Large Language Models as Recommendation Systems in Museums

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The rapid advancement of artificial intelligence (AI) has led to various applications in different domains, including recommendation systems (RSs). In the context of museums and cultural spaces, where visitors seek meaningful and engaging experiences, the utilization of advanced RSs can greatly contribute to their enjoyment and overall satisfaction.

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1. Introduction

The rapid advancement of artificial intelligence (AI) has led to various applications in different domains, including recommendation systems (RSs) [1][2][3][4]. These are software tools that assist their users in identifying content to suit their taste from a plethora of available options. They have been widely adopted in areas such as e-commerce and entertainment and play a crucial role in enhancing user experience by providing personalized suggestions, based on individual preferences and needs [5][6]. In the context of museums and cultural spaces, where visitors seek meaningful and engaging experiences, the utilization of advanced RSs can greatly contribute to their enjoyment and overall satisfaction [7][8].

Up until very recently, RSs in museums have been used to either suggest individual exhibits or specific routes to visitors [9], employing various methodologies, such as collaborative filtering, content-based filtering, and stereotyping. In the first case, recommendations are produced based on the content accessed by like-minded users, while, in the second case, the recommended content is similar to that already accessed by the user. In the last case, a “stereotype” is constructed for each visitor, either based on his/her characteristics (age, educational level, etc.) or produced via other means (e.g., answering questionnaires).

The advent of large language models (LLMs) has enhanced RSs by incorporating natural language understanding capabilities. LLMs can be trained on and analyze vast amounts of textual data available in museums, such as exhibit descriptions, relevant literature, and even external sources of information. In this way, they can model the museum space as a whole in a unified way and hopefully serve visitors by providing more accurate, rich, and context-aware recommendations, in ways similar to experienced human guides.

2. Large Language Models as Recommendation Systems in Museums

Recommendation systems have been extensively studied and applied in various domains, including e-commerce, entertainment, and online platforms. However, their application in the context of cultural heritage (CH) and, more specifically, in museums is relatively new and presents unique challenges and opportunities. Moreover, in the last couple of years, the continuous development of GPT has brought about significant changes in various sectors, reshaping interactions with technology. Among the fields profoundly impacted by the advancements in Generative Pre-trained Transformer (GPT), CH research stands out prominently [10][11][12][13][14].

Agapiou et al. [15] explored the feasibility of using ChatGPT [16], an advanced AI LLM, in remote sensing archaeology. The primary objective was to gain insight into the potential applications of this new language model and understand its capabilities. The authors formulated specific questions based on their scientific expertise and research interests, which were then posed to ChatGPT. The RS model provided responses that appeared satisfactory, although it should be noted that they lacked the comprehensiveness typically achieved through traditional literature review methods.

Grieser et al. [17] focused on offering suggestions to museum visitors according to their past interactions within the museum's physical space, as well as the textual information linked to each item they engaged with. The authors explored an approach to deliver these recommendations using a blend of language modeling techniques, geospatial analysis of the museum layout, and examination of historical sequences of locations visited by previous visitors. In the research, various methods of predicting visitor paths were examined and compared. The goal was to assess and analyze the effectiveness of these diverse methods for enhancing visitor experience.

Meanwile, Pu et al. [18] introduced a robust recommendation system based on the user's location, aimed at suggesting the most captivating destinations as the user moves around. The system operates by considering both the user's implied preferences and their current physical location, all without necessitating the user to overtly state their preferences or queries. The recommendation process involves identifying places within the physical position circle that also align with the mobile user's implied preferences, as indicated by the virtual preference circle. To estimate the user's implicit preferences, the authors employed a language modeling framework that took into account the user's past visiting patterns. This approach aids in determining the user's interests without requiring explicit input from them.

Also, another work [19] examined established museum chatbots and the platforms used to implement them. Additionally, it presented the outcomes of a systematic evaluation approach applied to both chatbots and platforms and introduced an innovative method for developing intelligent chatbots, specifically designed for museums. The said work prioritized the utilization of graph-based, distributed, and collaborative multi-chatbot conversational AI systems within museum environments. It highlighted the significance of knowledge graphs as a key technology, enabling chatbot users to access a vast amount of information while fulfilling the need for machine-understandable content in conversational AI. Furthermore, the proposed architecture aimed to provide an efficient deployment solution by employing distributed knowledge graphs that could facilitate knowledge sharing among collaborating chatbots, when necessary, as a valuable RS.

Finally, the implementation of an interactive AI RS device, powered by a robust database management system, has been tailored to cater to the distinct needs of various cultural tourists, thereby increasing visitor satisfaction and promoting deeper engagement with the exhibits [20]. Additionally, leveraging data analysis and learning algorithms, AI technology delves into the underlying cultural values, providing valuable insights and inspiration for designing exhibition content, thereby facilitating the digital transformation of museums. Through experimental research, the study demonstrates that the integration of an interactive AI device, based on a database management system, significantly improves the accuracy of the exhibition experience, enhances the effectiveness of voice guidance, streamlines visitor flow management, and incorporates an intelligent RS.

MAGICAL (Museum AI Guide for Augmenting Cultural Heritage with Intelligent Language model) [10] is a system based on GPT-4 that acts as a digital tour guide in museums. It uses the capabilities of the language model to compose texts and create dialogues with the visitor. For this purpose, the language model must be trained for use in a specific museum or a specific exhibition and be provided with all data necessary to take on the role of the expert. It maintains the style of speech given to it as instruction, can respond in many languages, always remains polite, and avoids any racial, religious, or other discrimination. It can create narratives with real or fictional characters to engage the visitor emotionally, and evaluation has shown that it is able to create recommendations.

Large language models are still unexplored for use in areas such as cultural heritage. They exhibit rapid development and even greater possibilities. GPT-4 is a text composition system that shows great flexibility. Although it is trained on a huge amount of data, it can be guided with great ease and take on various roles for applications in the fields of cultural heritage, education, tourism, video games, etc. In the experiments, it was demonstrated that it could be transformed into a very informative recommendation system, making natural language dialogues and even answering complex questions (Trichopoulos, G.; Konstantakis, M.; Alexandridis, G.; Caridakis, G. Large Language Models as Recommendation Systems in Museums [21].

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