CULTURAL HERITAGE APPLICATIONS USING EDGE INTELLIGENCE

Thamizharasi. K[1], Poornima. A[2], Sasikala. A[3]

[1]*Assistant Professor, Jeppiaar SRR Engineering College*
[2]*Student, Dept. Of Computer Science and Engineering, Jeppiaar SRR Engineering College*
[3]*Student, Dept. Of Computer Science and Engineering, Jeppiaar SRR Engineering College*

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Abstract - Recommending systems are progressively hitting an influential role in our life, enabling users to find what they need within large data collections, bedding an array of applications, from e-commerce to e-tourism. In this paper, we present a Big datum architecture bedding typical artistic heritage applications. On the top of querying, browsing, and interpreting artistic contents coming from scattered and heterogeneous repositories, we offer a novel user-centered recommendation strategy for artistic items invitation. Despite focusing the handling with operations within the cloud, the vision of edge intelligence has been exploited by having a mobile app (Smart Search Museum) to perform semantic searches and machine-learning based inference to be capable of implying museums, together with other items of interest, to users when they are interviewing a city, exploiting jointly recommendation techniques and edge artificial intelligence facilities. Experimental results on accuracy and user fulfillment show the goodness of the offered application.

Key Words: Big Data, Cultural Heritage(CH), edge Artificial Intelligence(AI), recommender systems.

1.INTRODUCTION

Provides vacation Route recommendation for passionate travelers using community contributed pictures with Geo Tagging, people attribute and textual information like keyword and image descriptions of photos available in neural networking sites. [1]Social media based recommendation is the most well-known access, and is widely utilized in products, services, and travel recommendations Location based collaborative filtering travel recommendation methods first mine in a city which has been interviewed by social users using Geo tags or GPS trajectories. Then similar users are detected by calculating the location co-occurrences from users' travel history, using review or keywords. Then similar users are detected by calculating the location co-occurrences from user's travel history. Finally, the poi's of a new city is recommended according to similar user's visiting history.

2. RELATED WORKS

Recommender systems are more and more playing an important role in our life, enabling users to find "What they need" within very large data collections and supporting a variety of applicationsfrom e-commerce to CH fruition and tourism.[2]The most recent survey highlights both the foundationsof such tools and ,related evolution.A lot of works based on the above characteristics have been developed in the last decadefor recommending the most suitable cultural contents for CH applications, especially considering several kinds of user information and different and features.[3]In particular, some of the most diffused ones are item-based Pearson correlation (IPCC) and user-based Pearson correlation (UPCC). The first one is a content-based strategy finding objects similar to the test one by assigning similarity weights to them based on the computation of Pearson correlation coefficients.[4]In turn, UPCC is a memory-based collaborative filtering algorithm (that works in a similar manner to IPCC) assigning weights to the users to capture similarities among them. In the following, we report a brief overview of these approaches, discussing how Big Data technologies and advanced user profiling can help to improve the related performances. Albanese et al. have introduced one of the first multimedia recommender systems supporting the browsing of digital paintings within a virtual museum. The authors model recommendation as well as a social choice problem, in which multimedia features and users' visiting patterns are used for unveiling items of interest by leveraging a PageRank-like strategy.On the base of the previous recommendation strategy, Bartolini et al.have proposed a framework to dynamically arrange suggested multimedia items within visiting paths for a given cultural environment, providing one of the first example in the literature of context-aware multimedia touristic guide. The application of sensory networks and edge computing has been investigated in,where smart sensors based on Bluetooth-based proximity connectivity and a mobile app have been designed and tested so as to devise intelligent CH environments.

Other recommendation strategies are in turn more focused on the suggestion of travel itineraries as a sequence of PoIs. [5]A recommendation engine (namely SECT) has been presented by it uses a Markov n-gram model to compute recommendation scores based on topic sequential patterns for travel products.Wen et al have instead proposed a keyword-aware representative travel route framework. [6]Combining historical mobility records and social interaction to build route candidates that fulfill users' requirements by analyzing the tradeoff among different PoIs' features.

Collaborative filtering algorithm combining user's tastes and preferences from social networks andheterogeneous relationships between POI multimodal contents has been exploited for suggesting personalized PoIs on the basis of a matrix factorization model. [7]Similarly, Longesh et al. have introduced a collaborative filtering strategy for trip recommendation, based yet on the quantum-behaved particle swarm optimization strategy.

3. SYSTEM DESIGN

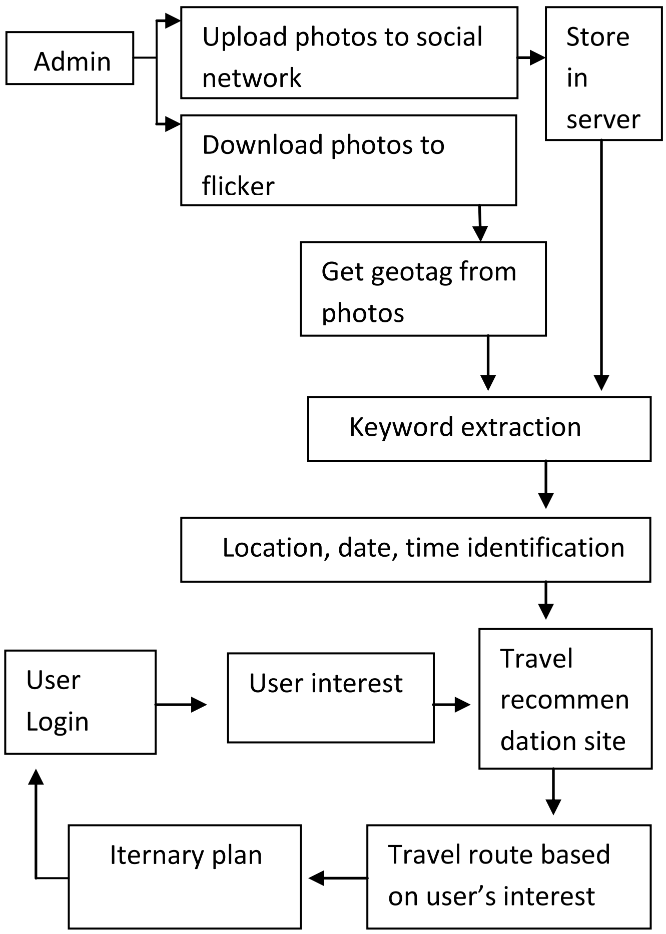

Fig. 1

In first module, we are creating a social networking profile that is specifically concentrated on users pictures. User will register their details and server stores user information in a database. [8]Users will transfer their pictures into the social networking site. While uploading, user provides tags for the picture, Geo Tagging information and access privilege. User share photos in Social Networking Website. In second module, Admin gathers photos by giving tags from Flicker Website. Admin download public photos from this website. Now preprocessing will be done. Geo Tagging will be applied to all downloaded public photos. Geo Tagging applied using Flicker API. User can view their drive where all uploaded pictured by the user listed in this drive. We are creating a Travel Recommendation Website for recommending locations to the user. Admin will get permission from Social Website to access public photos. After permission granted by the Social Website, Admin will perform preprocessing to the public photos with tags, and keyword extraction. In this module extract the keyword to get the specific places in experience.During preprocessing stage: location, date and time and tags of photos will be retrieved. These photos, ' information is stored into database. In this module, we will recommend vacation destinations for the user based on user input. User specifies their Point of Interest and requirements for getting Travel Recommendation. User input will be current location, place to visit, duration, type and purpose of visit and budget cost. Based on user personalized POI, Server generates a personalized travel plan.

4. EXPERIMENT

This section describes the performed experimentation whose aim is to evaluate the effectiveness of our recommendation strategy by using an Android app (Smart Search Museum). The related main services are shown in collecting users' data and preferences and suggesting them proper cultural itineraries. [9]Cultural data have been crawled from the Italian Ministry of Cultural Heritage and Activities (MiBACT) repository,8 composed by cultural objects.They are for the majority of cases museums, archaeological sites, and cultural place of interest with the related paintings, sculptures, and other kind of artifacts. [10]Moreover, these data together with the corresponding metadata (such as title, genre, authors, history, etc.) are accessible as open data by means of proper APIs.9 The efficiency of the proposed approach is strictly correlated with chosen hardware configuration. In particular, the evaluation has been made by using 2 E4v3 VM instance with 4 vCPU and 32 GB RAM as server, showing as running times are lower than 10 s. A group of users has been asked to test the application collecting their preferences, subdivided in two broad categories.

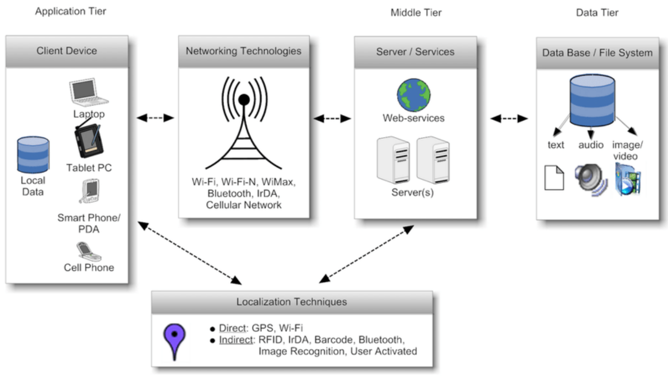

Fig. 1.1

More in detail, we consider user experts are people with high-school education and basic notions of history and art, while nonexpert users are young or old people without any specific knowledge about CH. Furthermore, we asked users to evaluate a workload, which is defined as the mental stress produced by the physical and social conditions of work, based on several tasks' characteristics. [11]It generates from a psychological point of view a mental strain that has physiological and cognitive effects as well as fatigue. Summarizing up, we can assume that the system offers a good experience during browsing activity and that the recommendations are effective making the user satisfied because the performance measure reaches high values and mental and physical demand assumes low values.

5. CONCLUSIONS

Here, nominating a new Big Data infrastructure for the management of cultural items: a multilayer architecture that offers APIs for the creation of new applications based on the modules as like as query engine, semantic search, and machine learning.The knowledge is dynamic thanks to the stream processing. This module captures a stream of data from social networks to continuously handle and update information on photos, feelings, descriptions, reactions, etc. Furthermore, the knowledge is enriched with the information stored in proper databases and ontologies (which can be accessed through batch processing and REST APIs, respectively). In addition, a new approach for the recommendation of cultural contents, adding the know-the-user subphase to prefiltering phase, in which the user profile is traced in order to accurately prefilter data using machine-learning algorithms. [12]The ranking phase calculates three scores (popularity, mood, and interest) combined in the next phase. Each of these scores is calculated by accessing the data collected by social networks and by system itself (through the history of past users). In order to test our system, an application of the Android devices was created: Smart Search Museum.Through this application you can access the map containing all the museums of a given area in Italy, memorize those already visited and create an itinerary for the final user. For managing the large amount of data, the proposed system leverages Big Data technologies, in particular distributed computing on Hadoop and NoSQL repositories. [13]The current main limitation is the relatively small size of the datasets used for the experiments and the number of users involved in the NASA-TLX for evaluation. The testing of our approach on large amounts of data will certainly strengthen our work, but enrolling a large population of users for the type of experiments described in this paper is not trivial and takes a long time. However, we are working to expand our experimental configuration and we expect to present further results in the near future.

6. FUTURE SCOPE

Places are segregated based on the Geo tag information, Number of Persons on the photo and can be later used with POI recommendation. [14]In the travel route recommendation system, we employ users' topic preferences as the law for collaborative filtering instead of location co-occurrences. Dynamic travel plans are recommended to the user based on POI. We propose a efficient keyword aware travel plans recommendations when a user is about to visit a new place. In contradiction to current location based collaborative filtering methods, we learn users' travel preferences from the text descriptions with keyword associated with their shared photos on social media, instead of from GPS trajectories or check-in records. In addition, users' similarities are measured with author topic model instead of location co-occurrence.In the system extract the past experience person keyword based extraction. The proposed data model is inspired by EDM and relies on two main entities: Users and Cultural Objects. Concerning cultural objects, in our vision they can be specific ruins of an archaeological site, sculptures and/or pictures exhibited within a museum, historical buildings and famous squares in a downtown, and so on. [15]In addition, a cultural object may be associated with a specific PoI, defined by a set of geographic coordinates, and corresponding either to a single point or to a set of lines and more complex polygons of the considered cultural environment. In the CH domain, a cultural object can be then described with respect to a variety of annotation schemata, for example, the archaeological view, the architectural perspective, the archivist vision, the historical background, and so on, that usually exploit different harvesting sets of metadata and possibly domain taxonomies or ontologies. For a concrete example, Choi defined a travel ontology to defines the inference rules to support semantic search for e-tourism, which can be integrated within a cultural recommender system.

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