On the formalization of the context-aware recommender systems design, building and evaluation processes

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***Abstract*—In this position paper, we argue for the necessity of formalizing the processes involved in designing, building and evaluating context-aware recommender systems, and outline a conceptual framework aimed to identify, describe and relate such processes.**

***Index Terms*—recommender systems; context-aware recommendations; context modeling; recommendation evaluation**

I. Purpose

The purpose of this paper is to highlight the need to formalize the processes involved in the design, building and evaluation of context-aware recommender systems (CARS).

The literature on CARS is extensive, but vastly consists of publications reporting ad hoc algorithms developed for specific recommendation use cases, and does not describe rigorously and consensually how the above processes have been implemented. This impedes the comparison and reproducibility of existing solutions, and therefore hinders progress in the field.

II. Approach

To facilitate the formal description of CARS, we propose the conceptual framework shown in Figure 1. The framework includes the flow of activities associated with the acquisition of contextualized data, the modeling of context, the splitting of data for training and testing, and the building and evaluation of CARS.

Contextual information (e.g., time, location, weather conditions, user's mood and social companion) associated with user preferences for items in a given domain or application is the foundation of a CARS [1]. This information can be acquired explicitly by the user or implicitly from signals external to the system [2] or observation of user interactions with the system [3], and may be selected and adapted according to its *relevance* [4]. In either case, it is mandatory to properly define the processing of the obtained data and the subsequent representation of the processed data according to certain context model.

This model must be described considering context dimensions (e.g., time) and factors or variables (e.g., hour-of-the-day, day-of-the-week), which may be numeric or categorical, continuous or discrete —with or without hierarchy and order relationships—, and may be accompanied by context similarity, relatedness and reasoning measures, exploitable by the recommendation generation and evaluation processes.

Data splitting, on the other hand, can be done in different ways, considering or not contextual variables, as well as other aspects, such as whether data partitions are made at user or system level, and with or without a cross-validation method [5]. This process must be carefully described, as it generates training and test datasets that will influence the subsequent building and evaluation of the system.

As established in the literature, the contextual information can be exploited by a recommender before, during or after its underlying item filtering algorithm. In all cases, both heuristic- or model-based approaches have been considered [6], [7]. The selection and implementation of such approaches could be influenced by the recommendation task at hand, which may entail specific goals and objective functions.

Thus, for the rigorous evaluation of the system, it is also necessary to properly define the addressed recommendation task and, whenever possible, to use both context-aware and non-context-aware metrics, aiming to measure the system's performance according to a trade-off between personalization and contextualization of its item suggestions.

III. Findings

As a result of a survey of the scientific literature on CARS, we highlight the following findings. We have found that descriptions and comparisons of context representations considered in CARS are vague, and use concepts without consensus, such as contextual dimension [8], factor [9], aspect and variable [10]. Additionally, we have seen that descriptions of context models generally do not include functions or techniques to measure and exploit similarity, relatedness and reasoning between specific contexts. We have also observed that there are no well-established methods for context-based data splitting and, finally, we have identified that, in general, the metrics used to evaluate CARS are not context-oriented [11], and that context-oriented metrics have been presented and reported in isolation [12].

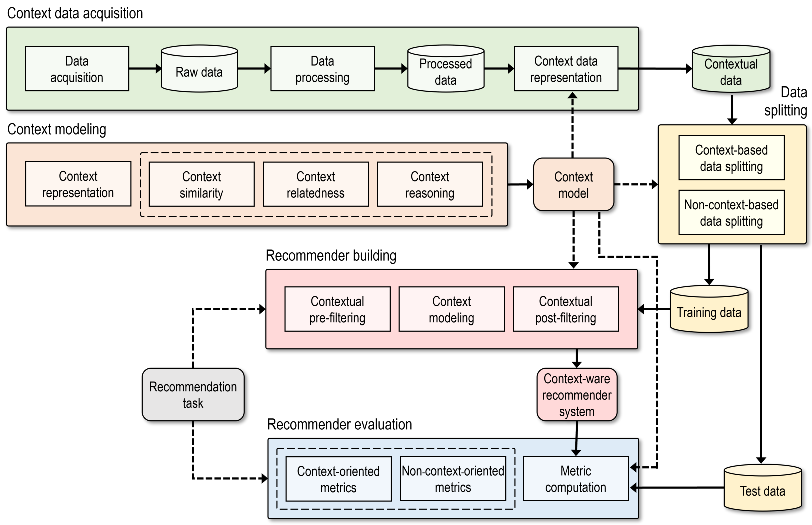

Fig. 1. Proposed conceptual framework that compiles and connects the processes involved in the design, building and evaluation of CARS.

IV. Research implications

Designing, building and evaluating CARS heavily depend on the dimensions and factors/variables considered as context, as well as the pursued recommendation task/goal.

In this sense, we believe that our conceptual framework could entail significant research implications. Firstly, it may serve as a starting point for formally reviewing the state of the art, allowing for clearly distinguishing which solutions have been proposed for each of the activities underlying the design, building and evaluation of CARS, and thereby facilitating the identification of research gaps and open challenges. Secondly, it may represent a tool for researchers to better present and compare their work on CARS, enabling the sharing and progress of research achievements.

V. Value

To the best of our knowledge, although there exist surveys on CARS, in the scientific literature, there is still no rigorous formalization of all the processes underlying CARS, except for the paradigms to recommendation generation, namely, contextual pre-filtering, contextual modeling, and contextual post-filtering [1], and their main algorithmic approaches, i.e., heuristic approaches (e.g., cosine similarity and Pearson correlation, k-means, graph- and ontology-based) and model-based approaches (e.g., Markov chains, matrix factorization, machine learning and neural networks) [13], [14]. Our conceptual framework holds the value of being the foundation to formalize the remainder of the activities, especially those related to the modeling of context and the evaluation of context-aware recommendations.

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References

[1] G. Adomavicius, K. Bauman, A. Tuzhilin, and M. Unger, “Context-aware recommender systems: From foundations to recent developments,” in *Recommender Systems Handbook*. Springer, 2021, pp. 211–250.

[2] M. del Carmen Rodríguez-Hernández and S. Ilarri, “AI-based mobile context-aware recommender systems from an information management perspective: Progress and directions,” *Knowledge-Based Systems*, vol. 215, p. 106740, 2021.

[3] A. Q. Macedo, L. B. Marinho, and R. L. Santos, “Context-aware event recommendation in event-based social networks,” in *Proceedings of the 9th ACM Conference on Recommender Systems*. ACM, 2015, pp. 123–130.

[4] M. Braunhofer and F. Ricci, “Contextual information elicitation in travel recommender systems,” in *Proceedings of the 23rd International Conference in Information and Communication Technologies in Tourism*. Springer, 2016, pp. 579–592.

[5] P. G. Campos, F. Díez, and I. Cantador, “Time-aware recommender systems: a comprehensive survey and analysis of existing evaluation protocols,” *User Modeling and User-Adapted Interaction*, vol. 24, pp. 67–119, 2014.

[6] U. Panniello, A. Tuzhilin, M. Gorgoglione, C. Palmisano, and A. Pedone, “Experimental comparison of pre- vs. post-filtering approaches in context-aware recommender systems,” in *Proceedings of the 3rd ACM Conference on Recommender Systems*. ACM, 2009, pp. 265–268.

[7] U. Panniello, A. Tuzhilin, and M. Gorgoglione, “Comparing context-aware recommender systems in terms of accuracy and diversity,” *User Modeling and User-Adapted Interaction*, vol. 24, pp. 35–65, 2014.

[8] M. Unger, A. Tuzhilin, and A. Livne, “Context-aware recommendations based on deep learning frameworks,” *ACM Transactions on Management Information Systems*, vol. 11, no. 2, pp. 1–15, 2020.

[9] W. Wang, G. Sun, S. Zhao, Y. Li, and J. Zhao, “Tensor ring decomposition for context-aware recommendation,” *Expert Systems with Applications*, vol. 217, p. 119533, 2023.

[10] X. Liu, J. Zhang, and C. Yan, “Towards context-aware collaborative filtering by learning context-aware latent representations,” *Knowledge-Based Systems*, vol. 199, p. 105988, 2020.

[11] S. Kulkarni and S. F. Rodd, “Context aware recommendation systems: A review of the state of the art techniques,” *Computer Science Review*, vol. 37, p. 100255, 2020.

[12] S. Raza and C. Ding, “Progress in context-aware recommender systems - an overview,” *Computer Science Review*, vol. 31, pp. 84–97, 2019.

[13] N. M. Villegas, C. Sánchez, J. Díaz-Cely, and G. Tamura, “Characterizing context-aware recommender systems: A systematic literature review,” *Knowledge-Based Systems*, vol. 140, pp. 173–200, 2018.

[14] S. Raza and C. Ding, “Progress in context-aware recommender systems — An overview,” *Computer Science Review*, vol. 31, pp. 84–97, 2019.