iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 8 **Issue:** III **Month of publication:** March 2020

DOI:

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 8 Issue III Mar 2020- Available at www.ijraset.com

Cultural Heritage Applications using Edge Intelligence

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Abstract: We propose an efficient keyword aware travel plans recommendations when a user is about to visit a new place. In contrast to existing 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. Places are classified based on the geotag information, Number of Persons on the photo and can be later used with POI recommendation. In the travel route recommendation system, we utilize 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.

I. INTRODUCTION

NOWADAYS, *recommender systems* represent one of the most important and popular applications of artificial intelligence(AI) and Big Data analytics [1], and in particular of information filtering techniques, necessary to realize the desired

Manuscript received February 11, 2019; accepted March 7, 2019. Date of publication March 28, 2019; date of current version July 3, 2019.This work was supported in part by the National Key Research and Development Program under Grant YS2017YFGH001945, in part by the National Natural Science Foundation of China under Grant 61801166,and in part by the National Research Foundation of Korea Grant funded by the Korean Government (Ministry of Science and ICT) under Grant 2017R1E1A1A01077913. Paper no. TII-19-0442. *(Corresponding author: Chang Choi.)*

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Digital Object Identifier 10.1109/TII.2019.2908056 transition from the era of "search" to the era of "discovery.'. According to *Fortune* magazine writer Jeffrey M. OBrien, it is interesting to note as " . . . *search is what you do when you arelooking for something while discovery is when something wonderful that you didn't know existed, or didn't know how to ask for, finds you...*"Generally speaking, a recommender system formally deals with a set of *users* $U = \{u1, . . . , un\}$ and a set of *items* $O = \{o1, . . . , om\}$. For each pair (ui, oj), it computes a *rank* rji that measures the expected interest of the user ui to the item oj (or the expected utility of the item oj for the user ui), using a recommendation algorithm that holds the following conditions.

1) It is usually based on *content-based*, *collaborative filtering*,or *hybrid* strategies [2], [3].
2) It generally considers different combinations of the following characteristics: user preferences and past behavior, preferences and behavior of the user community, items' features and how they match user preferences, user feedback, and contextual information and how recommendations change together with the context [4].
3) It eventually leverages on *prefiltering* and *postfiltering* tasks to reduce the items' set size and arranges the recommended objects in specific groups according to additional constraints [2]. Recommender systems started off becoming popular in ecommerce to support personalized product recommendations and the most well-known example is surely the functionality "customer who bought this item also bought . . . " provided by Amazon. Within such a context, a recommendation engine is an intelligent and

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sophisticated salesman who knows (or have discovered) users' tastes, preferences, and needs and thus can make more intelligent decisions about which recommendations would benefit the customer.

Even if recommendation engines were born in e-commerce domain, they are now gaining more and more popularity in other sectors. Some famous examples in this direction are "Recommended Videos" in YouTube, "Other Movies You May Enjoy" from Netflix, "People You May Know" of Facebook, "Jobs You May Be Interested In" in LinkedIn, or "Best Route" for Waze.

During the last years, another key sector where recommendation facilities are playing a key role consists in the tourism market and the cultural heritage (CH) [5]. Apart from the naïve examples of suggesting hotels (as done by the Booking portal) or restaurant (as done by Trip Advisor), recommender systems are being disruptive for CH as they are changing the way we enjoy museums and sites of historical and artistic interests. Indeed, thanks to them the fruition of CH is rapidly moved from an old vision, where a tourist could access static information consisting in a large amount of cultural signs, to a novel one [6], consisting in personalized and interactive services to match the visitors' needs by considering their cultural preferences and, furthermore, context information. In other terms, the user experience could be surely enhanced if, instead of using classic touristic guiding devices, she/he could be interact with a smart cultural environment capable of delivering the relevant information from the available CH digital sources, such as text descriptions, pictures, and videos related to cultural items of interest. In this way, tourists would be given the opportunity of enjoying multimedia stories in real time, thus enriching their cultural experience [7].

Within the context of a recommender application, each cultural space can be seen as grounded on a set of cultural Points of Interest (PoI), which correspond to one or more cultural items (e.g., specific ruins of an archaeological site, sculptures and/or pictures exhibited within a museum, historical buildings, and famous squares in a downtown) and CH applications can potentially use very huge quantity of heterogeneous data related to cultural items themselves, such as the following:

a) Annotations and descriptions provided by CH foundations archives or by open encyclopedias;
b) Multimedia contents video, text, image, and audio coming from social media (e.g., YouTube, and Flickr) or digital libraries;
c) Opinions and comments of users from common online social networks, like Facebook, Twitter, etc.

In addition, information about users (preferences and behaviors) and measures (e.g., humidity and temperature) captured by the different sensors deployed in a cultural environment [8] should be also taken into account together with web service data (any kind of useful data gathered by means of web services such as touristic attractions or accommodations in the same geographic area, or meteorological information and so on) in order to providemore smart services to the final users. In order to meet variety, velocity, and volume of all the described kinds of CH information, recommendation applications have to rely upon a Big Data infrastructure with such technical features [9], [10]: capability to gather information from distributed and heterogeneous data sources, advanced data management techniques, and technologies and proper data analytics. Such platforms have also to be based on a service oriented architecture paradigm and on edge computing features. In this way, different apps running on given devices can easily access to the platform services, locally processing in a more efficient way some data useful for recommendation algorithms directly on the hardware of users' devices (Edge AI) [11], [12], so as to place data, processing and services at the edge of the network instead of entirely in the Cloud. The current literature of recommender systems and applications applied to the CH context is vast [2], [4], [9], [13], where different technological solutions, driven from Big Data Analytics, Internet of Things (IoT), and AI, have been exploited and integrated. From one point of view, most of these solutions leverage of cloud computing and/or a proper means for the centralized processing. In this sense, we leverage on edge intelligence in addition to cloud computing for a more scalableand user-centric analysis of the cultural data. From another point of view, the few solutions designed for mobile computing, such as the one described in [6], mainly apply a very simple data processing strategy and may not encompass information from social media. In order to goes beyond the state-of-the-work, the main contribution of this paper is threefold.

i) We present a new BigData architecture supporting typical CH applications, improving and technologically reviving that related to the CHIS project [10] (a prototype forquerying, browsing, and analyzing CH contents coming from distributed and heterogeneous repositories).
ii) We propose a novel user-centered recommendation strategy, empowered with edge intelligence, for cultural items suggestion within CH environments, extending and revisiting recent related works, such as [13].
iii) As proof of concept, we realize a mobile app (*Smart Search Museum*) capable of suggesting museums together with other items of interest to users when they are visiting a city, exploiting jointly recommendation techniques and edge AI facilities . The rest of this paper is organized as follows. Section II discusses the related work on Big Data architectures and recommender systems used for CH domain. Section III describes in details the data model for managing cultural objects and our recommendation strategy, while Section IV illustrates the proposed system architecture. Section V outlines the case study for museums'

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suggestion and presents several experimental results related to the effectiveness of recommendation techniques and mobile app avails for users. Finally, Section VI reports future developments and several conclusions.

II. LITERATURE SURVEY

In 2015 R. Logesh , V. Subramaniyaswamy, V. Vijayakumar, developed A hybrid quantum-induced swarm intelligence clustering for the urban trip recommendation in smart city. Quantum-behaved Particle Swarm Optimization (QPSO) is new swarm intelligence algorithm with improved ability over PSO by producing an effective solution for global optimization problems with fewer adjustable parameters. Utilizing the clustering mechanisms with collaborative filtering for grouping similar users as clusters can enhance the efficiency of the recommendation generated.The demerits are Bio-inspired algorithms are very familiar in solving the optimization problems which traditional approaches failed to have an effective or an efficient solution. The utilization of traditional clustering algorithms such as K-means clustering has some drawbacks in obtaining optimal solutions for large- scale application problems. In 2016 , Chang Choi, Junho Choi, Htet Myet Lynn developed Travel Destination Recommendation Based on Probabilistic Spatio-temporal Inference. The merits are the travel destination recommendation provides the travelers with more accurate suggestions to the closet and relevant destination from user's current location and improves the travelling experience. The demerits are the collaboration filtering algorithm is used in recommendation system but this approach will suffer from the problem of data sparseness and the first rate problem. In 2017, Li Gao, JiaWu, Chuan Zhou, Yue Hu developed Collaborative Dynamic Sparse Topic Regression with User Profile Evolution for Item Recommendation. The merits are The model CDUE significantly obtains the better performance in terms of the Precision and MRR metrics. This model also provides good interpretive ability using the topics learned from the data. The demerits are The contents of items are assumed to be stable over time. They thus fail to capture the dynamic changes in the item's contents. The objective over the data in all time intervals is less scalable.

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III. EXISTING SYSTEM

Social Media -based recommendation approaches are effective and efficient, but suffer from the well-known "time complexity problem and cost satisfaction" in recommendation systems, due to travel data being very sparse. In this circumstance, it makes accurate similar user identification very difficult if the user has only visited a small number of POIs.

The category topics are usually determined by the naive category information from recommended systems in Topic Model Method(TM). From the predetermined categories, it is convenient to calculate user preferences. Unfortunately, for rich photo sharing networks like Flicker, there is no such defined category information. Thus the naive topic-based recommendation approach cannot be utilized directly in travel recommendations.

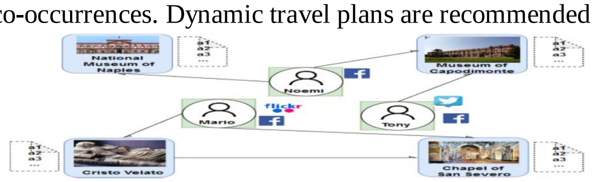
A. *Problem Definition*

1) Static Travel Plans
2) Not supports personalized POI Recommendations
3) Category Information is undefined
4) Static Datasets for POI

IV. PROPOSED SYSTEM

A. We propose an efficient keyword aware travel plans recommendations when a user is about to visit a new place. In contrast to existing 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.

B. Places are classified based on the geotag information, Number of Persons on the photo and can be later used with POI recommendation. In the travel route recommendation system, we utilize 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.



Advantage

1) Dynamic travel plans with sequence route.
2) Time complexity.
3) Travel Route navigation

V. REQUIREMENT SPECIFICATION

A. *Hardware Requirements*

1) Hard Disk : 500GB and Above
2) RAM : 4GB and Above
3) Processor : I3 and Above

B. *Software Requirements*

1) Windows 7 and above
2) JDK 1.7
3) Tomcat 7.0
4) MySQL5.0

C. *Technologies Used*

1) J2EE (JSP, Servlet)
2) Struts Framework
3) JavaScript , HTML ,CSS
4) JDBC

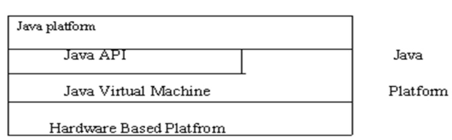
D. *The Java Platform*

A platform is the hardware or software environment in which a program runs. The Java platform differs from most other platforms in that it's a software-only platform that runs on top of other, hardware-based platforms. Most other platforms are described as a combination of hardware and operating system.

The Java platform has two components :

1) The Java Virtual Machine (JVM)
2) The Java Application Programming Interface (Java API)

You've already been introduced to the JVM. It's the base for the Java platform and is ported onto various hardware-based platforms. The Java API is a large collection of ready-made software components that provide many useful capabilities, such as graphical user interface (GUI) widgets. The Java API is grouped into libraries (packages) of related components. The following figure depicts a Java program, such as an application or applet, that's running on the Java platform. As the figure shows, the Java API and Virtual Machine insulates the Java program from hardware dependencies.



As a platform-independent environment, Java can be a bit slower than native code. However, smart compliers, weel-tuned interpreters, and just-in-time byte compilers can bring Java's performance close to that of native code without threatening portability.

E. *Apache Tomcat Server*

Apache Tomcat (formerly under the Apache Jakarta Project; Tomcat is now a top level project) is a web container developed at the Apache Software Foundation. Tomcat implements the servlet and the Java Server Pages (JSP) specifications from Sun Microsystems, providing an environment for Java code to run in cooperation with a web server. It adds tools for configuration and management but can also be configured by editing configuration files that are normally XML-formatted. Because Tomcat includes its own HTTP server internally, it is also considered a standalone web server.

F. Environment

Tomcat is a web server that supports servlets and JSPs. Tomcat comes with the Jasper compiler that compiles JSPs into servlets.
The Tomcat servlet engine is often used in combination with an Apache web server or other web servers. Tomcat can also function as an independent web server. Earlier in its development, the perception existed that standalone Tomcat was only suitable for development environments and other environments with minimal requirements for speed and transaction handling. However, that perception no longer exists; Tomcat is increasingly used as a standalone web server in high-traffic, high-availability environments.
Since its developers wrote Tomcat in Java, it runs on any operating system that has a JVM.

VI. SYSTEM DESIGN AND IMPLEMENTATION CONSTRAINT

A. System Design

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. Users will upload their pictures into the social networking site. While uploading, user provides tags for the picture, GeoTagging information and access privilege. User share photos in Social Networking Website. In second module, Admin collects photos by giving tags from Flickr Website. Admin download public photos from this website. Now Preprocessing will be done. GeoTagging will be applied to all downloaded public photos. GeoTagging applied using Flickr API. User can view their drive where all uploaded pictures 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 past 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 travel destinations for the user based on user input. User specifies their Point of Interest and requirements for getting Travel Recommendations. User input will be current location, place to visit, duration, type and purpose of visit and budget cost. Based on user personalized POI, Server generate a personalized travel plan.

B. Constraints in Analysis

1) Constraints as Informal Text
2) Constraints as Operational Restrictions
3) Constraints Integrated in Existing Model Concepts
4) Constraints as a Separate Concept

C. Constraints in Design

1) Determination of the Involved Classes
2) Determination of the Involved Objects
3) Determination of the Involved Actions
4) Determination of the Require Clauses
5) Global actions and Constraint Realization

D. Constraints in Implementation

A hierarchical structuring of relations may result in more classes and a more complicated structure to implement. Therefore it is advisable to transform the hierarchical relation structure to a simpler structure such as a classical flat one. It is rather straightforward to transform the developed hierarchical model into a bipartite, flat model, consisting of classes on the one hand and flat relations on the other. Flat relations are preferred at the design level for reasons of simplicity and implementation ease. There is no identity or functionality associated with a flat relation. A flat relation corresponds with the relation concept of entity-relationship modeling and many object oriented methods.

VII. CONCLUSION

Thus the personalized travel plans are generated for the user based on POI travel recommendations of the user using personalized travel route recommendation on Multi-Source Big Social Media

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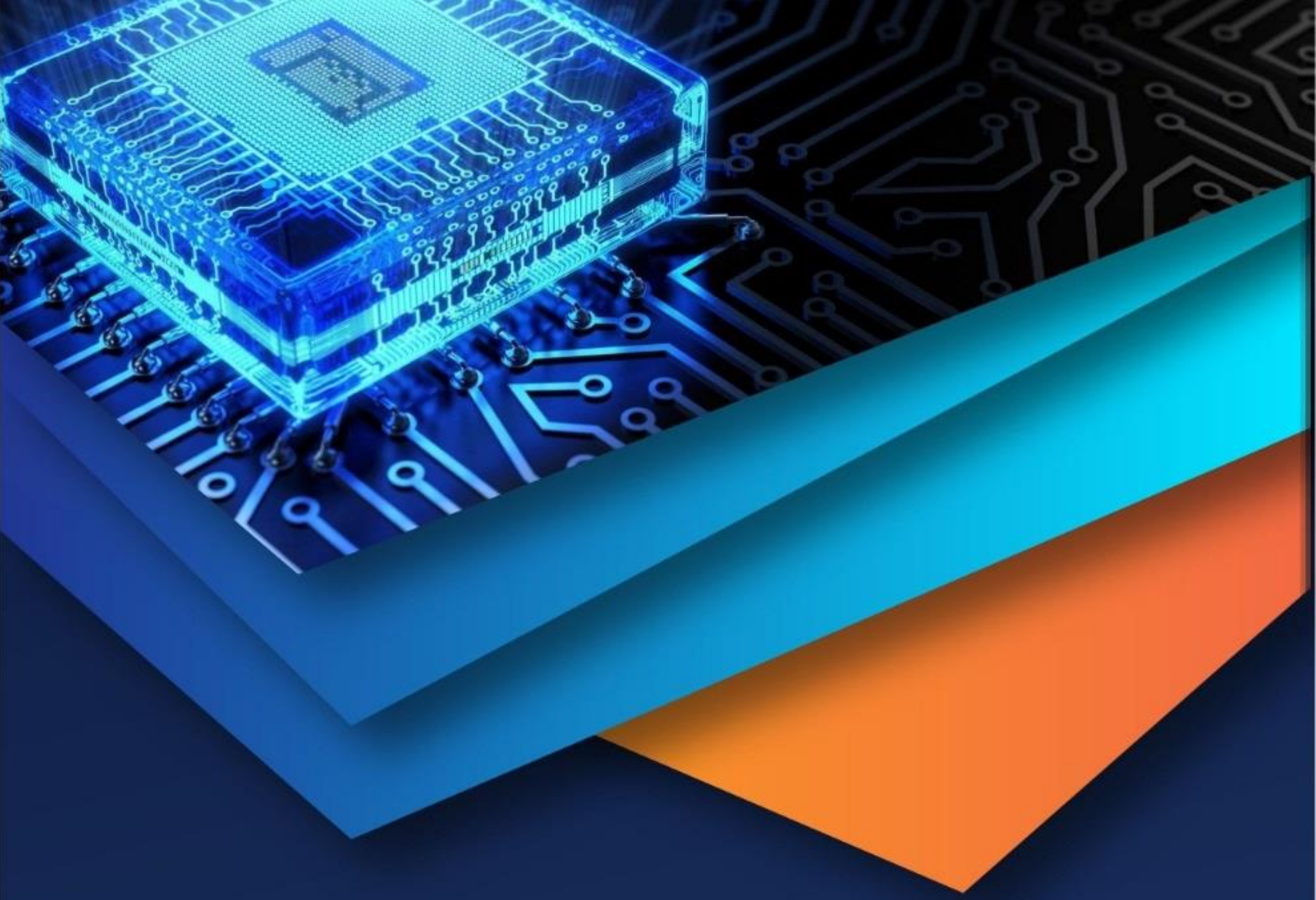

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