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Location and User Activity Preference Based Recommendation System

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***ABSTRACT*—**With the recent surge of location based social networks (LBSNs), activity data of millions of users has become attainable. This data contains not only spatial and temporal stamps of user activity, but also its semantic information. LBSNs can help to understand mobile users' spatial temporal activity preference (STAP), which can enable a wide range of ubiquitous applications, such as personalized context-aware location recommendation and group-oriented advertisement. However, modeling such user-specific STAP needs to tackle high-dimensional data, i.e., user-location-time-activity quadruples, which is complicated and usually suffers from a data sparsity problem. In order to address this problem, we propose a STAP model. It first modelsthe spatial and temporal activity preference separately, and then uses a principle way to combine them for preference inference. In order to characterize the impact of spatial features on user activity preference, we propose the notion of personal functional region and related parameters to model and infer user spatial activity preference. In order to model the user temporal activity preference with sparse user activity data in LBSNs, we propose to exploit the temporal activity similarity among different users and apply nonnegative tensor factorization to collaboratively infer temporal activity preference. Finally, we put forward a contextaware fusion framework to combine the spatial and temporal activity preference models for reference inference. We evaluate our proposed approach on three real-world datasets collected from New York and Tokyo, and show that our STAP model consistently outperforms the baseline approaches in various settings.

Keywords— Location based social networks, spatial, temporal, tensor factorization, user activity preference.

1, INTRODUCTION

The main aim of this project is to make high utility of LBSN to infer User Spatio Temporal Activity preference so as to provide personalized context aware Place Of Interest (POI) recommendation and to integrate efficient mobile theft identification system and context aware profile changer.The ubiquity of GPS-equipped smart phones, Location Based Social Networks (LBSN) has gained increasing popularity in recent years. In LBSNs, users interact not only with their friends by sending messages, sharing photos, but also with physical Points Of Interest (POIs) showing their presence in real-time, leaving their comments, etc.. These large-scale user generated digital footprints bring an unprecedented opportunity to understand the spatial and temporal features of user activity. In LBSNs, user activity is mainly represented by check-in which indicates that a user visited POI at a certain time. Along with POI categories that are often associated with user activities, we can semantically characterize the activities of a user in a place. By mining these activity records, we are able to understand user spatial temporal activity preference which can then enable various location based applications like POI recommendation.

2. THE LBSN PROCESS MODEL

2.1 User Mobile identification and profile building

First the Registration is carried by identifying the user mobile by retrieving the parameters like simnos and memory card identity no.After User mobile registration user can sign in to our application and can set up a context aware profile.

2.2 Service Thread Implementation

The user mobile identity and context aware profile monitoring process is implemented using Service thread which runs in background. This thread is activated when user installs the application after registration and sign in process gets completed first time.

2.3User Preference modeling based on PFR

Preference modeling is done through spatial and temporal activities of a particular user in a independent way and then clubbing together. First the Spatial preference of a user is calculated by identifying the frequented region of a user.

2.4Integrated Location Based Services (Theft & Profile Management, Personalized POI)

All the Location based services discussed above are integrated together as all the services use location service in a continuous way when run independently. Battery efficiency and memory utility can be improved when application using similar services or resources are grouped together to give integrated services.

3, SYSTEM ANALYSIS

3.1 Existing System

A mobile application called Around Me helps users to explore the nearby places, which first lets them select activity category and then shows the specific POIs. Modeling user spatial temporal activity preference is able to improve the user experience of location based services. However, modeling user spatial temporal activity preference from user check-ins in LBSNs is not trivial.

1. Since the check-in data is usually sparse and is represented as user location-time-activity quadruples it is difficult and complicated to directly discover the regularity from such sparse high-dimensional data.

2. To consider spatial dimension, the existing works usually segment a city into disjoint grid cells and discretely infer user preference in individual cells which may cause inaccuracy due to the discretization process. For example, when a user is located at the border of two adjacent cells, a movement with a very short distance may incur the change of cells and cause different preference inference results.

3. check-ins are user voluntarily reported activities and users do not regularly perform checkins, due to the reasons such as lack of time and privacy concern, etc.

4, MAIN FEATURES OF TRANSPOSE-MINIFY FRAMEWORK

4.1 Functionality: are the required functions available, including Interoperability and security.

4.2 Reliability: maturity, fault tolerance and recoverability

4.3Usability: how easy it is to understand, learn, and operate the software System

4.4 Efficiency: performance and resource behavior.

4.5 Maintainability: Maintaining the software.

4.6 Portability:can the software easily be transferred to another environment, Including installability

5.TECHNIQUES IN LBSN

5.1 J2EE (Jsp, Servlets)

Both servlets and JSP pages contain Java code that is processed by a Web server. However, servlets are primarily Java programs, while JSP pages are primarily HTML files.

5.2 Struts Framework

This page will give you a short overview of Struts Framework and its main components. After finishing reading this, continue on to the tutorial to create a simple Struts-based

Web application. It Implements the JSP Model 2 Architecture.Stores application routing information and request mapping in a single core file, struts-config.xml

5.3JavaScript

JavaScript is a client-side scripting language, which means the source code is processed by the client's web browser rather than on the web server. This means JavaScript functionscan run after a webpage has loaded without communicating with the server.

5.4Android

Android phones typically come with several built-in applications and also support third-party programs. Developers can create programs for Android using the free Android SDK (Software Developer Kit).

6, IMPLEMENTATION OF LBSN

6.1 Steps

- User Mobile identification and profile building
- Service Thread Implementation
- User Preference modeling based on PFR
- Integrated Location Based Services(Theft & Profile Management, Personalized POI)

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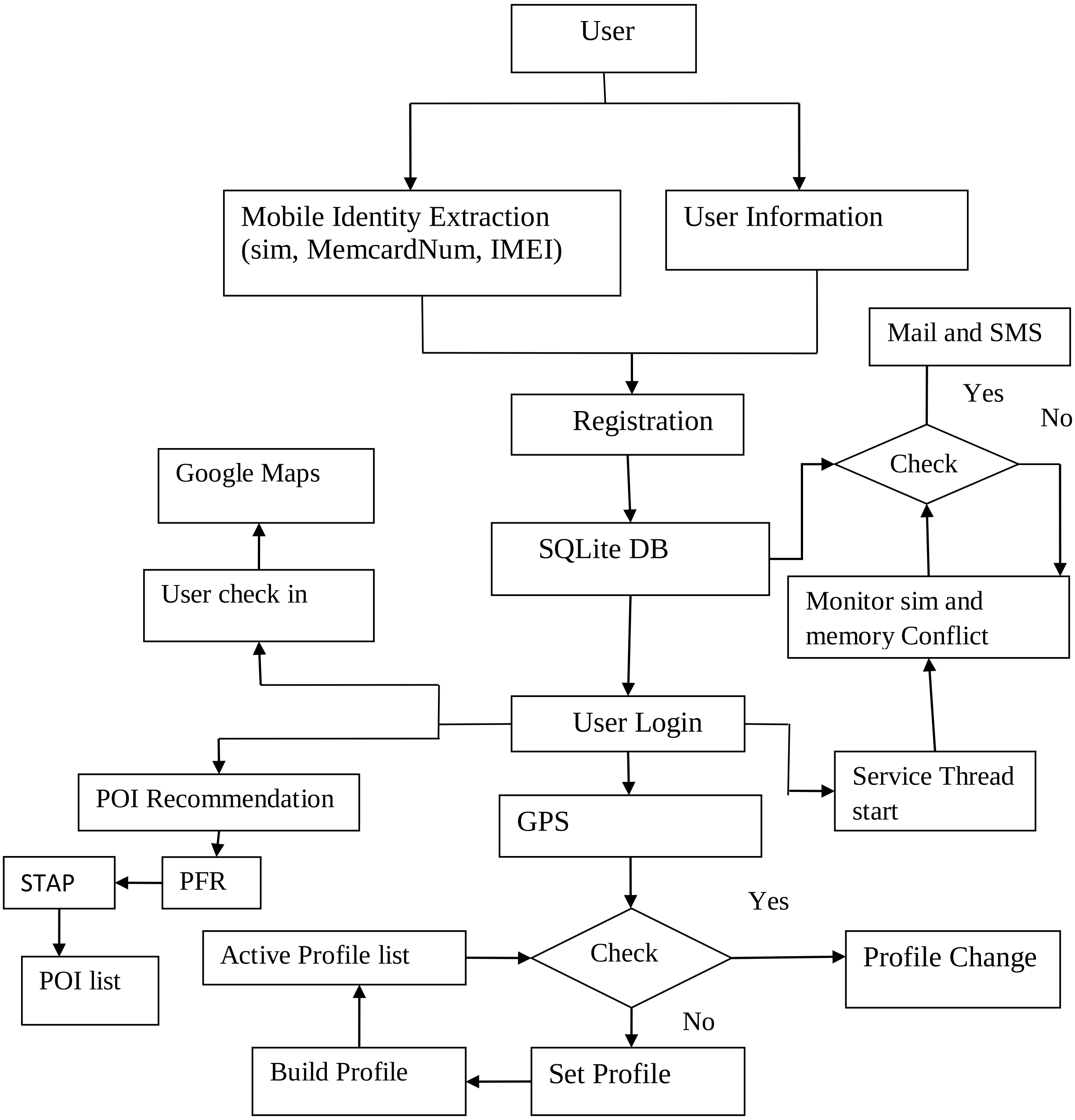

Figure.1 LBSN architecture

VIII. CONCULSION AND FUTUREWORK

Integrated services help to improve Battery efficiency and memory utility.When application using similar services or resources are grouped together to form Integrated services users can be delighted with a single touch from their smart phones to acquire services. Understanding user spatial temporal activity preference can benefit users by providing them with customized location based services. However, it is difficult to directly tackle such four dimensional data. This paper presents STAP, a spatial temporal activity preference model. To reduce the problem complexity, STAP separately considers the spatial and temporal features of user activities by introducing the notion of spatial specificity and temporal Correlation. First, we define Personal Functional Regions to quantitatively measure one's preference bias in her frequented regions and use them to infer spatial activity preference. Second, temporal correlation suggests that users with the similar lifestyle tend to have similar activity preference at the similar time. Finally, we propose a context-aware fusion framework to make best use of the advantage of both features in activity preference inference.

Global Positioning System technology started as a military investment but has quickly expanded to the business and commercial sectors. Over the next ten years we can expect to see more changes in the technology and more practical applications across different aspects of everyday life.

REFERENCES

[1] Z. Wang, D. Zhang, D. Yang, Z. Yu, and X. Zhou, "Discovering and profiling overlapping communities in location based social networks," IEEE Trans. Syst., Man, Cybern. Syst., vol. 44, no. 4, pp. 499–509, Apr. 2014.

[2] H. Gao, J. Tang, and H. Liu, "Exploring social-historical ties on locationbased social networks," in Proc. ICWSM, 2012, pp. 114–121.

[3] D. Zhang, B. Guo, and Z. Yu, "The emergence of social and community intelligence," IEEE Computer, vol. 44, no. 7, pp. 21–28, Jul. 2011.

[4] J. Chang and E. Sun, "Location3: How users share and respond to location-based data on social networking sites," in Proc. ICWSM, 2011, pp. 74–80.

[5] A. Noulas, S. Scellato, N. Lathia, and C. Mascolo, "Mining user mobility features for next place prediction in location-based services," in Proc. ICDM, 2012, pp. 1038–1043.

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