NAAR-AURA: New Aquitaine-Aragon Retrieval-Augmented User Recommendation Assistant

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Abstract. The rapid growth of available data, artificial intelligence technologies, and large-scale digital services has transformed the field of Recommender Systems (RS). Recent advances in Large Language Models (LLMs), Retrieval-Augmented Generation (RAG), and multimodal data processing offer new opportunities to deliver personalized, context-aware, and adaptive recommendations. However, these advances also raise important challenges related to privacy, energy consumption, sustainability, connectivity constraints, and multilingual support. This paper presents the NAAR-AURA project, which develops sustainable, context-aware recommender systems for tourism and environmental applications. By combining RAG-based architectures, privacy-preserving data management, and energy-aware recommendations, it aims to improve recommendation quality while reducing computational costs and environmental impact.

Keywords: Recommender Systems · Retrieval-Augmented Generation · Sustainability and Green Software · Tourism and Personalization.

1 Introduction

In the current context of large volumes of available data, automatic content generation, and multiple options to choose from, *Recommender Systems* have become useful tools to alleviate *Information Overload* and the increasing number of available options in digital environments [2]. They are currently applied in diverse domains, including environmental management and tourism.

These systems have continuously evolved, especially in recent years, progressing from simple heuristic algorithms to systems based on Artificial Intelligence (AI) capable of providing recommendations with greater quality and accuracy [11]. Traditional approaches, such as collaborative filtering and content-based filtering (including hybrid approaches), rely on relatively small datasets and limited contextual information (about users and items to be recommended) [2].

The emergence of Artificial Intelligence, particularly transformer-based architectures and Large Language Models (LLMs), is reshaping the recommender systems landscape. Modern AI techniques enable more natural interactions with users, support multilingual communication, and exploit large-scale heterogeneous data sources to provide more accurate and context-sensitive recommendations. Despite these advances, several important challenges remain unresolved:

- **Privacy**. Most recommenders rely on centralized storage and processing of personal data, creating risks regarding user privacy and data ownership.
- **Connectivity and computational requirements**. Advanced recommendation models often depend on cloud infrastructures and significant computational resources, making them difficult to deploy in environments with limited connectivity.
- **Multilingualism and inclusiveness**. Many current systems perform poorly for minority languages and specific cultural contexts due to limited linguistic resources and training data [10]. Moreover, it is needed to adapt the different systems to specific contexts by exploiting large-scale data from multiple information sources [5] and considering the integration of data from multiple (open) information sources.

To address some of these limitations, RAG has emerged as a promising approach. RAG enables language models to access external knowledge sources before generating responses, reducing retraining requirements and facilitating the incorporation of updated information [6]. This capability is particularly relevant in domains where information changes continuously, such as tourism and environmental management. At the same time, the growing adoption of AI systems raises concerns about sustainability. Large models, cloud infrastructures, and continuous data processing consume significant amounts of energy. Consequently, there is increasing interest in developing software systems that balance performance, personalization, and environmental responsibility [9].

2 Sustainable Recommender Systems

The sudden surge of large-scale machine learning models, deep learning models [13] (especially based on *transformers*), reinforcement learning models [1], the use of multimodal sensors [8], and agent-based artificial intelligence (especially driven by generative AI [3]) has radically transformed the landscape of recommender systems (RS). Furthermore, until now, little attention has been paid to the impact that RS have on sustainability [12]. Traditionally, evaluation metrics have focused on accuracy, ranking quality, prediction error, novelty, diversity, and serendipity; while the environmental costs and sustainability associated with recommendation algorithms have received considerably less attention.

The emergence of initiatives such as the RecSoGood workshop series and the Recommender Systems for Sustainable Development (RS4SD) workshop reflects a growing awareness of the need to integrate sustainability considerations into recommendation technologies. Similarly, recent research communities are exploring the integration of generative AI, language agents, and conversational systems into recommendation frameworks [4].

Modern recommender systems rely on heterogeneous data and computationally intensive AI models, increasing energy consumption, privacy risks, and potential biases. Therefore, there is a growing need for sustainable recommender systems that maintain recommendation quality while minimizing environmental impact, protecting privacy, and promoting efficient resource use. Consequently, there is a growing need to design recommender systems that not only maximize recommendation quality but also minimize environmental impact, protect privacy, and promote responsible use of computational resources.

3 Project Vision and Goals

The NAAR-AURA project aims to develop a new generation of recommender systems whose main goal is designing scalable and adaptable recommendations by balancing effectiveness and sustainability considerations and achieving four operational goals:

- **O1 Sustainable Architecture Design**. Design a top-down architecture that allows building next-generation recommender systems, based on agents specialized in data management, privacy, context-aware personalization, and energy efficiency, which can be adapted to develop RS in specific domains.
- **O2 Sustainable Data Management**. Develop data governance and data management policies that consider privacy aspects and avoid redundant processing, unnecessary data collection, and semantic enrichment of data.
- **O3 Context-Aware Personalization**. Create recommendation mechanisms that dynamically adapt to user preferences, environmental conditions, device capabilities, and energy constraints.
- **O4 Tourism-Oriented Prototypes**. Implement and evaluate recommendation prototypes focused on tourism scenarios within the Aquitaine–Aragon region to demonstrate feasibility and real-world impact.

The project builds on previous privacy-aware mobile context-aware recommender systems [7] by incorporating sustainability and energy-aware optimization. Future work focuses on generalizing existing architectures, integrating sustainable data management and context-aware personalization, reducing redundant processing, optimizing energy consumption, and evaluating the proposed solutions.

4 Conclusion

The convergence of recommender systems, generative AI, and RAG technologies creates unprecedented opportunities for delivering personalized and adaptive services. Nevertheless, these advances also generate significant challenges regarding sustainability, privacy, computational costs, and digital inclusion. NAAR-AURA proposes a research agenda centered on sustainable recommender systems that integrate energy efficiency, contextual awareness, privacy protection, and open-data exploitation as fundamental design principles. The tourism and environmental sectors provide particularly suitable application domains due to their dependence on dynamic information, heterogeneous data sources, and regional development needs. By combining RAG techniques, sustainable software principles, and context-aware personalization mechanisms, the project seeks to contribute to the development of a new generation of recommender systems capable of providing high-quality recommendations while minimizing environmental impact and supporting sustainable digital transformation.

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