

International Journal of Computer Science and Mobile Computing



A Monthly Journal of Computer Science and Information Technology

ISSN 2320-088X
IMPACT FACTOR: 5.258

IJCSMC, Vol. 5, Issue. 3, March 2016, pg.723 – 727

Location and User Activity Preference Based Recommendation System

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Abstract---The high utility of Location Based Social Network (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. In order to reduce the problem complexity, separately consider the spatial and temporal characteristics of user activity preference in LBSNs.

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

I. INTRODUCTION

The ubiquity of GPS-equipped smart phones, location based social networks (LBSNs) have gained increasing popularity in recent years. In LBSNs, users inter-act 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 a 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. For example, a user, Jane, is having French food (i.e., being at a French restaurant) at [40.7586, -73.9791] at 21:10 on Friday. By mining these activity records, we are able to understand user spatial temporal activity preference (STAP) which can then enable various location based applications. The most straightforward application is POI recommendation. For example, knowing Jane is currently interested in going to a Chinese restaurant, a recommendation of Chinese food in a nearby POI would be persuasive. Moreover, knowing a group of users' activity preference, real time group-oriented advertisement can be better enabled. For example, a clothing store is offering a group discount, if we know five users in the area are interested in the clothing store, an invitation to them would be welcome by business owners.

II. LITERATURE SURVEY

D.Lian and X.Xie[1], Users' daily activities, such as dining and shopping, inherently reflect their habits, intents and preferences, thus provide invaluable information for services such as personalized information recommendation and targeted advertising. In this light, we propose a novel collaborative boosting framework comprising a text-to-activity classifier for each user, and a mechanism for collaboration between classifiers of users having social connections. The collaboration between two classifiers includes ex- changing their own training instances and their dynamically changing labeling decisions.

We propose an iterative learning procedure that is formulated as gradient descent in learning function space, while opinion exchange between classifiers is implemented with a weighted voting in each learning iteration. We show through experiments that on real-world data from Sina Weibo, our method out-performs existing off-the-shelf algorithms that do not take users' individuality or social connections into account.

Y.Jihang, Z.Zhe, and C.Hong[2], Location-based social networks have been gaining increasing popularity in recent years. To increase users' engagement with location-based services, it is important to provide attractive features, one of which is geo-targeted ads and coupons. We propose a framework which uses a mixed hidden Markov model to predict the category of user activity at the next step and then predict the most likely location given the estimated category distribution. The advantages of modeling the category level include a significantly reduced prediction space and a precise expression of the semantic meaning of user activities. Extensive experimental results show that, with the predicted category distribution, the number of location candidates for prediction is 5.45 times smaller, while the prediction accuracy is 13.21% higher. Moreover, knowing a group of users' activity preference, real time group-oriented advertisement can be better enabled. This says the use of spatial network.

P. Fabio, A. Xueli, K. Fahim, and I. Hiroki[3], Location-based social networks (LBSNs) have become a popular form of social media in recent years. In this paper, we propose a social-historical model to explore user's check-in behavior on LBSNs. Our model integrates the social and historical effects and assesses the role of social correlation in user's check-in behavior. For each user-time-activity triplet. In order to avoid the negative value in the recovered tensor this is meaningless for preference measure. Nightlife and Entertainment spots are those easier to infer, whereas College and Shopping areas are those featuring the lowest accuracy rates. Then, considering a candidate set of activity types in a geographic area, we aim to elect the most prominent one. We demonstrate how the difficulty of the problem increases with the number of classes incorporated in the prediction task, yet the classifiers achieve a considerably better performance compared to a random guess even when the set of candidate classes increases.

N. Anastasios, M. Cecilia, and F.-M. Enrique[5], Location-based social networks (LBSNs) have attracted an inordinate number of users and greatly enriched the urban experience in recent years. Due to the strong correlations between a user's check-in time and the corresponding check-in location, recommender systems designed for location recommendation inevitably need to consider temporal effects. Our model integrates the social and historical effects and assesses the role of social correlation in user's check-in behavior. In particular, our model captures the property of user's check-in history.

In forms of power-law distribution and short-term effect, and helps in explaining user's check-in behavior. The experimental results on a real world LBSN demonstrate that our approach properly models user's check-ins and shows how social and historical ties can help location prediction.

In this work, we combine a dataset sourced from a telecommunication provider in Spain with a database of millions of geotagged venues from Foursquare and we formulate the problem of urban activity inference in a supervised learning framework. In particular, we exploit user communication patterns observed at the base station level in order to predict the activity of Foursquare users who check-in at nearby venues.

III. PROPOSED SYSTEM

We develop an application with integrated location based services which incorporates a novel user Spatial Temporal Activity Preference (STAP) model for personalized poi recommendation, an efficient framework for theft identification and a context aware methodology for automatic profile management, leveraging battery consumption and memory utility. First, in order to reduce the problem complexity, we separately consider the spatial and temporal characteristics of user activity preference in LBSNs. Second, to capture the spatial features, instead of segmenting a city into grid cells, we build Personal Functional Regions for each user using her check-ins, which can then be used to infer ones spatial activity preference. Third, to resolve the data sparsity problem in capturing temporal features, we exploit other similar users' activities and collaboratively build one's temporal activity preference model. Finally, a context-aware fusion framework is proposed to combine them together. The theft identification Framework is implemented as a background Service and it runs ever on the device as a service thread like a daemon thread. This LBSN Service is orchestrated as a light weight implementation so as to consume less battery and memory for multiple location based services.

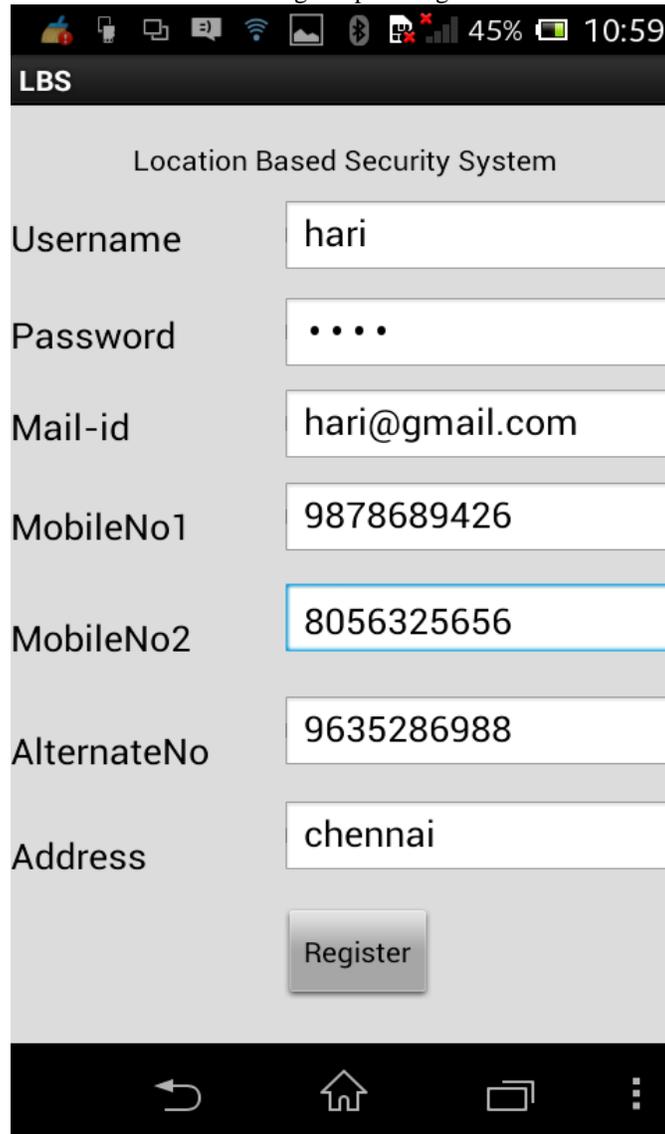
IV. IMPLEMENTATION

First, for sequential pattern mining approaches, both order 1 and order 2 Markov model obtain unsatisfied results. In LBSNs, users have a choice to share their location information. Therefore, although user activities follow certain sequential patterns in their daily life, user check-ins do not fully contain their daily activities due to privacy concern or lack of time. Moreover, since we consider activities with fine granularity including 251 categories rather than nine top categories, the large number of categories further aggravates the sparsity issue in the Markov model when searching for frequent patterns.

Second, for temporal based approaches, tensor factorization methods, i.e., NTF and HOSVD, can better capture user activity preference than the frequency based approach, i.e., MFT. This observation shows that collaborative filtering can efficiently handle the sparse check-in data.

For user temporal activity preference inference. Furthermore, the improvement of NTF over HOSVD shows the advantage of considering non-negative constraint. The proposed temporal model using NTF can effectively capture the temporal characteristics of user activity preference.

Particularly for the users whose activities show strong temporal regularities.



Third, spatial based approaches lead to better performance than temporal based methods. This observation shows that the spatial regularity of user activity in LBSNs is more significant than the temporal regularity. Specifically, Nearby Preference performs better than Nearby-pop baseline due to the consideration of POI preference. The

improvement of PFR over Nearby-Preference shows the advantages of eliminating noisy data in capturing spatial features of user activity preference. In other words, the infrequent activities of a user may not actually reflect her preference. The proposed PFR can delicately capture the spatial characteristics of user activity preference, particularly for the users whose activities exhibit obvious spatial specificity.

Finally, compared to the static weighted fusion method SW-Fusion, the context-aware fusion framework achieves the best performance. It takes advantage of both spatial and temporal features under varying contexts. An interesting observation is that the improvement of considering the temporal model from merely considering the spatial model is relatively small.

Due to the increasing popularity of LBSNs, users generate tremendous amount of digital footprints in their daily life. Research on understanding user activity by mining these digital footprints has attracted extensive attention in recent years. Since the objective of this paper is to infer user STAP in LBSNs, we first briefly survey these research works on user activities from two perspectives:

- 1) user mobility per-spective which focuses on modeling user mobility patterns by leveraging spatial temporal regularities and
- 2) user preference perspective which usually focuses on inferring user preference on the unvisited POIs. We then present the research works considering POI categories as user activities, as well as the related works for our spatial and temporal models.

i) User Mobile identification and profile building

First the Registration is carried by identifying the user mobile by retrieving the parameters like sim no and memory card identity no. If the mobile is a dual sim mobile both sim no are registered in a local database like sql lite. The current Gps Co-ordinates are also recorded. User has to give some additional parameters like additional mobile numbers mail id so as our application will send sms and mail to the particular mobile number and mail id regarding theft or any monitor able activities regarding user phone.

After User mobile registration user can sign in. This states the POI of the person.

ii) 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. The Service Thread runs forever even the phone gets restarted by using Boot Complete Receiver. The Service Class continuously monitors Gps Location and triggers the profile. It also continuously checks for sim number, Memory card number and IMEI.

iii) User 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. A Region is said to be a frequented region if user check in frequently in particular area and is calculated as a ratio between check ins in that region to total check ins is greater than the frequency threshold. ($\text{freq} = A_{u,r}/A_u \geq \text{sfreq}$).user check in is sorted in a descending order and evaluated for PFR for each check in by considering the nearby region around the check in.

The Region should be a frequented region as well as the particular user has strong preference bias on that frequented region and that is considered to be a Personal Functional Region for the user. Temporal preference is calculated by collaborative Filtering Algorithm by manipulating similar user preference and evaluated for activity preference for every One hour time epoch in a week.

Temporal Activity Preference is calculated based on the temporal patterns of similar users.. Then, considering a candidate set of activity types in a geographic area, we aim to elect the most prominent one. We demonstrate how the difficulty of the problem increases with the number of classes incorporated in the prediction task, yet the classifiers achieve a considerably better performance compared to a random guess even when the set of candidate classes increases.

iv) Integrated 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. The Service Thread continuously monitors GPS, SIM nos, Memory card No, IMEI for automatic profile change, Theft Identification and personalized poi recommendation and notifies user by sending sms and email to registered alternate mobile number and email provided.

The spatial and Temporal preference model extracted is clubbed together to give a personalized poi recommendation. POI is recommended by identifying the nearest PFR from user current location and the temporal pattern is evaluated for user activity preference and respective points of interest will be recommended for the user in a Top Down Scenario based on priority.

V. CONCLUSION

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 based network.

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.

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