Journal of Engineering Science and Technology
Vol. 17, No. 2 (2022) 0956 - 0963

HIGH LEVEL DYNAMIC PROFILING FOR CONTEXT-AWARE RECOMMENDER SYSTEM

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Abstract

Context-aware recommender systems have captured researchers in the recent years. One of the major pillars in the design of the context-aware recommender system is the user profile, especially in the transportation domain. The user profile provides rich information for the system to deliver better recommendation. However, the user usually lazy to deal and create his own profile, such behaviour where not considered much in the research. In this study, a dynamic user profile creation is proposed by recommending a profile for the user after number of successful search input. Automaticity also increased by adding a dynamic list insertion mechanism for business owners to facilitate searched list items and to provide a vision to the market. The system introduced as a high-level design which can be part of context-aware recommender system.

Keywords: Context-aware, Dynamic profiling, Transportation, Recommender system.

1. Introduction

Context-aware recommender systems (RS) are systems that attracted researchers in the recent years [1-3], in particular in smart cities, where contextual information about a driver become valuable to contribute on a smart ecosystem environment.

This information is utilized by different systems in an integrated manner with the existence of multiple processes [4]. The acquisition process of contextual data requires accurate and efficient mechanisms such that reliability can be achieved when data are mapped for each user/driver [5].

Context-aware RS is a system that recommends locations, products and/or services/items to a user (in this case a driver in the transportation domain). Richness of data about a driver such as location, time and profile can determine level of successful recommendation [6]. Absence of these data can degrade the recommender engine outcome. With a given profile of user and a target service/item, RS can predict users' rating for that service/item which indicates the degree of his/her preference towards the item. [7]. A user profile can be defined as a structured data representation that is used to obtain characteristics about a user [8].

On the other hand, the user usually not so enthusiasm about creating a profile for something that she/he may use once. Major users definitely fall under lazy model theory [9], where the user with minimum efforts wants to achieve his goals specially when selecting product or service.

There are researches that address the profile issue and how to enrich it with accurate information [6, 10, 11]. The user profile can be viewed from two major perspectives: the context-aware RS can utilize the user profile without the user knowing that a profile is already created for him. The other view is that the user can have access to a profile that she/he already created. However, not only the profile information is important but also how the user accept a profile is another major concern since it represents his preferences. For letting the user to engage with less possible effort, there is a need for automatic profile creation. The existence of automatic profile creation was discussed and studied from the point of view where the user has no choice but accepting the automated profile construction, but this had created problems when the RS deliver unsatisfied recommendations [12]. A challenge can exists if a user is not happy with the profile created to him, such incident can cause a level of engagement (by the user) that could be eliminated and a process (by RS) that could be avoided.

From business side, there is a need to understand what the user wants in future, by for example analyse keywords associated with his search query [13]. Such analysis can deliver better vision for user intent. Researches on this field have focused on developing search recommendation frameworks to enhance the outcomes of the search [13], but less focused on the interaction level between available items/services for search and the automaticity of inserting new searchable items/services.

As a result, we propose a new user profile creation algorithm that overcomes the highlighted concerns in order to deliver an enhanced experience for automated profile construction for drivers/users especially in the transportation domain.

The major contributions of this paper are to propose a high-level dynamic profiling algorithm and to propose dynamic insertion algorithm that both can be used as part of context-aware RS in transportation domain.

The remaining parts of the paper is organised as follows. Related work is discussed in Section 2 and proposed approached is presented in Section 3.

2. Related Work

In this section related and recent studies are reviewed to investigate profile consideration in the context-aware recommender systems/frameworks.

Hoque et al. [14] proposed a recommendation system based on profile adaptation and context awareness for tourism. The main aim of the system is to suggest a series of locations and their routes to a user based on their personality, profile preferences, and location. They introduced two main algorithms, one of them is associated with user profile that was manually created by the user. After having the profile ready, the algorithm is ready to recommend point of interest. The system lacks the automaticity of profile generation.

A context-aware chatbot was introduced by Clarizia et al. [15]. The aim of the system is to recommend contents and services according to tourist profiles and context. In this system, context-aware manager component is responsible to maintain user profile. However, authors did not consider automatic generation of user profile.

Khazaei and Alimohammadi [11] proposed a context-aware recommender system based on group-oriented location. The main objective of the system is to recommend a number/list of interesting locations for a group by analysing the preference profile of each group member within a location category. The system then creates a group profile which indicates the types of categories selected by the group. Even though the group profile can be built automatically, however, the system highly depends on coexisted users' profiles such that the study assumes for each user there is a profile created manually.

High level online recommender system for accessible tourism destinations based on modular design was proposed by Brodeala [16]. The aim of the study was discussing the possible creation of a RS to support accessible tourist by recommending accessible destinations. Moreover, the RS under study can ease the process of end-to-end trip planning for people with disabilities. The author provided decent discussion about the importance of user profile and how it can assist the recommender system in delivering the needed locations for accessible people. The user profile was identified as second major pillar in the proposed system. However, the author focused on how to model user profile, the ability to link user profile with content and analysing user profile creation but did not focus on the automaticity of profile creation and profile acceptance.

3. Proposed Approach

In this section, the proposed approached is detailed. Major building blocks of the proposed system are (the driver, the feedback from the driver, knowledge base (KB), data collecting devices, user interface, KB monitoring, a dynamic profiling mechanism, see Fig. 1.

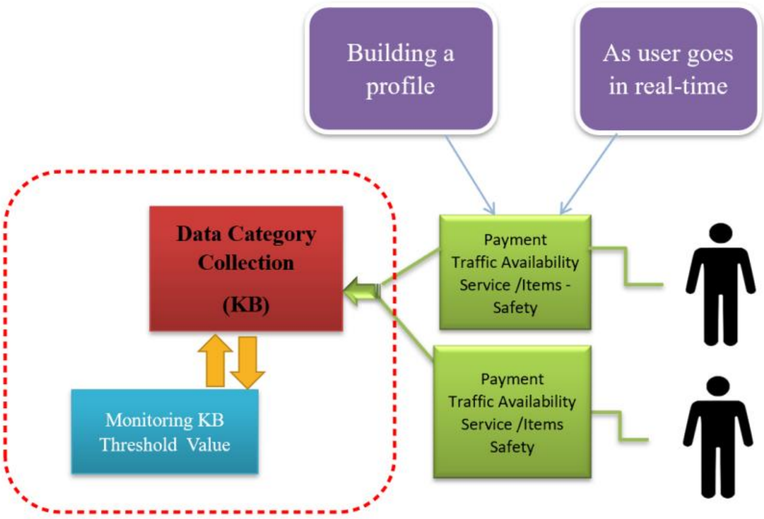

Fig. 1. High level building block of the context-aware system architecture.

3.1. Context-aware system architecture

In order for the system to operate it requires data coming from the user which is in the form of searched keyword. Moreover, the system needs business owners to setup and input their list of items/services in the intended searchable database. The user interface allows the user to do a search for an/a item/service. The searched keyword is a critical element that feeds the KB. KB is the searchable database including collection of items/services associated with different business owners. Each item/service has a counter that is monitored by KB monitoring element. The monitoring element is responsible to check threshold value (predetermined by business owners during setup phase) for each item/service and compare it with its associated counter in the KB. As users search in real-time the system autonomously starts acquiring data and performs major dynamic operations.

Driver's feedback and input are associated with two mechanisms: users' dynamic profiling and business owner's dynamic list insertion.

3.2. Users' dynamic profiling

Every time a user starts searching, the query output will be monitored such that if it is available or not and then will be stored in the database with his created profile. If the output for an item is found, then an action or more occur according to the output value that is based on a matched matrix as depicted in Fig. 2.

After number of searches (considering outputs (1) and (3)), the user's profile of interest (including items/services) will be recommended to him as user profile. He/She can either accept or reject this profile (after reviewing it). For fives successful searches in a week, the user's profile is ready for recommendation. This condition is placed to avoid cold start problem. The number 5 will be reduced after one month since the first recommendation has triggered in the system (see Table 1 for reduction details).

		Match found in the Database: yes	Match found in the Database: no
Match found in all business owners' lists	**yes**	1	2
	no	3	4

if (yes, yes) then output = (1) ➔ update user profile
if (yes, no) then output = (3) ➔ update business owner list & user profile
if (no, no) then output = (4), ➔ update business owner list

Fig. 2. Matching matrix for search output.

Table 1. Successful search attempts reduction mechanism.

Reduction period	Reduction amount
After one month	-1
After two months	-2
After three months	-3

The intended profile will be regenerated for number of times to the same user. The regeneration depends on average number of rejections (until the time of profile acceptance) as depicted in equation 1.

$$ANDPR = \frac{\sum_1^n r_p}{n} \quad (1)$$

where *ANDPR* represents the average number of offers for the dynamic profile that have been rejected by the users. n is the number of users and r_p is the sum of all rejected dynamic profiles. Figure 3 shows the pseudocode for the dynamic profiling algorithm (Algorithm 1 ANDPR).

In addition, the users' feedback can also provide rich information for the business owners profiles. In this case feedbacks from users' queries are used to deliver number of searches for a particular item/service and to deliver the average of rejected offers.

Algorithm 1 *ANDPR*

Input: User search terms U_s;
Available items/services set S;
Output: List of needed items/services L_m;

```
ARR                          //Average rejection rate
avgRejCntr=0                 //initializing the main rejection counter
Lm [2d dynamic array]=0      //initializing 2d dynamic array where each
                             //user has search list
YesNoVal                     //matrix value
searchCntr                   //Global counter variable for each user
BPThr                        //Business owner set a local threshold value
                             //for each item/service
ThrCntr
Get user ID                  //check if user is new or not
```

```
    if ID not matched then
        create new ID for user
end if
    for each u ∈ U_s do
        if (f(u) = 1) then          //based on matched matrix from search
                                    //function f
            update (L_m) UP         //update user's temp profile who did the
                                    //query
    searchCntr ++
        else if f(u) = 3 then       //match found in DB and in some business
                                    //owners
            update (L_m) UP & BP    //update user's temp profile & business
                                    //owner list (who do not have the
                                    //them/service)
            searchCntr ++
            ThrCntr(u)++            //updating the threshold value
        else if f(u) = 4 then       // no match
            update (L_m) BP         // updating all business profile
            ThrCntr(u)++
        end if
        if searchCntr = 5 then      //Five search successful results
            start recommendation i
        end if
end for
end if
```

Fig. 3. ANDPR algorithm.

3.3. Business owner's dynamic list insertion

To increase level of automaticity in the system, a dynamic list insertion method is introduced.

Business owner usually list their items/services in a shared database such that the user can check their availability during the search process. In case the business owner does not want to place all items/services into the shared database (for example the business owner wants to understand the market before placing such an item/service), then the business owner (admin in his case) can enable a feature in the system called dynamic list insertion.

This feature will be optionally available for the admin such that it allows the user to search for items/services not listed in the shared database. The dynamic list insertion algorithm detects each search process for item/service not listed in the shared database and save it with a counter. The counter then is compared with a threshold value predetermined by the admin. The admin/business owner will be notified when new item is inserted in his items/services list. Figure 4 shows the algorithm flowchart.

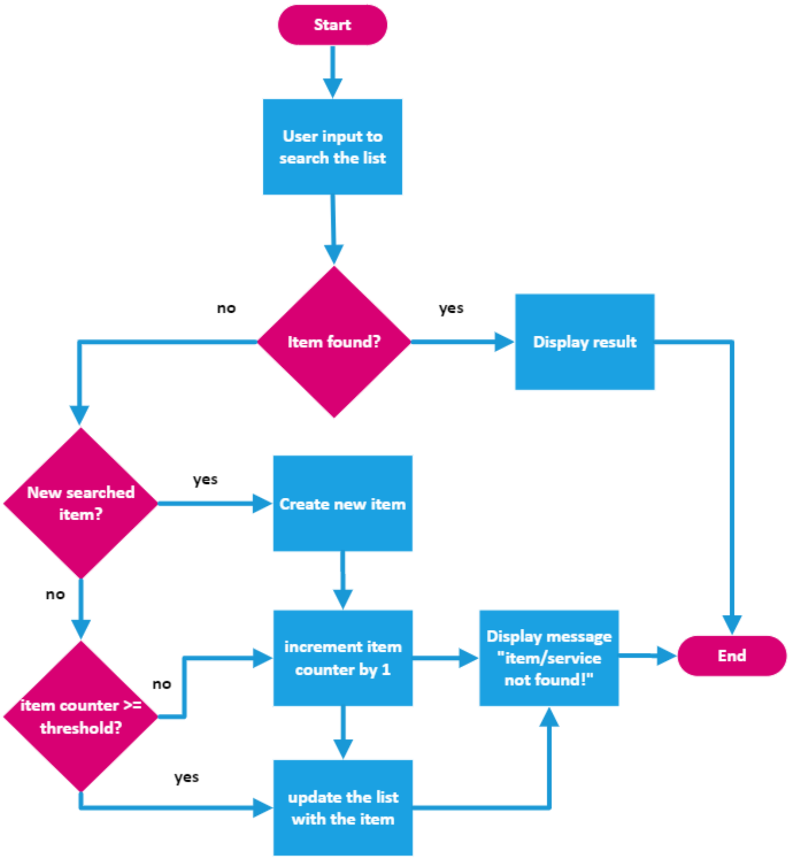

Fig. 4. Dynamic list inserting algorithm flowchart.

4. Conclusions

Context-aware recommender system requires rich information from the user in order to deliver close recommendation to the user. It is challenging how to acquire the needed information from the user as he goes while doing a search or in the move between locations. Dynamic user profiling mechanism delivers a profile template for the user and takes away a hassle process from him. However, the mechanism requires testing to investigate proposed parameters. Furthermore, the dynamic list insertion mechanism can provide a level of market vision, where the business owner may not need to introduce all what he has on the market before sensing the users' requirements. Both mechanisms are useful, however, they can be also enhanced by incorporating other aspects such as privacy, availability, and artificial intelligence.

References

1. Renjith, S.; Sreekumar, A.; and Jathavedan, M. (2020). An extensive study on the evolution of context-aware personalized travel recommender systems. *Information Processing and Management*, 57(1), 102078.

2. Sassi, I.B.; Mellouli, S.; and Yahia, S.B. (2017). Context-aware recommender systems in mobile environment: On the road of future research. *Information Systems*, 72, 27-61.
3. Bentaleb, A.; El Bouzekri, Y.; Lahcen, A.A.; and Boulmalf, M. (2018). Context aware recommender systems for tourism: a concise review. 5*th International Congress on Information Science and Technology* (*CiSt*), Marrakech, Morocco, 149-154.
4. Santamaria-Granados, L.; Mendoza-Moreno, J. F.; and Ramirez-Gonzalez, G. (2021). Tourist recommender systems based on emotion recognition - A scientometric review. *Future Internet*, 13(1), 2.
5. Eke, C.I.; Norman, A.A.; Shuib, L.; and Nweke, H.F. (2019). A survey of user profiling: State-of-the-art, challenges, and solutions. *IEEE Access*, 7, 144907-144924.
6. De Pessemier, T.; Dhondt, J.; and Martens, L. (2017). Hybrid group recommendations for a travel service. *Multimedia tools and applications*, 76(2), 2787-2811.
7. Halilaj, L.; Lüttin, J.; Rothermel, S.; Arumugam, S. K.; and Dindorkar, I. (2021). Towards a knowledge graph-based approach for context-aware points-of-interest recommendations. *In Proceedings of the* 36*th Annual ACM Symposium on Applied Computing*, Korea, 1846-1854.
8. Smith, T.; and Huong, C. (2020). Context aware recommender system for online grocery markets in indonesia. *Journal of Information and Technology*, 4(2), 49-56.
9. Tétard, F.; and Collan, M. (2009, January). Lazy user theory: A dynamic model to understand user selection of products and services. 42*nd Hawaii International Conference on System Sciences*, Waikoloa, USA, 1-9.
10. Ojagh, S.; Malek, M.R.; and Saeedi, S. (2020). A social–aware recommender system based on user's personal smart devices. *International Journal of Geo-Information* (*ISPRS*), 9(9), 519-547.
11. Khazaei, E.; and Alimohammadi, A. (2019). Context-aware group-oriented location recommendation in location-based social networks. *International Journal of Geo-Information* (*ISPRS*), 8(9), 406-429.
12. Logesh, R.; Subramaniyaswamy, V.; Vijayakumar, V.; and Li, X. (2019). Efficient user profiling based intelligent travel recommender system for individual and group of users. *Mobile Networks and Applications*, 24(3), 1018-1033.
13. Venugopal, K.R.; and Nimbhorkar, S.S. (2020). Related search recommendation with user feedback session. *In Web Recommendations Systems*, Spain, 87-108.
14. Hoque, T.T.; Ferreira, L.; Faria, L.; Martins, C.; Mesquita, R.; Conceição, L.; ... and Ramos, C. (2018). Tourism and heritage routes including visitants profile adaptation and context awareness. *International Conference on Computational Science and Computational Intelligence* (*CSCI*), Las Vegas, USA, 947-953.
15. Clarizia, F.; Colace, F.; De Santo, M.; Lombardi, M.; Pascale, F.; and Santaniello, D. (2019). A context-aware chatbot for tourist destinations. 15*th International Conference on Signal-Image Technology and Internet-Based Systems* (*SITIS*), Sorrento, Italy, 348-354.
16. Brodeala, L.C. (2020). Online recommender system for accessible tourism destinations. *In Fourteenth ACM Conference on Recommender Systems*, 787-791.