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Nearest ATM in My Location

Lakshmi Varsha .D
Student
Department of Computer Ccience and Engineering, Sri Vidya College Of Engineering and Technology, Virudhunagar, Tamilnadu, India.
varshadpak@gmail.com
7639165577

Nandhini S. M
Student
Department of Computer Science and Engineering, Sri Vidya College Of Engineering and Technology, Virudhunagar, Tamilnadu, India.
nandinism3010@gmail.com
8682847497

Ramya .P
Assistant professor
Department of Computer Science and Engineering, Sri Vidya College Of Engineering and Technology, Virudhunagar, Tamilnadu, India.
Ramya9116@gmail.com
9789604611

***Abstract:** In this application, we have to initialize the available ATMs of all banks and its locations. We also have to initialize the end user mobile number to access it. In order to find the nearby ATMs, the user has to give the current location of that particular user. We will give the ATMs that are available in the nearest area and also provide the distance and Rating for them. It makes full use of the mobile user's location sensitive characteristics to carry out rating prediction. Refer to these social networks involving geographical information as location-based social networks. Such information brings opportunities and challenges for recommender systems. It makes full use of the mobile user's location sensitive characteristics to carry out rating prediction. The relevance between user's ratings and user-item geographical location distances called as a user-item geographical connection. It is discovered that human's rating behaviors are affected by geographical location significantly. The personalized Location Based Rating Prediction model is proposed by combining three factors: user-item geographical connection user-user geographical connection and interpersonal interest similarity. In particular, the geographical location denotes user's real-time mobility especially when users travel to new cities and these factors are multiple together to improve the accuracy and applicability of recommender systems.*

***Keywords:** GPS, Geographical Information, Rating Prediction Model, Recommendation, Geo Social Factor.*

I. INTRODUCTION

The rapid development of mobile devices and everywhere Internet access, social network services, such as Facebook, Twitter, Yelp, Foursquare, Epinions, become prevalent. According to statistics, smartphone users have produced data volume ten times of a standard cell phone. In 2015, there were 1.9 billion smartphone users in the world, and half of them had accessed to social network services. During mobile device or online location-based social networks (LBSNs), we can share our geographical position information or check-ins. This service has attracted millions of users. It also allows users to share their experience, such as reviews, ratings, photos, check-ins and moods in LBSNs with their friends. Such information brings opportunities and challenges for recommender systems. Mainly, the geographical location information bridges the gap between the real world and online social network services. For example, when we search an ATM considering convenience, we will never choose a faraway one. To find the available ATM of all banks in the current nearest location. The geographical mobile user in a relevance measure model the relevance of a message to a Mobile user is changing as the user is moving. Moreover, if the geographical location information and social networks can be combined, it is not difficult to find that our mobility may be influenced by our social relationships as users may rather visit the places or consume the items their friends visited or consumed before. In our opinion, when users take a long trip, they may keep a good emotion and try their best to have a nice trip. Most of the services they consume are the local featured things. They will give high ratings more easily than the local. This can help us to limit rating prediction. In addition, when users take a long distance traveling a far away from new city as a stranger. They may depend more on their local friends. so, users' and their local friends' ratings may be similar. It helps us to constrain rating prediction. Furthermore, if the geographical location factor is unseen, when we search the Internet for a travel, recommender systems may recommend us a new attractive spot without considering whether there are local friends to help us to plan the trip or not. But if recommender systems consider geographical location factor, the recommendations may be more humanized and thoughtful. These are the motivations why we utilize geographical location in sequence to make rating prediction. With the above motivations, the goals of this paper are;To mine the application between user's ratings and user item geographical location distances, called as user-item geographical connection, To mine the relevance between users' rating difference and user-user geographical location distances, called as user-user geographical connection, and To find the people whose interest is related to users. In this paper, three factors are taken into thought for rating prediction: user-item geographical connection, user-user geographical connection, with interpersonal interest similarity. These factors are fused into a location-based rating prediction model. Experimental results show significant improvement compared with existing approaches. The remainder of this paper is organized as follows. The problem we focus on in this paper is defined. Meanwhile, a brief introduction of some related works and compared algorithms is given. We introduce the dataset in detail. The proposed modified location-based rating prediction model is introduced. Experiments and planning are given and conclusions.

II. RELATED WORK

A. A Survey Paper on ORec: An Opinion-Based Point-of-Interest Recommendation Framework

As location-based social networks (LBSNs) quickly grow, it is a timely topic to study how to recommend users with motivating locations, known as points-of-interest(POIs). Most existing POI recommendation techniques single-use the check-in data of users in LBSNs to learn their preferences on POIs by assuming a user's check-in frequency to a POI explicitly reflects the level of her preference on the POI. but, in reality, users usually visit POIs only once, so the users' check-ins may not be sufficient to derive their preferences using their check-in frequencies only. Actually, the preferences of users are exactly indirect in their opinions in text-based tips commenting on POIs. In this paper, we propose an opinion-based POI recommendation framework called ORec to take full advantage of the user opinions on POIs spoken as tips. In ORec, there are two main challenges: (i) detecting the polarities of tips (positive, neutral or off-putting), and (ii)integrating them with check-in data including social links between users and geographical information of POIs. To address these two challenges, (1) we develop a supervised aspect-dependent approach to detect the polarity of a tip, and (2) we devise a method to fuse tip polarities with social links and geographical information into a unified POI recommendation framework. Finally, we conduct a comprehensive performance evaluation for ORec using two large-scale real datasets collected from Foursquare and Yelp. Experimental results show that ORec achieves significantly superior polarity detection and POI recommendation accuracy compared to other state-of-the art polarity detection and POI recommendation techniques.

B. Exploiting Sequential Influence for Location Recommendations

Providing location recommendations becomes an important feature for location-based social networks (LBSNs) since it helps users explore new places and makes LBSNs more prevalent to users. In LBSNs, geographical influence and social influence have been intensively used in location recommendations based on the facts that geographical proximity of locations significantly affects users' check-in behaviors and social friends often have common interests. Although human movement exhibits sequential patterns, most current studies on location recommendations do not consider any sequential influence of locations on users' check-in behaviors. In this paper, we propose a new approach called LORE to develop sequential influence on location recommendations. First, LORE incrementally mines in order patterns from location sequences and represents the sequential patterns as a dynamic Location-Location Transition Graph (L2TG). LORE then predict the probability of a user visiting a location by Additive Markov Chain (AMC) with L2TG. Finally, LORE fuses sequential influence with geographical influence and social influence into a unified recommendation framework; in particular, the geographical influence is modeled as two-dimensional check-in probability distributions rather than one-dimensional distance chance distributions in existing works. We conduct a comprehensive performance evaluation for LORE using two large-scale real data sets collected from Foursquare and Gowalla. Experimental results show that LORE achieves significantly superior location recommendations compared to other state-of-the-art recommendation techniques.

III. PROPOSED SYSTEM

It also allows users to share their experiences such as review ratings photos check-ins LBSNs with their friends. Such information brings opportunities and challenges for recommender systems. The geographical location in sequence bridges the gap between the real world and online social network services. User search a restaurant considering convenience we will never choose a faraway one this can help us to constrain rating prediction users to take a long distance traveling a far away from new city as strangers. Recommender systems consider geographical location factor the recommendations may be more humanized and thoughtful. The relevance between user's ratings and user item geographical location distances called as user geographical connection and to mine the relevance between users rating differences and user-user geographical location distances connection to chart. To find the people whose interest is similar to users three factors are taken into consideration for rating prediction. It is discovered that users usually give high scores to the items which are very far away from their activity centers. It can help us to understand users' rating behaviors for the recommendation. The relevance between users' rating differences and geographical distances. It can help us to understand users' rating behaviors for the recommendation, for user-user geographical connection and interpersonal interest similarity into a Location Based Rating Prediction model. In MobiFeed our objective is to efficiently list news feeds for a mobile user at her current and predicted locations such that each news feed contains messages belong to at least different categories and their total application to the user is maximized.

IV.SYSTEM ARCHITECTURE

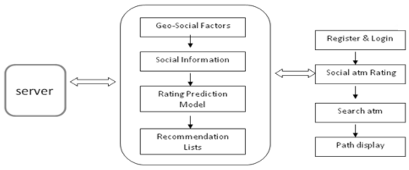

Fig. 1 system architecture of nearest atm in my location

IV. MODULES IN OUR PROJECT

A. Registration

At first, users has to register the device with the necessary details given the registration form and has to click the submit button and then submitted details are successfully updated in the database. Login users and to share their experiences such as reviews rating in social factors. Login users in update our profiles and like a type of category splitting data stored in the server location prediction content only user GPS current location.

B. Server Updates

News feed for selecting messages based on their category their application to user movement. The user needs some time to read the messages each news feed will be displayed on user mobile device for a time period. Note that each message can be displayed to a user only once. Admin maintains the server for any category news feed update in client site information.

C. Geographical Social Factors

User and item latent feature matrices can be calculated by machine learning methods for prediction.

D. User Geographical Connection

As mentioned before mobile social network services have a pervasive influence on users' daily life. Based on the analysis of data of Foursquare users tend to activities in nearby areas. The researchers find that the activity radius of users is no more than ten miles and the activity radius of most users are no more than fifty miles. The distances are classified into nine groups with different ranges to make sure that the density of ratings in each region is balanced.

E. User-user Geographical Connection

The user-user geographical connection can be learned in the same way analyzes the relevance of users' rating differences and user-user geographical distances. For each user, the difference between his/her rating and his/her friends' to the same item is calculated. Meanwhile, we compute the geographical distance between them. There are three users, A, B, and C. User A and B's activity center is New York, while user C's activity center is Philadelphia. We can presume A & B are all New York City natives, while C is a visitor. We assume that A and B are friends, B and C are friends. Users A, B and C all have ratings to the item Pizza in New York.

F. Path Display

The path display function can employ any existing location prediction algorithm if it can predict a user's location at a specified future time in a road network. MobiFeed user current location historical trajectories the road map and a future time the path prediction algorithm estimates location. It would be easier to draw a user current location based or our different category news feed receiving for an update.

G. Recommendation

The mobile user receiving our recommendation like based setting in global access for the domain. As for user-item geographical connection, we first express user geographical connection by curve fitting and then adjust users' ratings according to user geographical connection with the consideration of diverse user-user distances. When users travel to new cities and this factor are fused together to improve the accuracy and applicability of recommender systems and collect to information charting with another user.

H. Rating prediction model

A user geographical information located by smartphone bridges the gap between physical and digital worlds. Location data functions as the connection between user's physical behaviors and virtual social networks structured by the smartphone. Mobile Users Geographical Locations based received for recommendation domain likes setting. User Social services our rating and received for global rating service prediction.

CONCLUSION

In this paper, we extract: 1) the relevance between users' ratings and user-item geographical location distances, 2) the relevance of users' rating differences and user-user geographical location distances. It is exposed that humans' rating behaviors are affected by geographical location significantly. A personalized Location Based Rating Prediction (LBRP) model is proposed by combining three factors: user-item geographical connection, user-user geographical connection, and interpersonal interest similarity. In particular, the geographical location denotes user's real-time mobility, mainly when users travel to new cities, and these factors are fused together to improve the accuracy and applicability of recommender systems.

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