Group - 55

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Information Retrieval

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Proposed Methods((features/ data analysis)

1. Introduction

Individuals seeking meaningful experiences frequently face hurdles while exploring cultural differences. Scattered information and a lack of personalization might make browsing numerous cultural resources difficult. Existing systems usually rely on fundamental classification or geographic location, failing to address unique user preferences. In our project we have examined a potential user preference learning cycle for a cultural discovery online application. This flow attempts to overcome these restrictions by dynamically tailoring suggestions depending on user interactions.

2. Problem Statement

The realm of cultural exploration presents a multifaceted challenge for enthusiasts seeking experiences. With abundant information scattered across diverse platforms, individuals often struggle to navigate the resources available on historic sites, museums, and cultural heritage. While existing systems may categorise data, they cannot usually provide personalised recommendations, hindering genuine discovery and engagement.

2. Proposed Flow Breakdown

The proposed flow utilizes a user-centric approach for gathering user preferences and generating personalized cultural exploration recommendations. It consists of three main steps:

- **Data Acquisition:**
  - The system requires information about cultural locations and entities which can be accessed through two main approaches:
    - **Datasets:** Utilizing pre-existing cultural datasets offers a structured and comprehensive source of information. Datasets like Wikidata, Europeana, or UNESCO World Heritage Sites offer details on historical landmarks, museums, and cultural artifacts. However, these datasets require cleaning and pre-processing.
    - **API Calls:** (APIs) provided by historical sites, and wikipedia can be used as an alternative. These APIs allow real-time access to information and multimedia content (e.g., images, virtual tours, audio guides). However, the availability and compatibility of APIs from these sources is yet to be checked.

User Preference Learning (Image Choice):

- The core of personalisation lies in understanding user interests. This step leverages user interaction through a visually appealing user interface.
  - **Frontend Development:** Building a user interface that displays a diverse set of images representing various options between contrasting cultures and heritages.(Similar to how spotify offers different genres and artists for personalised user knowledge.)

    User Interaction: Users are presented with pairs of images, and they click on the image that most interests them. This click event is captured by the system and used to build a profile of user preferences.

- **Recommendation Generation (Similarity Score):**
    - Based on the user's image selections, the system generates personalised recommendations for cultural exploration.
        - **Data Model:** The system has a data model that stores user preferences (chosen images) and links them to corresponding entities within the acquired data (datasets or APIs).
        - **Similarity Score Calculation:** To personalise recommendations, the system calculates a similarity score for each cultural location/entity. A simple approach involves assigning a score based on how well the location's attributes (e.g., historical period, cultural focus) match the user's chosen images. For example, if a user consistently chooses images of forts, the system would assign higher scores to locations categorised as forts and mahal.

3. Technical Considerations

- **Data Acquisition:** Both datasets and APIs offer advantages and disadvantages. Datasets provide a readily available source of information but may require pre-processing, while APIs offer real-time data but require evaluation for compatibility and access.
- **User Preference Learning (Image Choice):** Frontend development plays a crucial role in creating an engaging user interface with well-curated images. The system relies on user interaction through clicks to capture user preferences.
- **Recommendation Generation (Similarity Score):** A data model is essential for linking user preferences to cultural locations/entities. Calculating similarity scores can be

achieved through basic techniques like counting matching cultural categories, but this offers limited personalization potential.

4. Potential Improvements

The proposed flow and implemented prototype offers a user-friendly initial approach; however, it has limitations:

- **Limited User Input:** Relying solely on image selection might only capture part of the range of user interests. Users may have specific preferences for historical periods, cultural activities that image choices alone cannot capture.
- **Simple Similarity Score:** Basic similarity calculations based on image categories offer limited personalization potential. The system may recommend locations that partially align with user interests but miss more nuanced preferences. Same problem is faced in the prototype where we used TF-IDF scores.

These limitations can be addressed through potential improvements:

Multiple User Input Methods:

- **Hybrid Recommendation System:** As user data accumulates (clicks, saved locations, feedback on recommendations), the system can leverage more sophisticated recommendation techniques:
  - **User-Item Interaction Matrix:** Build a matrix that tracks user interactions (clicks, saves) with different cultural locations.
  - **Collaborative Filtering Algorithms:** Implement algorithms like K-Nearest Neighbors (KNN) or Matrix Factorization to identify users with similar

preferences based on the user-item interaction matrix. The system can then recommend locations that these similar users have interacted with positively.

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Conclusion

The proposed user preference learning flow offers a promising foundation for building a personalized cultural exploration web application. While the initial approach of image selection provides a user-friendly way to gather basic user interests, its limitations become evident as the need for a more nuanced understanding of user preferences arises.

By incorporating additional user input methods that explore historical period preferences, cultural focus areas, and learning styles, the system can paint a more comprehensive picture of user interests. This enriched user profile can then be leveraged by the system to generate more relevant and personalized recommendations.

Furthermore, integrating a hybrid recommendation system that utilizes collaborative filtering techniques opens doors for even greater personalization. By analyzing user interaction data and identifying users with similar preferences, the system can recommend locations that have resonated with users who share similar interests. This collaborative aspect injects a layer of real-world exploration into the recommendation process, potentially leading users to discover hidden gems or cultural experiences they might not have found on their own.

Ultimately, the success of this proposed flow lies in its ability to evolve and adapt based on user interaction and accumulated data. As the system gathers more user data and feedback, the accuracy and effectiveness of its recommendations will continue to improve. This ongoing cycle of learning and refinement will pave the way for a more engaging and enriching cultural exploration experience for users, empowering them to discover and connect with cultural experiences that resonate with their unique interests and preferences.