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Mobile Service Rating Prediction of Client's Geographical Location using Multi-Source Big Social Media

P. Suresh[1], R. Lokanath Reddy[2]

Computer Science Engg Dept., Chadalawada Ramanamma Engineering College, Titupati, Andhra Pradesh, India[1,2]

Abstract: Recently, advances in intelligent mobile device and positioning techniques have fundamentally enhanced social networks, which allow users to share their experiences, reviews, ratings, photos, check-ins, etc. The geographical information located by smart phone bridges the gap between physical and digital worlds. Location data functions as the connection between user's physical behaviours and virtual social networks structured by the smart phone or web services. We refer to these social networks involving geographical information as location-based social networks (LBSNs). Such information brings opportunities and challenges for recommender systems to solve the cold start, scarcity problem of datasets and rating prediction. In this paper, we make full use of the mobile users' location sensitive characteristics to carry out rating predication. It is discovered that humans' rating behaviors are affected by geographical location significantly. Moreover, three factors: user-item geographical connection, user-user geographical connection, and interpersonal interest similarity, are fused into a unified rating prediction model. We conduct a series of experiments on a real social rating network dataset Yelp. Experimental results demonstrate that the proposed approach outperforms existing models.

Keywords: huge information, Geographical region, Social community offerings, score prediction, smart phones, user rating self perception.

I. INTRODUCTION

Recently, with the rapid development of mobile devices and ubiquitous Internet access, social network services, such as Facebook, Twitter, Yelp, Foursquare, Epinions, become prevalent. According to statistics, smart phone users have produced data volume ten times of a standard cellphone. In 2015, there were 1.9 billion smart phone users in the world, and half of them had accessed to social network services [1,2]. Through 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 experiences, such as reviews, ratings, photos, check-ins and moods in LBSNs with their friends. Such information brings opportunities and challenges for recommender systems. Especially, the geographical location information bridges the gap between the real world and online social network services [3,4].

For example, when we search a restaurant considering convenience, we will never choose a faraway one. 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 prefer to visit the places or consume the items their friends visited or consumed before. In our opinion, when users take a long journey, 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 constrain rating prediction. In addition, when users take a long distance travelling a far away new city as strangers. They may depend more on their local friends [5]. Therefore, users' and their local friends' ratings may be similar. It helps us to constrain rating prediction. Furthermore, if the geographical location factor is ignored, when we search the Internet for a travel, recommender systems may recommend us a new scenic 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. Despite these prevalent assumptions about network geometry, very little work to date has actually examined the geometry of the Internet's infrastructure [6-8]. In this paper, we present initial results bearing on these questions. For example, with respect to the Waxman assumptions, we find that assumption 1 (uniform distribution of routers) is very inaccurate — the actual distribution pattern of routers is highly irregular. On the other hand, we find evidence that supports assumption 2 — the connectivity patterns of routers show a strong relationship to distance. In the process of obtaining these results, we ask a number of basic questions. Regarding router placement, we ask: Where do the routers comprise the Internet physically located? And: What factors drive the geographic placement of routers? Turning to connectivity, the key questions we wish to answer are: Where are the links between Internets routers physically located? And: To what extent does router connectivity appear to be sensitive to physical distance? Our third set of questions concerns the

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autonomous system (AS) structure of the network: How does geographical size (number of locations) relate to previously studied measures of AS size? How do ASes disperse their resources geographically? And: How do inter domain links differ from intradomain links geographically? The answers we find to our main questions are consistent across three different regions of the world, across two very different sources of data, and across two different geographic mapping techniques.

In our opinion, when users take a long journey, 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 constrain rating prediction. In addition, when users take a long distance travelling a far away new city as strangers. They may depend more on their local friends.

Therefore, users' and their local friends' ratings may be similar. It helps us to constrain rating prediction. Furthermore, if the geographical location factor is ignored, when we search the Internet for a travel, recommender systems may recommend us a new scenic 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 information to make rating prediction.

II. EXISTING SYSTEM

Location data functions as the connection between user's physical behaviors and virtual social networks structured by the smart phone or web services. We refer to these social networks involving geographical information as location-based social networks (LBSNs). Such information brings opportunities and challenges for recommender systems. (9, 10)

Disadvantages

- Sparsity problem of datasets
- cold start problem
- rating prediction problem

III. PROPOSED SYSTEM

In this paper, we make full use of the mobile users' location sensitive characteristics to carry out rating predication. We mine: 1) the relevance between user's ratings and user-item geographical location distances, called as user-item geographical connection, 2) the relevance between users' rating differences and user-user geographical location distances, called as user-user geographical connection. It is discovered that humans' rating behaviours are affected by geographical location significantly. Moreover, three factors: user-item geographical connection, user-user geographical connection, and interpersonal interest similarity, are fused into a unified rating prediction model.

Advantages

- We mine the relevance between ratings and user item geographical location distances.
- We mine the relevance between users' rating differences and user-user geographical distances.
- We integrate three factors: user-item geographical connection, user-user geographical connection, and interpersonal interest similarity, into a Location Based Rating Prediction (LBRP) model.

IV. SOFTWARE REQUIREMENT SPECIFICATION

User Requirement

Requirements analysis in systems engineering and software engineering, encompasses those tasks that go into determining the needs or conditions to meet for a new or altered product, taking account of the possibly conflicting requirements of the various stakeholders, such as beneficiaries or users. It is an early stage in the more general activity of requirements engineering which encompasses all activities concerned with eliciting, analyzing, documenting, validating and managing software or system requirements. Requirements analysis is critical to the success of a systems or software project. The requirements should be documented, actionable, measurable, testable, traceable, related to identified business needs or opportunities, and defined to a level of detail sufficient for system design.

Software Requirement

These include the software essential for running the project including system platform, language etc. for this project we require

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H/W System Configuration:-
- Processor - Pentium –III
- RAM - 256 MB (min)
- Hard Disk - 20 GB
- Key Board - Standard Windows Keyboard
- Mouse - Two or Three Button Mouse
- Monitor - SVGA

S/W System Configuration:-
- Operating system : Windows 7/UBUNTU.
- Coding Language : Java 1.7 , Hadoop 0.8.1
- IDE : Eclipse /Android Studio
- Database : MYSQL

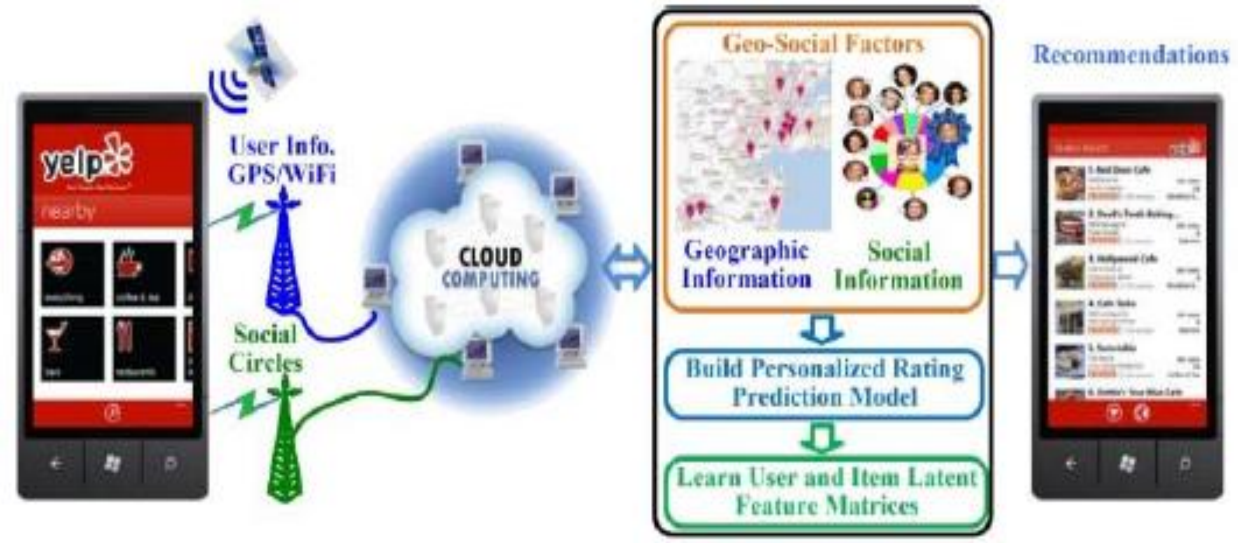

Fig.1. System overview of our personalized recommendation via geographical social networking, including smart phone user of mobile social network services, cloud computing, rating prediction, and the recommendation lists

V. GEOGRAPHICAL SOCIAL ELEMENTS

Geographical social elements encompass interpersonal interest similarity, person-item geographical connection and user-b user geographical connection. The person-item and person-buser geographical connections are measured via scores through diverse geographical distances. Interpersonal interest similarity is measured with the aid of the similarity among person's interest vector and friend's interest vector [1]. Observe that, the geographical distance between two lati-tude/longitude coordinates is calculated via using the Haversine geodesic distance equation proposed in [5].

VI. PERSON-ITEM GEOGRAPHICAL CONNECTION

As noted earlier than, cellular social network services have pervasive impact on users' each day life. Primarily based on the analysis of data of Foursquare, users have a tendency to activities in near with the aid of regions. The researchers discover that the interest radius of forty five% customers is not any extra than 10 miles, and the interest radius of 75% customers is not any extra than 50 miles. Moreover, the identical conclusion is drawn in [2].

VII. USER-PERSON GEOGRAPHICAL CONNECTION

So that you can expect greater correct rankings, user-consumer geographical connection is included into our version to learn consumer characteristic matrices. The simple concept is that the ratings users to objects should fit person-consumer geographical connection we mined. As for consumer-item geographical connection, we first explicit consumer-person geographical connection by using curve fitting, after which adjust customers' rankings consistent with person-person geographical connection with consideration of numerous person-user distances.

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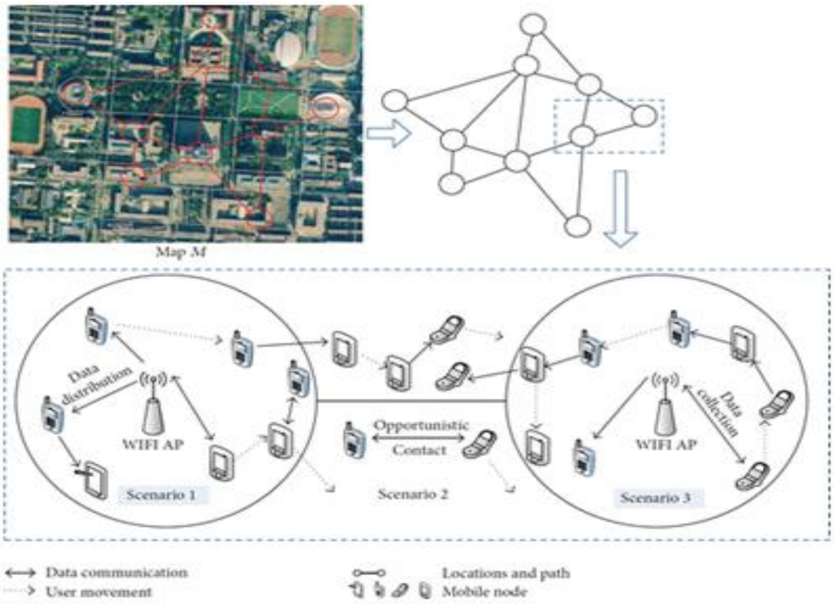

Fig.2. Participatory sensing scenario

VIII. OUTPUT SCREENS

The following are the screen shots:

1.1. Home Page

1.2. USER SIGNUP

Description: new user registration.

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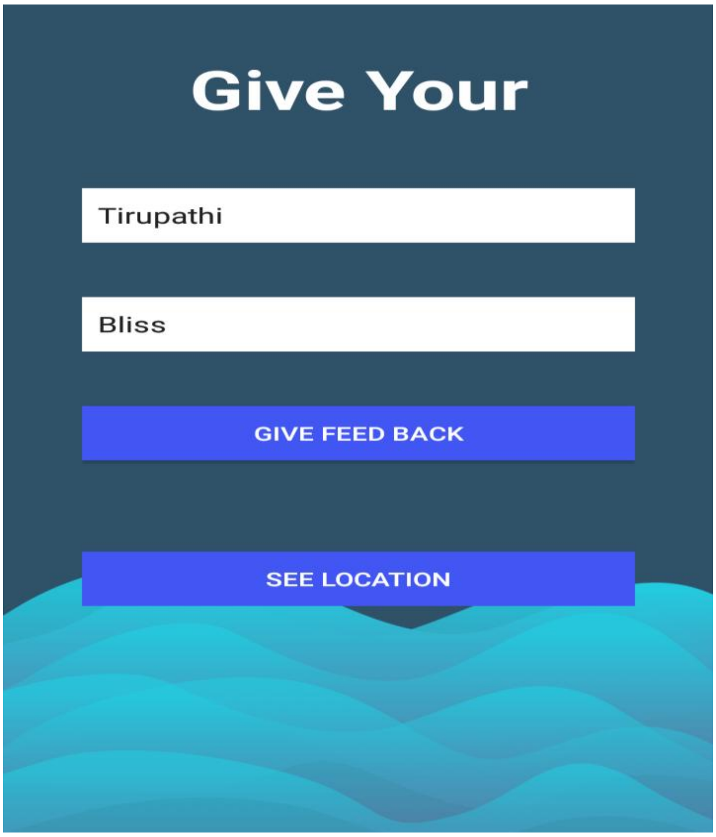
1.3. User Login

1.4. Selecting Location



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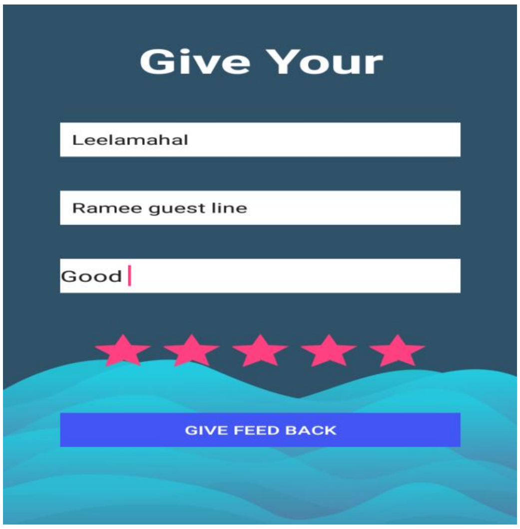
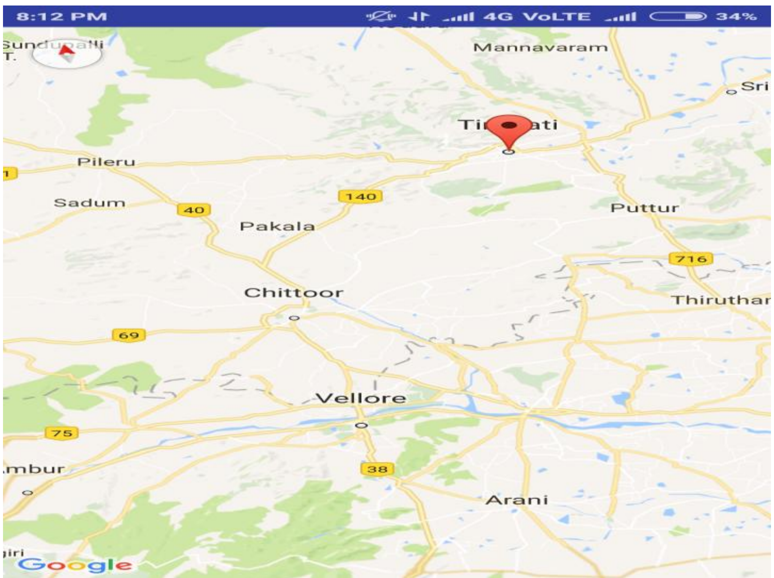
1.5. Rating Information

1.6. Giving Rating



1.7. Shown Location:



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IX. CONCLUSION AND FUTUREWORK

In this paper, we mine: 1) the relevance among users' ratings and consumer-object geographical vicinity distances, 2) the relevance between users' score differences and person-consumer geographical place distances.
It's miles observed that humans' score behaviors are stricken by geographical area notably. A customised area based rating Prediction (LBRP) model is proposed by way of combining 3 elements: consumer-item geographical connection, user-person geographical connection, and interpersonal interest similarity. Especially, the geographical area denotes consumer's real-time mobility, mainly whilst users travel to new towns, and these elements are fused together to improve the accuracy and applicability of recommender systems. In our destiny paintings, test-in behaviors of users could be deeply explored via thinking about the element in their multi-hobby centers and the attribute of POIs.

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