user profile aspects. Section 3 introduces Level Of Interest (LOI) measures that estimate the degree of importance of elements to a given user. Several user profile models are discussed in section 4. Section 5 introduces mobile user profile and its recent studies. The privacy issue and various approaches handled within user profiling are investigated in section 6. Conclusion is presented in section 7.

II. User Profile Aspects

A. Static User Profile

The static user profile involves general static dimensions of the user's characteristics. The user explicitly creates its profile through rating items, filling registrations, or making a private account. Hence, user preferences are determined by analyzing the available data.

User preferences can be learned explicitly through rating or voting. For instance, Barragans Martinez, B. et al. give initial choices about movies by asking users what they like about genres of movies[10]. Hence, preferences are updated by explicit voting of users or implicit inference of their behaviors. Additionally, users can provide their preferences through a user feedback like a review [2,3, 4].

The static user profile may also incorporate demographic data that refer to personal characteristics, including age, gender, education, abilities, and experience. Users with the same demographic data have similar behaviors and preferences. Lika, B., et al. infer a user's preference for new users through the identification of the other users who have the same demographic data [5]. The static user profile provides accurate recommendations. However, it is time-consuming and is very tedious for the user.

B. Dynamic User Profile

A Dynamic User Profile was introduced to implicitly infer users' preferences by tracking their behavior or incorporating user-generated data. User-generated data can be tags [6,7], reviews[2,3, 4] and social interactions with other users such as online friending, posts, comments, and tags. Huang, C.,L., et al. capture a user's interests by analyzing user tag information[8]. The research considers the frequency, duration, and recency of social tags to face dynamic changes of user's interests over time. Sun, Z., et al. incorporate social network information such as user's friendships and tags to predict the missed user's preference[9].

Furthermore, user preferences may be learned from the user's context. The user's context is the information that can be used to depict the user's situation, including time, geospatial data or group of related people such as friends or family members. Kawashima, H., et al. infer implicitly the user's degree of interest for each product within the distance between users and products[14]. The position of products and users has been determined by using RFID. Fang, B., et al. estimate implicitly the user's preference for a brand store by averaging time spent in a store, frequency of entering the store and promotional offers factors[5]. Blanco-Fernandez, Y., et al. applied a Time-aware filtering technique to get users' preferences by considering the change of preferences over time[15]. The Dynamic User Profile aspect provides less recommendation quality when the user has little prior data (represented in the cold start problem).

C. Hybrid User Profile

This aspect of user profile combines advantages of both static and dynamic user profiles to obtain accurate user preferences and intentions. It considers the static user's characteristics and learns about their behavioral data. For instance, Costa-Montenegro, E., et al. detect implicitly the preferred mobile applications, depending on a combination of historical consumed applications, used patterns, and previous tagging of applications and history of ratings[16]. This profile aspect is more efficient and improves recommendation accuracy as it continuously updated to reflect the user's temporal preferences.

III. Level of Interest

User profiles consist of a set of interesting elements to the user along with his level of interest (LOI) for each. LOI measures the degree of importance of elements to a given user. LOI can be calculated explicitly by asking users to rate an item or implicitly by tracking users' behaviors. User LOI is affected by a set of factors that characterize his/her behavior. A general algorithm to calculate LOI has three steps described as follows:

1. List a set of factors that describe the user's behaviors and activities regarding interesting elements. For example, in a scenario where restaurants are recommended to users, the factors that reflect their preferences may include various times of visits, time spent, visiting days and today's dish.
2. Calculate the user's degree of interest regarding each factor. Factors have different data types. In some cases, normalization should be applied to handle these factors.
3. Compute LOI.

Multiple LOI methods have been proposed in the literature to calculate LOI. Each has its advantages and disadvantages. A brief review of these methods is presented in the following sections.

A. Average Method

The user's level of interest in an item is estimated by a set of factors that characterize the items. Each factor has a weight. The average method refers to the sum of factors' weight divided by several factors (see equation 1). This measure is learned from the behavior pattern and preferences of users who provide personalized services. The average method considers all factors that have the same impact from the user's point of view. But in reality, some factors have greater influence than others. For example, today's dish for one user has a high impact on determining interesting restaurants rather than spent time or frequent visits. Fang, B. et al. implicitly learn the user's preference for a physical brand store[5]. User's level of interest is calculated for the brand store using an average method based on three factors: time spent in a store (factor ST), frequency of entering the store (factor FR) and matching between promotional offers in-store and user's preferences (factor MA).

$$\mathbf{LOI} = \frac{(\mathbf{factor}_{\,1} + \mathbf{factor}_2 \ldots\ldots + \mathbf{factor}_{\,n})}{\mathbf{n}} \qquad (1)$$

B. Weighted Sum Method

The weighted sum method performs the sum of all factors and gives weight and influence to some over others according to the user's preference and judgment (see equation 2).

$$LOI_i = \lambda.factor_1 + \mu.factor_2 + \ldots\ldots\ldots\ldots\ \xi.factor_n \qquad (2)$$

where λ, μ, and ξ ∈ [0, 1] (with λ+ μ+ ξ = 1). Specifically, each one represents the impact of each factor.

In the literature, a weighted sum is used in several ways.Barragans Martinez, B., et al.compute the user's preference as a combination of explicit (old) and implicit rate[10](see equation 3).

$$new_{pref} = \alpha \times old_{pref} + (1-\alpha) \times implicit\_rate \qquad (3)$$

Where α represents the importance degree of old preference in comparison with a new preference. The higher the value of α is the more the influence of old preference has.

Celdrán, A., H., et al. measure the user's level of interest for the recommended products according to his or her tracking after a recommendation[17]. User's level of interest is estimated by a sum of response time, visiting time, assiduity and the distance between the user and the visited items, taking into consideration the influence of each.

C. Weight Method

The weight method refers to the proportion of the user's frequent behavior of an item to all items. Abdillah, O. and M. Adriani,M. learn users' preferences about restaurants from the user's reviews forum[3]. User's review on a restaurant is described by a set of words and each word has a weight level of interest (word frequency to the number of all words). User's level of interest of each restaurant category type is computed using the proportion of the number of the visit of category X to the number of the visit of all other categories.

D. Keyword Weighting Method

Term Frequency-Inverse Document Frequency, TF-IDF, measures the weight of a keyword. It is widely used in information retrieval. TF-IDF weight method (see equation (4)) is used in the Keyword user profile model to determine the degree to which the keyword can reflect the user's interests. This method is mostly used in user profile models that are designed for information retrieval and search engine applications. It is also applied in various recommender system domains [18], [19] ,[20].

$$TFIDF\ (t,d,n,N) = TF(t,d) \times IDF(n,N) \qquad (4)$$

Where

$$TF(t,d)\frac{keyword\ t\ frequency\ in\ document\ d}{total\ keywords\ in\ document\ d}$$

$$IDF(t) = log_2(\frac{N\ documents}{documents\ with\ term\ t})$$

IDF = Inverse Document Frequency,

TF= Term Frequency, considering keyword t and document d where t appears in n of N documents.

E. Probability Method

Probability is the measure of the expectation to the user`s future preference for an item. Probability values can be between 0 and 1 (where 0 means dislike and 1 indicates like). Ruotsalo, T. et al. present user's preferences as a probability which can be learned or manually entered for objects[21].

Different user's level of interest methods has already been discussed above. These methods are set into comparison according to the source of data processed, computation method, factors, and application, as shown in table 1.

Table 1 : LOI Methods Summary.

LOI method	Refrence	Factors	Factor data types (i.e. numeric, text)	Data source	Application domains
Weighted sum	[17]	Frequency of visit, duration time, recency	Numeric	User's location, preferences and item's content	Shopping
	[1]	Explicit rate, user's behavior	Numeric	User's behavior	movies
	[8]	frequency, duration and recency of	Numeric	social tags	Web sourcing domain
Average	[5]	Frequency of visit, time spent and promotional offers	Mixed	RSS information from mobile device	shopping
Weight	[3]	Frequency of visit and frequency of words	Numeric	user reviews forum	Recommender system for restaurant
Keyword weight	[22]	Term frequency, inverse document frequency	Numeric	documents	Search engine
	[23]				Information retrieval
Probability	[21]	Like or dislike	Numeric	User's feedback	Smart museum

IV. User Profile Models

A user profile is a digital demonstration of unique information for a particular user. As for the user profile modeling it refers to the construction of the data structure that carries the user's features. A user profile model is significantly defined as the data structure or a template for constructing user profiles for different users [7]. Various user profile models have been developed in the literature. Each has its advantages and disadvantages. The main characteristics of these models are summarized in Table 2.

A. Keyword Profile Model

In the Keyword Model, the user profile is represented as a set of preferred keywords or categories that can be extracted or directly provided by users. A Keyword weight is a numerical demonstration of a user's level of importance and reveals how significant it is. The model generalizes favorites and this can lead to an imprecise recommendation. However, it keeps privacy and does not navigate the user's private characteristics. It is a simple representation model. Personalized search engines are the most suitable applications for this model. Diederich, J., et al. have produced the keyword user profile using tags connected with items[18]. A recommender system based on a proposed tag based-profile has been developed in the research domain to recommend publications, keywords, and persons. Lengsfeld. C.S. and Shoureshi. R.A. proposed a web page recommender system based on a keyword user profile[19]. Keywords are extracted from a web page that the user browses. Shmueli-Scheuer, M. et al. introduce user profiles through the extracted keywords of the documents associated with the user over time[24]. Bhattacharyya, P., et al.create a keyword user profile to produce exciting fields in the online social network[20].

B. Vector Profile Model

This approach represents user profile as a vector of numeric values that denote a user's degree of importance consistent to each element of the item. It also can add other users' features as demographic data. It reflects the most commonly used model. It offers an accurate suggestions based on the good descriptions of items. Kim, J.K. and Cho, Y.H. modelled the customer profile as a vector of ratings corresponding to products[25]. Ratings are collected implicitly from shopping process actions like numerous click-through, basket placement, and purchase. Yang, W. S. and Hwang, S.Y. proposed a travel recommender system in mobiles to create the users' profiles as a vector of ratings of their visited attractions[26]. Barragans Martinez, B., et al. have created a user profile for movie preferences using a rating vector that can be provided explicitly by the user or concluded implicitly from the viewing history[10].

C. Semantic Profile Model

Ontology is the method to present semantics in a user profile. An ontology presents the user profile as a set of concepts with the associations between these concepts within a domain. Ontology considered as a superior choice for the next generation user profiles due to the great knowledge representation and related inference tools [27]. Some researches [26, 27] model a generic user profile that presents the main static user's information , while others[7] integrates personal and contextual information such as time and location. Some studies learn user profiles from the domain context [27]. The semantic profile model has been used in numerous domains, including personalized web search engines [22], information retrieval[23], tourism [30] and e-commerce [12,29].

D. Uncertainty Profile Model

Uncertainty models are established to handle imprecise favorite data stored in the profile. Implicit rating is concluded from online user's actions. It is considered an uncertain value. The user profile can have a confidence degree linked with each rating and it is therefore considered a weighted element in the exploitation stage. IF- sets rules [32] and fuzzy ontology [33] are used to model vague and imprecise preferences to help to recommend a product that fits the best to user expectations. The essential advantage of this model is to reason about incomplete and uncertain data of the user's behavior.

E. Probabilistic Profile Model

The probabilistic user profiling model presents user preferences as a probability. User preferences are given as a probability that can be inferred or manually entered for objects [21]. They are learned dynamically in accordance with the user's relevant reaction on the object by using "I like" or "I dislike". Yin, H., et al. modeled a user profile using a location-aware probabilistic generative model, LA-LDA, considering the three important location-based observations[34].

F. Histogram Profile Model

This model creates the profile as a histogram of relative frequencies where the information is signified as an arrangement of independent samples of predefined categorized data (a probability mass function) to keep privacy. It signifies the general concepts associated with weight, and frequencies produced by the user. For example, in the news recommender system, a predefined set of topics is determined then the user profile is modeled by the histogram of the distribution of user's clicks on each news topic category[35]. Moreover, it is used for a mobility user profile where the user profile is represented as the probability distribution of each location to the set of visited locations [36]. This type of user profile model is usually introduced in content-based recommender systems [37] and it has recently been suggested by researchers to keep the privacy in recommendation systems [36, 37,38,39].

Table 2 : User Profile Models.

User profile model	Presentation	Capabilities	Reference	Application
Keyword profile model	Keywords associated with weight	1. Simple to build 2. General description	[18]	research domain RS
			[19]	Web page RS
			[24]	
			[20]	Online social network
Vector profile model	Vector of numeric values	1. Simple 2. Most widely used	[25], [26], [10]	Various applications
Semantic profile model	Semantic presentations	1. Semantic relationship between concepts 2. Support reasoning 3. interoperability, reuse and sharing 4. an explicit representation of a shared formal representation	[22]	web search engine
			[23]	information retrieval
			[30]	Tourism
			[15], [31]	e-commerce
Uncertainty profile model	Confidence degree associated with preference weight	1. Handel an imprecise data	[32], [33]	Shopping
Probabilistic profile model	Like or dislike probabilities		[21], [34]	Smart museum Location-based systems
Histogram profile model	An arrangement of independent samples of predefined categorized data	1. Privacy-preserving representation	[35]	News RS
			[40]	Social tagging RS
			[38]	Advertising RS
			[39]	Web-Browsing RS

V. Mobile User Profile

Recently, the user profile with the advent of smartphones has started to incorporate contextual information such as and user's physical location, as most users always carry their phones all the time and need more assistant applications for supporting their daily activities. Furthermore, a mobile user profile helps to personalize services and support context-aware applications[40, 11,41]. Studies have different perspectives in tackling this profile. For instance, some studies[42, 43,44] **present mobility user profiles.** These profiles describe the user's movement behavior using positioning technologies such as global positioning system (GPS) and cell towers. Akyildiz, I. F. and Wang, W. proposed the mobility profile that consists of a user movement behavior that can be used to predict the next locations [42]. Bayir, M.,A., et al. **have** proposed a user profile to incorporate both a popular travel path for the user and his or her contextual data[43]. Loseto, G., et al. have annotated mobile user profiles by a semantic web language to represent travel time paths and transportation modes to infer the kind of user activity[44].

Other articles[40, 45, 46, 47] present user profile to help in personalizing the shopping process in a mobile environment. For instance, Yang, W.,S., et al. profiles customers through their new terms in the vendor web page and their physical location to help provide customers with interesting shopping vendor web pages[4]. Hella, L., et al. combined shopping interests (stable and temporary interesting shopping items) and personal information into an ontology-based-user profile to personalize mobile shopping activities[45]. Skillen,K.-L., et al. developed a mobile user profile that modeled capabilities, health conditions, preferences, and interests into an ontology model to personalize shopping items for people with dementia[46]. Morse, J., et al. built mobile user profiles by tracking application usage, i.e., by tracking browsing, purchasing, locations, and other activities to prefetch content similar to previous requests[47].

Some articles proposed user profiles to personalize content for several user activities. For example, Paireekreng, W. and Wong, K.,W.proposed a model to personalize mobile contents such as multimedia, news, and services according to mobile user demographic attributes[48]. Some studies address mobile search personalization. For example, Gupta, D. and Chavhan, N. introduced an ontological user profile to personalize mobile search by defining the semantic relationship between extracted terms from visited web pages[49]. Iwata, M., et al. aimed to model profile user situations using an acceleration sensor, GPS, and time to personalize locations search[50].

VI. User Profile Privacy

Personal information, physical location information, interests, transaction data, and social interaction information can be incorporated to construct a user profile. These data can give a chance to Internet Service Providers (ISPs) to share and sell these pieces information to the third party for getting revenues or even hateful purposes. Therefore, the use of profiles brings the risk of privacy. The privacy issue has been handled in user profiling within various approaches.

A. Anonymization Approach

Anonymization approach aims to remove any personal information that identifies users, while keeping the structure of user preferences safe. In other words, the user's information can be partially uninvolved or obscured, while the remained information is exploited to make a recommendation. When making a recommendation, the user interacts with the recommender system through a trusted agent, either software or hardware. This trusted agent is responsible for filtering information and hiding it from the service provider. As a result, the service provider cannot link the actions of a user to a certain person.

Various studies apply the anonymization approach[51, 52, 53,54]. For instance, the k-anonymity model is applied to anonymize location[51, 52]. This model depends on generalizing location by generating a Spatio-temporal region that contains at least k other users. However, these works protect location information only and do not consider personal information. On the other hand , the k-anonymization concept is utilized to hide location, identity, and other sensitive information of mobile[53,54]. Numeric attributes are represented as interval value and nominal attributes as a concept hierarchy. Shin, H., et al. proposed the k-anonymity model to generalize both location and profile to the extent specified by the user[55]. The k-anonymity is a widely popular privacy solution due to its easy mathematical manipulation.

B. Pseudonymous Method

This approach introduces a pseudonym for a user profile to preserve privacy([56], [57]). The system retains the same pseudonym across different sessions and generates recommendations without knowing the true identity of the user of the pseudonym, as a result privacy is well-preserved.

C. Client-Based Approach.

Several studies [58, 59,60] apply client-based methods where privacy protection is done in accordance with the user`s physical storage. In this approach, the user's profile is created, manipulated, and stored in his device and the personalized service is accomplished at the client-side. Thus, the physical security of the user's device is an important issue.

D. Probability Mass Function Approach

Recently, researchers have introduced the profile as a histogram of relative frequencies where the information denoted as an arrangement of independent samples of predefined categorized data (a probability mass function)[36,37,38,39]. Entropy measures are widely used to estimate the privacy level. For instance, Rodriguez-carrion, A., et al. presented the mobility profile as the probability distribution of each location to the set of visited places[36]. Similarly, Liu, J. et al. define the user profile as a probability distribution of the general search topics in the web search domain[35]. Beigi. G., et al. present the user's browsing history distribution over a set of predefined topics and handle the tradeoff between privacy and user's utility[61].

E. Randomization and Differential Privacy Approaches

Randomization approaches (also called Perturbation) modify user's information and add a degree of uncertainty (noise). Polat, H. and Du, W. applied random perturbation by adding a random value (from a fixed distribution) to the user's rating [62]. The mean rate is assigned to unknown ratings. Moreover, the authors study the impact of the privacy-preserving approach on accuracy. Berkvosky, S. et al. introduced Dynamic Random Perturbation where the user is involved for each request to determine what data to disclose and how much protection is set on the data[63].

A differential privacy-based approach adds noise to the recommendation output so that the delivery of results is insensitive to the histories of any particular user[64]. In other words, this approach tries to ambiguous the link between the user's input information and the recommendation output. The level of noise is determined by the method used to employ data, and the balance between output accuracy and privacy of the input should be considered.

VII. Conclusion

In conclusion, the literature includes several articles focusing on user profile in specific domains and they do not pay due attention to the generic ones that can be employed in cross-domains to get good recommendations. Therefore, there is a need for a generic user profile model with specific characteristics. It should be domain independence to be useful in various advertisements and shopping areas. Furthermore, it should anonymize the user through abstracting the user's interests while maintaining the level of details needed to produce acceptable quality recommendations.

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