Multidimensional User Profile Model to Support System Recommendations in Complex Social Networks: Application to Hashtag Recommendations

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Abstract: Recommendation systems play a crucial role in providing relevant information through data analysis. One of the pivotal challenges in the recommendation process is modeling user profiles. However, many existing models focus on a single aspect to describe users, overlooking other valuable data. In response to this limitation, this paper introduces a comprehensive multidimensional model that captures various dimensions of a user within their complex social network. This model encompasses demographic, social, behavioral and homophilic dimensions, with the goal of offering more holistic recommendations tailored to different contexts. Towards the end of this article, we introduce a focused application of the multidimensional model. This specific application revolves around providing hashtag recommendations within the X platform (Twitter platform). This serves as a tangible demonstration of how the proposed model can be applied in a practical context within a real social network. The main goal is to comprehensively assess the model's efficacy in generating recommendations by utilizing a varied set of user-related information. To accomplish this, we introduce and evaluate a recommendation approach driven by our proposed user profile model, showcasing relevant and notable results.

1 INTRODUCTION

The use of recommender systems (RS) has expanded dramatically over the last decade, mostly due to their enormous business value (Deldjoo et al., 2021). In fact, RS are considered as a helpful tool for helping the user in cutting the time needs to find personalized products, documents, friends, places and services (Alhijawi and Kilani, 2020). Thus, RS have become an important part of the web sites (SKazienko et al., 2011). In particular, e-commerce sites since they help people to make decision, what items to buy (Kazienko and Kolodziejski, 2006), or which movie to watch (Degemmis et al., 2007). For example, According to the statistics revealed by Netflix, 75% of the downloads and rentals come from their recommendation service (Deldjoo et al., 2021).

One of the requirements to create a successful and usable recommender system is to build a detailed user model (Martijn and Verbert, 2022). This model serves as a foundation for the system to suggest items effectively or adjust the interface accordingly (Graus and Ferwerda, 2019).

In this context, many user models have been proposed. For example, in many RS, a user has been represented by his preferences or his interests. For other recommendation systems, only his behaviors have been considered. Furthermore, with the widespread use of social networks such as Facebook, X (Twitter), LinkedIn, an enormous amount of information could be analyzed and considered in the recommendation process. This is why the user profile model needs to be further enriched to take into account a greater amount of information.

Thus, in this paper, we propose a new hybrid multidimensional user profile model that provides a comprehensive representation of a user within his social network, including all relevant information that can be used for generating recommendations. The model considers the social, demographic, behavioral and homophilic dimensions to ensure a thorough understanding of the user's preferences and interests. Similarly, a model-driven graph-based hashtag recommendation approach is proposed in order to demonstrate

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how the proposed model could be utilized in a real-world context.

The remainder of this article is structured as follows. Section 2 investigates related works to user profile models devoted to recommendation systems. The new proposed user profile model for recommendation support is depicted in section 3. In section 4, we evaluate the performances of our model by integrating it in a hashtag recommendation system, proving the practical usefulness of the contribution via a real data based example. In the last section, we conclude and present an outlook on future works.

2 RELATED WORKS

Various techniques and algorithms have been developed to build and use user profile models for recommendation systems (Ko et al., 2022).

In this context, the proposed user profile models could be classified into four categories, notably: content-based, demographic, collaborative filtering and contextual models.

To start with, content-based models or behaviour-based models are widely used in recommender systems (Middleton and De Roure, 2004; Zhang et al., 2023). These models rely on the user's historical behavior and preferences, often utilizing a binary classification model to represent what users find interesting and uninteresting (Middleton and De Roure, 2004). By analyzing the content of items that the user has interacted with, these models recommend similar items that align with their preferences (Jerry et al., 2024).

As for demographic models in recommendation systems, they rely on user demographic information such as age, gender, and location. These models leverage this information to recommend items that are popular among users with similar demographic characteristics (Tahmasebi et al., 2021). An important aspect of demographic models is their role in mitigating the cold-start problem, a common challenge in recommendation systems (Safoury and Salah, 2013; Alhijawi and Kilani, 2020; Tahmasebi et al., 2021). By leveraging demographic data, these models improve the accuracy of user profile modeling, enabling more precise predictions for cold-start users, even in platforms like Reddit (Sharma et al., 2021).

When it comes to collaborative filtering models or social models, they are based on the user's interactions with other users. They recommend items based on the preferences of users with similar tastes. The key to the success of personalized recommendation lies in the correct use of "collective intelligence," and one user behaves similarly to some other users (Qian et al., 2023).

Finally, contextual models take into account the user's current context, such as time, location, and mood, and recommend items that are relevant to the user's current situation (Rattanajitbanjong and Maneeroj, 2009; Minsung et al., 2024).

These existing profile models in recommendation systems, while offering benefits, are not without criticisms. One major criticism is their potential oversimplification of user preferences, as they often rely on limited feedback sources that may fail to capture the intricacies of individual tastes. Furthermore, the representation of user preferences within profiles can be incomplete, overlooking certain dimensions and resulting in less comprehensive recommendations. These models may also neglect the importance of serendipity and exploration, focusing solely on personalized recommendations based on past behavior. Privacy concerns arise due to the collection and utilization of user data for profiling purposes. Additionally, profile models face challenges in handling the cold-start problem for new users or items with limited data. Their limited adaptability to evolving user preferences further raises concerns. Recognizing these limitations, researchers should explore hybrid or alternative approaches to enhance recommendation accuracy and ensure a more satisfying user experience.

Furthermore, with the emergence of social networks today, a vast amount of data can be analyzed to improve recommendations. In this regard, an indispensable component is a multidimensional profile that represents users across various dimensions such as social, demographic, behavioral and homophilic within a specific context.
This profile will be described in the next section.

3 PROPOSED MULTIDIMENSIONAL USER PROFILE MODEL

In this paper, we aim to propose a new generic multidimensional user profile model to support recommendations in complex social networks. This model, given in Figure 1, is:

- **Generic.** Our proposed model is designed to be generic and applicable across multiple recommendation systems. It can effectively support various domains, including movies, products, and even social connections.
- **Multidimensional.** Our model is characterized by its multidimensional nature as it incorporates

various user dimensions, including social, behavioral, and demographic factors. By considering these diverse aspects, our model can capture a more comprehensive understanding of users' preferences and characteristics.

- **Dynamic.** Our model is designed to be dynamic and adaptable, capable of evolving based on the specific context and domain it operates in. It recognizes that user data is not static but rather evolves over time. As users interact with the system, their preferences, behaviors, and demographic information may change or be updated.
- **Contextual-Based.** Due to its generic nature, our model has the flexibility to support a wide range of contexts. It can seamlessly adapt and provide recommendations in various domains and scenarios. Whether it's recommending movies, books, music, restaurants, or any other type of item, our model can handle different contexts effectively.

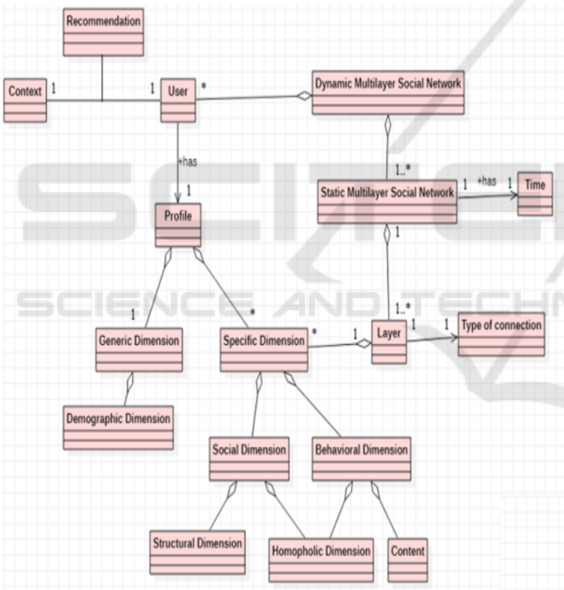

Figure 1: Proposed multidimensional user profile model.

As illustrated in Figure 1, user is at the core of the proposed model, and it is crucial to represent him accurately by considering all relevant information which are: Dynamic multilayer social networks, user's Profile and recommendation's Context. These three classes are outlined below.

3.1 Dynamic Multilayer Social Networks

The first essential aspect to consider in system recommendations is the users' environment, which includes their participation in complex social networks. Indeed, users are not isolated entities but are interconnected within complex social structures that influence their preferences and behaviors. Moreover, as the use of social media has become much more widespread than before (Roozbahani et al., 2022), a user has been involved in multiple social networks simultaneously including popular platforms such as Facebook, Twitter, Instagram, and many others. This phenomenon has given rise to what is commonly referred to as a multilayer social network (Li et al., 2023).

Furthermore, a key characteristic of these multilayer social networks is their evolution and their continual change over time (Ceria et al., 2022). This is why, in our model, we are considering dynamic multilayer social networks.

Illustratively, Figure 2 captures a segment of a dynamic multilayer social network, akin to the structure found in platforms like Twitter. Within this network, users cultivate two discernible relationship types: one layer encapsulates connections formed through the act of following, and another layer delineates interactions encompassing tweets and retweets. Moreover, this intricate structure is depicted at two specific instances, labeled as t1 and t2, emphasizing the dynamic character of the network and revealing the progression of relationships and interactions over time.

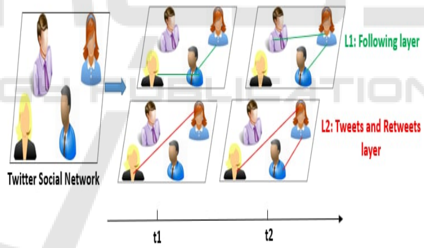

Figure 2: Twitter as a dynamic multilayer social network.

Within the dynamic multilayered social network, each user is characterized by a profile. This will be the subject of the next section.

3.2 User's Profile

User's profile includes all necessary knowledge for effective query evaluation and production of relevant information tailored to each user (Rebhi et al., 2017a). It is usually integrated into the system to impart the user knowledge to the system to enable personalized adaptations and avoid "unnecessary" dialogues between the system and the user (Liu et al., 2009). As shown in Fig.1 and based on what we have recurrently found in the literature, a user's profile could be considered as a combination of two dimensions: generic and specific.

Generic Dimension. Regarding personal information, including details such as name, birthday, address, nationality, education, profession, and physical factors like weight, height, and eye color, these demographic elements collectively contribute to understanding a user's context (Beel et al., 2013; Al-Shamri, 2016; Rebhi et al., 2017a). They aid recommender systems in comprehending individual preferences, facilitating the delivery of culturally relevant and suitable recommendations. By integrating such information, the recommendations become more personalized, thereby enhancing the likelihood of user satisfaction and engagement with the platform.

Specific Dimension. Concerns data that is specific to each layer of the social network. This data could be social data or behavioral data. As for social data (Li et al., 2019), it involves structural interactions within each layer. Much more, the ways in which users interact with each other within layers. For example, friendships on Facebook or links of tweets and retweets on Twitter. Additionally, these connections or links between users might exhibit a homophilic dimension (Aiello et al., 2012). This means that users with similar interaction patterns or behaviors tend to connect more. For instance, the presence of a high number of common friends between two users indicates a similarity in their social networks, reflecting a homophilic aspect in their interactions.

For the behavioral dimension (Dhelim et al., 2022), it pertains to the patterns of actions and activities undertaken by users within each layer of the network. This dimension involves the analysis of user behavior and activities to comprehend and model how individuals navigate, communicate, and engage with others on the social network. Furthermore, the key aspect of the behavioral dimension is content. The content encompasses two significant aspects:

- Posting Content. Understanding the type and frequency of content that users post, such as status updates, photos, videos, or links, offers insights into their interests and preferences.
- Reactions to Content. Assessing how users respond to various types of content, including their emotional reactions, aids in gauging the impact of content on the community.

Moreover, the behavioral dimension can incorporate homophilic elements, with the number of common posts between two users serving as an exemplary illustration of such a dimension. Homophily denotes the inclination of individuals to connect with others who share similarities with them in certain aspects. In the context of social networks, this similarity is manifested in their behavioral patterns. For instance:

- Number of Common Posts. Users frequently posting about similar topics or sharing common interests may exhibit a higher number of common posts, indicating a homophilic dimension. This suggests that these users engage with and express similar content, reinforcing the idea that they share commonalities.
- Shared Interests: Analyzing the types of content that users engage with or post about can unveil shared interests. Users with a significant overlap in the topics they post about or the content they interact with demonstrate a homophilic connection based on shared interests.
- Similar Posting Patterns. Examining the timing, frequency, and style of posts can unveil similarities in posting behavior. Users with comparable posting patterns are likely to have homophilic connections, aligning their behaviors in the way they contribute to the social network.

This user's profile is always linked to a context in which the recommendation process is executed.

3.3 Recommendation's Context

The term ”context” lacks a singular definition, given its diverse applications across various fields (Casillo et al., 2023). Considering the expansive nature of the concept (Zimmermann et al., 2007), multiple definitions have been proposed.

From the array of context definitions, we embrace one of the most widely accepted and formalized concepts (Zainol and Nakata, 2010), as articulated by (Dey, 2001): ”context is any information that can be used to characterize the situation of an entity. An entity, in this context, refers to a person, place, or object considered relevant to the interaction between a user and an application, including both the user and the applications themselves.” In the realm of recommendation systems, a situation is akin to the snapshot of the multilayer social network at a specific moment. Consequently, the recommendation context encompasses any information pertaining to this situation that holds relevance for the recommendation process.

To structure our multidimensional model, we draw upon the generic context model proposed by (Zainol and Nakata, 2010), incorporating three distinct context categories: Extrinsic Context, Interface Context, and Intrinsic Context. These categories correspond to the triggering elements of the recommendation process, addressing the ”who” question through user profile attributes (Intrinsic Context), the ”why” question via recommendation needs (Interface Context), and the ”where” question concerning the environment itself (Extrinsic Context) (Zainol and Nakata, 2010).

4 EVALUATION: APPLICATION TO HASHTAG RECOMMENDATIONS

To evaluate the proposed multidimensional user profile model, our objective in this section is to introduce an application for hashtag recommendation. To accomplish this, we furnish information about the utilized data, the recommendation approach employed, and the resulting outcomes.

4.1 Data Set Description

To validate the proposed modeling approach, we used a set of data collected from X social network (formerly Twitter) (Danisch et al., 2014). From this data set, we extracted a significant sample of 20000 tweets corresponding to 1000 users. We have thus obtained a set of tweets, including the user identifier, tweet identifier, tweet body (list of hashtags in the tweet), the timestamp at which the tweet was issued, and whether the tweet is a response to another tweet or not. We note that these tweets and retweets are fully formed of hashtags. We chose users with different social characteristics (i.e. a different number of tweets, retweets, followers and hashtags). We process to data cleaning by eliminating stop words and short hashtags (composed of less then 3 characters). Thus, from a starting list of 135420 hahstags, we eliminated 3451 stop words and short ones to maintain 131969 hashtags.

With this data, the first thing to do is to build our multidimensional model. Thus, we instantiate our user profile model taking X (Twitter) as our dynamic social network. We differentiate 5 time periods during which tweets are sent, notably T0, T1, T2, T3 and T4. From X, we distinguish two layers: Following layer, tweets and retweets layer. Figure 3 represents an example of instantiation of the proposed model at a moment T1. For clarity, we have just represented one user (U1).

In the initial 'Following' layer, we examine the social dimension, emphasizing the connections formed through user following and the count of shared followers. In contrast, within the second layer involving tweets and retweets, our focus shifts to the relationship established through retweets among users. Here, in terms of the behavioral dimension, our attention centers on the hashtags included in each tweet. Location and age are the subject of demographic dimension. Those dimensions form the generic profile of each user.

After establishing our model, our aim is to offer the most pertinent hashtag recommendations for each user. To fulfill this objective, the subsequent section introduces an approach to recommendation guided by this model.

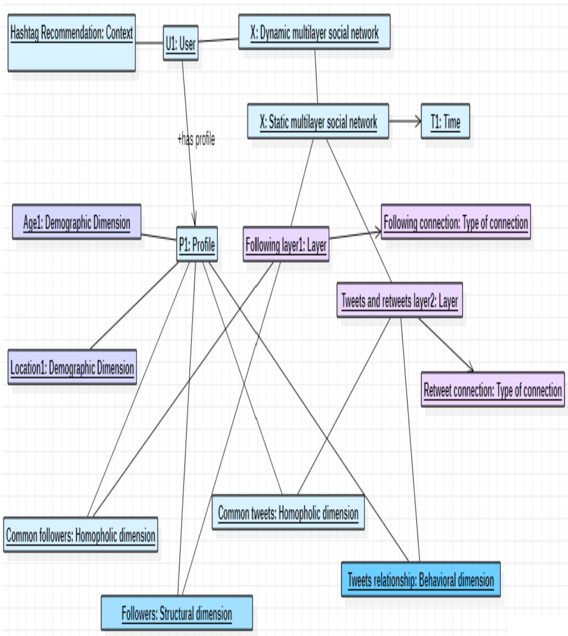

Figure 3: Instance of the proposed multidimensional user profile model.

4.2 Used Model-Driven Hashtag Recommendation Approach

Drawing from our multidimensional model and within the recommendation context, which is in our case hashtag recommendations for individual users, our objective is to identify relevant suggestions. In line with this, as depicted in Figure 4, we advocate for the implementation of a hybrid recommendation approach. This approach is based on three phases. The initial phase involves graph construction, transforming the model into an exploitable structure. Subsequently, a community detection algorithm is employed to identify clusters for each user. Finally, a hashtag selection process is executed to provide pertinent hashtag recommendations tailored to each user.

These phases will be detailed in the following.

Phase 1: Graph Construction. To exploit the proposed model with its different dimensions, we choose to use graph as a powerful mathematical abstraction, especially for user profile (Daoud et al., 2009; Caro-Martínez et al., 2023). To do so, we reuse the temporal multirelational information graph-based model (Rebhi et al., 2017b) for representing entities (i.e., actors in social network) and their relationships (Rebhi et al., 2022). For the collected data, each user is described by a set of tweets. To simplify

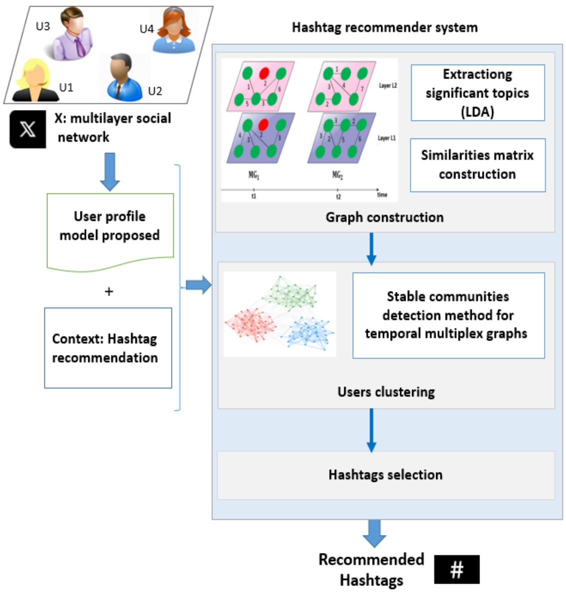

Figure 4: Hashtag recommendation case study.

the analysis of tweets, we apply Latent Dirichlet Allocation(LDA)(Blei et al., 2003). This step is of major importance, as LDA allows us to analyze the semantics of hashtags in our context and group them into significant topics. LDA is applied to each user profile to extract the meaningful topics that represent it. In our data, for each profile, we tested different values of k (number of significant topics), and ultimately, we chose the value k=3. This decision was based on the observation that for a number of topics greater than 3, we did not observe a significant difference in the hashtags within each topic. Consequently, there is a stabilization of the content within each group of hashtags. As a result one user is represented by 3 topics. For example, for the user U1, the 3 topics are: (america, usa, news); (science , technology , Google , tech) and (job, team).

Then, at each time t_i and for each layer j, a similarities matrix $MS_j^{(i)}$ is defined as follows:

$$MS_j^{(i)} = (ms_j^{(i)})_{1\leq k,l\leq Nbr} \quad . \tag{1}$$

Indeed, each element $(ms_j^{(i)})_{k,l}$ represents the similarity between the node N_k and the node N_l within the layer j at t_i. For the tweets and retweets layer, we consider similarities between users based on each extracted meaningful topics. As for following layer, we consider, similarities based on age and location.

Phase 2: Users Clustering. Once, we have constructed the graph, our aim now is to form users clusters. To do so, we propose to apply the Stable Communities Detection Method for Temporal Multiplex Graphs (Rebhi et al., 2021). We opted for this approach due to its effectiveness and its capability to build communities by utilizing the diverse dimensions proposed in our model (Rebhi et al., 2021). Applied to our data , we obtain 8 clusters grouping similar users.

Phase 3: Hashtags Selection. Now, as each user belongs to his pertinent cluster, we use these representative hashtags from each cluster and sort them based on their decreasing frequency within the cluster. We then suggest to each user, in order, the most frequent and recent hashtags in the cluster that they have not already used.

4.3 Results and Discussion

The proposed Hashtag recommendation approach is applied to the collected data, considering only the first four time instances (T0, T1, T2, and T3). The final instance is allocated for validation, where the obtained recommendations are assessed by comparing them with the hashtags users have actually shared at T4. Therefore, we measure the performance of our system in retrieving the same hashtags contained in this last tweet. Furthermore, to compare the performance of our system with existing works, we have chosen to position ourselves in relation to the study by (Dovgopol and Nohelty, 2015), which proposed two recommendation methods. The first relies mainly on Naive Bayes, while the second utilizes cosine similarity with the KNN method. As evaluation metric, we choose to calculate the Recall which is in our case represents the system's ability to provide all relevant hashtags in response. For us, relevant hashtags are those that appear in the last tweet T4. We depict results of recall after respectively 10, 20 then 30 hashtags recommended. Results are displayed in table 1.

Table 1: Recall results.

Recall	R10	R20	R30
Our system	0.8157	0.8504	0.9175
Naive Bayes	0.6312	0.6987	0.7278
Cosine with KNN	0.7237	0.7687	0.8097

As shown in Table 1, for our recommender system, the recall for 10 recommended hashtags is 0.8157 , 0.8504 for 20 hashtags, and 0.9175 for 30 recommended hashtags. For the Naive Bayes system, the recall values are 0.6312, 0.6987, and 0.7278, respectively. Regarding the cosine similarity measure with KNN, the recall values are 0.7237, 0.7687, and 0.8097. Hence, our system produced recall values superior to those of the two systems we benchmarked against.

We calculated the improvement rate in terms of recall for our system by comparing it with the two methods of (Dovgopol and Nohelty, 2015). Our system shows a significant improvement rate of 15.7% compared to other comparative approaches in terms of recall.

The results obtained affirm the efficacy of the model-driven approach in retrieving a greater number of relevant hashtags compared to other methods. In contrast, the Naive Bayes and KNN approaches rely predominantly on a profile composed solely of user-shared hashtags. As a result, depending solely on hashtag similarity may not consistently yield accurate recommendations, highlighting a limitation of these two approaches. In contrast, our proposed approach capitalizes on all dimensions offered by our model, encompassing social interactions, shared hashtags, and similarity with diverse users. Additionally, it takes into account the inherent characteristics of the social network itself, including its multi-layered structure and dynamism. Indeed, by incorporating information about the user's social network connections, we can create a more comprehensive representation of the user. This multilayer dynamic social network perspective allows us to capture the influence of social ties, community dynamics, and evolving relationships on user preferences and decision-making. Thus, taking into account the user's environment in this way enables us to leverage the power of social influence and network effects for more accurate and effective recommendations.

5 CONCLUSION

This paper has proposed a multidimensional user profile model designed to enhance system recommendations within intricate social networks. The model comprehensively captures diverse dimensions of a user's presence in their complex social network, including demographic, social, behavioral, and homophilic aspects. The overarching objective is to provide more comprehensive recommendations tailored to distinct contexts. As a practical application, we have implemented this model in the realm of hashtag recommendations within Twitter platform, demonstrating its utility within a real social network recommender system. Employing a recommendation approach, we sought pertinent recommendations, showcasing that the proposed modeling approach enables the acquisition of relevant suggestions for each user.

In future works, we aim to test the performance and the scalability of the proposed modeling approach for recommender systems in other contexts using real large-scale multilayer social networks or benchmarks.

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