**Available Online at www.ijcsmc.com**

**International Journal of Computer Science and Mobile Computing**

**A Monthly Journal of Computer Science and Information Technology**

**ISSN 2320–088X**

**IMPACT FACTOR: 6.017**

*IJCSMC, Vol. 7, Issue. 7, July 2018, pg.58 – 72*

# PREDICTION OF SERVICE RATINGS THROUGH SMART PHONES BASED ON GEOGRAPHICAL LOCATIONS

**G. Karthick**
Research Scholar,
Department of Computer Science & Engineering, Annamalai University
Annamalainagar – 608 002,
Tamil Nadu, India.
Email: karthick18588@gmail.com

**Dr. R. Saminathan**
Assistant Professor,
Department of Computer Science & Engineering, Annamalai University
Annamalainagar – 608 002,
Tamil Nadu, India.
Email:samiaucse@yahoo.com

**Dr. S. Saravanan**
Assistant Professor,
Department of Computer Science & Engineering,
Annamalai University
Annamalainagar – 608 002,
Tamil Nadu, India.
Email:ssaravau@gmail.com

***Abstract:- Recently, advances in intelligent mobile device and positioning techniques have fundamentally enhanced social networks, which allows 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 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 (LBSN's). Such information brings opportunities and challenges for recommender systems to solve the cold start, sparsity problem of datasets and rating prediction. In this paper, use of the mobile users' location sensitive characteristics to carry out rating predication. Moreover, three factors: user-item geographical connection, user-user geographical connection, and interpersonal interest similarity, are fused into a unified rating prediction model. Conduct a series of experiments on a real social rating network dataset Yelp. Experimental results demonstrate that the proposed approach outperforms existing models.***

***Keywords: LBRP, LBSN, GPS, POI.***

## 1.0 INTRODUCTION

Recently, with the rapid development of mobile devices and ubiquitous Internet access, social network services, such as Face book, Twitter, Yelp, Foursquare, Epinions, become prevalent. According to statistics, smart phone users have produced data volume ten times of a standard cell phone. In 2015, there were 1.9 billion smart phone users in the world, and half of them had accessed to social network services. Through mobile device or online Location Based Social Networks (LBSN's), 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 LBSN's 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.

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. 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.

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.

The amount of information in the world is increasing far more quickly than our ability to process it. All of us have known the feeling of being overwhelmed by the number of new books, journal articles, and conference proceedings coming out each year. Technology has dramatically reduced the barriers to publishing and distributing information. Now it is time to create the technologies that can help us sift through all the available information to find that which is most valuable to us. One of the most promising such technologies is collaborative filtering [15, 17, 11, 12]. Collaborative filtering works by building a database of preferences for items by users. A new user, Neo, is matched against the database to discover neighbors, which are other users who have historically had similar taste to Neo. Items that the neighbors like are then recommended to Neo, as he will probably also like them. Collaborative filtering has been very successful in both research and practice, and in both information filtering applications and E-commerce applications. However, there remain important research questions in overcoming two fundamental challenges for collaborative filtering recommender systems.

The first challenge is to improve the scalability of the collaborative filtering algorithms. These algorithms are able to search tens of thousands of potential neighbors in real-time, but the demands of modern systems are to search tens of millions of potential neighbors. Further, existing algorithms have performance problems with individual users for whom the site has large amounts of information. For instance, if a site is using browsing patterns as indications of content preference, it may have thousands of data points for its most frequent visitors. These long user rows" slow down the number of neighbors that can be searched per second, further reducing scalability.

The second challenge is to improve the quality of the recommendations for the users. Users need recommendations they can trust to help them find items they will like. Users will "vote with their feet" by refusing to use recommender systems that are not consistently accurate for them. In some ways these two challenges are in conict, since the less time an algorithm spends searching for neighbors, the more scalable it will be, and the worse its quality. For this reason, it is important to treat the two challenges simultaneously so the solutions discovered are both useful and practical.

The proposed Geo Based Recommender Model contains the following three factors: 1) user-item geographical connection which denotes the relevance between rating and user-item geographical distance, 2) user-user geographical connection which denotes the relevance between user-user rating difference and user-user geographical distance, 3) interpersonal interest similarity which means whose interest is similar to yours. These three factors are combined with the rating matrix *R* to decrease the rating prediction errors.

The proposed personalized Location Based Rating Prediction model (LBRP) has three main steps considering obtain three geo-social factors, interpersonal interest similarity, user-user geographical connection, and user-item geographical connection, through smart phone with the Wi-Fi technology and Global Positioning System (GPS), It builds up personalized rating prediction model combining with the three factors in the cloud, and to train the model in the cloud to learn user and item latent feature matrices for rating prediction to recommend suitable items of user's interest.

## 2.0 LITERATURE SURVEY

The first generation of recommender systems [1] with traditional collaborative filtering algorithms [3 - 9] is facing great challenges of cold start for users (new users in the recommender system with little historical records) and the sparsity of datasets. Fortunately, with the popularity and rapid development of social networks, more and more users enjoy sharing their experiences, reviews, ratings, photos, and moods with their friends. Many social- based models [10, 11, 12] have been proposed to improve the performance of recommender system. X.-W. Yang, H. Steck, and Y. Liu [13] propose to use the concept of 'inferred trust circle' based on the domain-obvious of circles of friends on social networks to recommend users favorite items. M. Jiang, P. Cui, R.

Liu, Q. Yang. [14] prove that individual preference is also an important factor in social networks. In their Context Model, user latent features should be similar to his/her friends' according to preference similarity. Y. Zheng, L. Zhang, Z. Ma, X. Xie, and W. Y. Ma [16] utilize the power of semantic knowledge bases to handle textual messages and recommendations. Our previous works [16], [17] focus on objective evaluation in order to recommend the high-quality services by exploring social users' contextual information. Except for ratings prediction, there are some systems [15, 17] focusing on location recommendation. Many researchers mine user's interests from the user's location history to make recommendations. Y. Zheng, L. Zhang, Z. Ma, X. Xie, and W. Y. Ma [16] propose a hierarchical-graph-based similarity measurement with consideration of the human mobility features. The location based recommender system using the user similarity outperforms those using the Cosine similarity. J. Bao, Y. Zheng, and M. F. Mokbel [15] combine user's location and preference to provide effective location recommendations. Y. Zheng, L. Zhang, Z. Ma, X. Xie, and W. Y. Ma [16] propose a user topic based collaborative filtering approach for personalized travel recommendation.

M. Jiang, P. Cui, R. Liu, Q. Yang. [14] introduce a location recommendation framework with temporal effects based on observed temporal properties. They explore the number of checkins made by a user at a location to recommend a new location user may prefer. Y. Chen, and J. Canny [8] fuse matrix factorization (MF) with geographical and social influence for POI (Point-of-Interest) recommendations on LBSNs, and propose a Multi-center Gaussian Model to model the geographical influence of users' check-in behaviors. Y. Chen, H. Feng, and X. Qian, propose several location recommendation frameworks by exploiting geographical influence [8], [12], [48], temporal influence, categorical correlations, spatiotemporal sequential influence, user opinions, etc. M. Jiang, P. Cui, R. Liu, Q. Yang. [14] conduct an in-depth usage mining on real-world check-in data and present a POI category transition based approach to estimate the visiting probability. For multi-modality datasets, M. Jamali, and M. Ester, [10] summarizes existing data fusion methods, classifying them into three major categories to help people to find proper data fusion methods.

A tourism recommender system is designed by Konstan, and J. Reidl [2] based on geo tagged web photos. In this recommendation system, users can enter an image of the desired scenery or a keyword describing the place of interest and the system suggests destinations which match the user interest or visual characteristics. Y. Koren, proposed an algorithm [3] for location recommendation using the correlation of locations from a large number of user-generated GPS trajectories. The algorithm considers the user's travel experience and the of locations. The location correlation is integrated into a collaborative filtering algorithm for personalized location recommendation.

Y. Koren, proposed a method called Context Rank [4]. In this context information of geo tagged photos is used to enhance personalized recommendation. Using photos GPS location landmarks are detected and then popularity of each landmark is estimated. The representative tags and images are extracted from each landmark. Context Rank also make use of users travel history to calculate user similarity. The user preferences of a landmark is predicted using geotagged photos and tags. For the final recommendation a learning to rank algorithm is used. A hybrid context aware system for tourist guidance [5] is proposed by J. Wang. The system suggests Points of Interests (POI) to tourists according to their profile and context. In order to predict and suggest POIs both content based and collaborative filtering methods are used. Soft computing and data mining techniques are also used. The general frame work consists of user profiles, social network history and POI data. N. N. Liu, M. Zhao, and Q. Yang, proposed a model for new venue recommendation [6]. A new model is proposed where personalized random walk is performed over a user-place graph which combines social network and venue visit frequency data. The paper examines the problem of recommending unvisited venues from behavioural, social and spatial data. For new venue recommendation, the model make use of the variety of user preference signals that location based services collect about their users.

Q. Liu, E. Chen, H. Xiong, C. Ding, and J. Chen proposed a spot recommendation system [7] continuously available in user's home areas and away areas. The system can recommend spots to a user which are highly rated by other nearby users whose preference is similar to that of the user. Collaborative filtering method is used for spot recommendation. The system can recommend spots which are nearby or far away from the home location of the user.

A HITS-based POI recommendation algorithm [8] had been proposed by Y. Chen, and J. Canny. In this paper the POI recommendation issue is examined. The popularity of POI depends on both number of users checked in as well as their check in behaviour. HITS model for POI recommendation considers the user activities, user relations etc. This approach can be used for personalized recommendation.

## 3.0 BIG DATA AND HADOOP

**Big Data:**

Big data means really a big data; it is a collection of large datasets that cannot be processed using traditional computing techniques. Big data is not merely a data; rather it has become a complete subject, which involves various tools, techniques and frameworks. Big data involves the data produced by different devices and applications. Big data technologies are important in providing more accurate analysis, which may lead to more concrete decision-making resulting in greater operational efficiencies, cost reductions, and reduced risks for the business. To hardness the power of big data, you would require an infrastructure that can manage and process huge volumes of structured and unstructured data in real-time and can protect data privacy and security. In this approach, an enterprise will have a computer to store and process big data. In Fig.1 data will be stored in an RDBMS like Oracle Database, MS SQL Server or DB2 and sophisticated software's can be written to interact with the database, process the required data and present it to the users for analysis purpose.

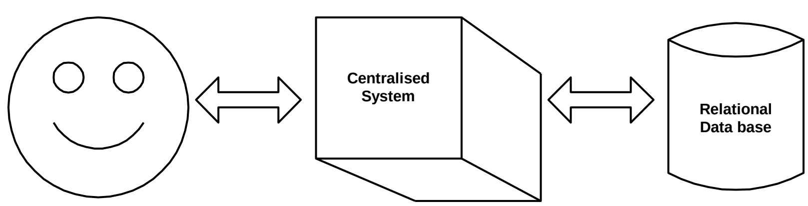



**Fig. 1 Data Storage in RDBMS**

This approach works well where less volume of data that can be accommodated by standard database servers, or up to the limit of the processor which is processing the data. But when it comes to dealing with huge amounts of data, it is really a tedious task to process such data through a traditional database server. Google solved this problem using an algorithm called MapReduce. This algorithm divides the task into small parts and assigns those parts to many computers connected over the network, and collects the results to form the final result dataset as shown in the Fig.2.

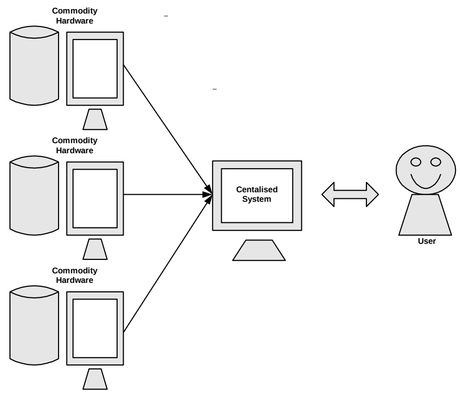



**Fig. 2 Stored data in Commodity Hardware**

**Hadoop:**

Doug Cutting, Mike Cafarella and team took the solution provided by Google and started an Open Source Project called HADOOP in 2005 and Doug named it after his son's toy elephant. Now Apache Hadoop is a registered trademark of the Apache Software Foundation. Hadoop runs applications using the MapReduce algorithm, where the data is processed in parallel on different CPU nodes. In short, Hadoop framework is capable enough to develop applications capable of running on clusters of computers and they could perform complete statistical analysis for huge amounts of data as shown in Fig.3.

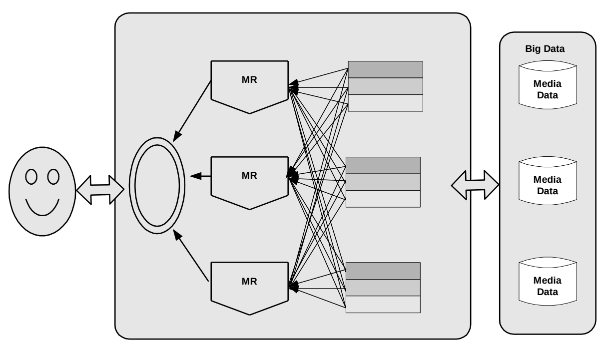



**Fig. 3 Process of MapReduce**

Hadoop is an Apache open source framework written in java that allows distributed processing of large datasets across clusters of computers using simple programming models [18]. A Hadoop frame-worked application works in an environment that provides distributed storage and computation across clusters of computers. Hadoop is designed to scale up from single server to thousands of machines, each offering local computation and storage [19].

**Hadoop Architecture**:

Hadoop framework includes following four modules namely Hadoop Common, Hadoop YARN, Hadoop Distributed File System (HDFS) and Hadoop MapReduce as shown in Fig. 4.

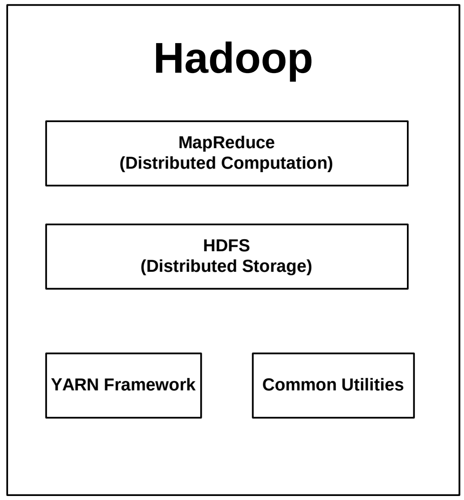



**Fig. 4 Distributed Computation and Storage with Cluster Management Technology (YARN)**

### Hadoop MapReduce

Hadoop MapReduce is a software framework for easily writing applications which process big amounts of data in-parallel on large clusters (thousands of nodes) of commodity hardware in a reliable, fault-tolerant manner. The framework takes care of scheduling tasks, monitoring them and re-executes the failed tasks. The MapReduce framework consists of a single master JobTracker and one slave TaskTracker per cluster-node. The master is responsible for resource management, tracking resource consumption/availability and scheduling the jobs component tasks on the slaves, monitoring them and re-executing the failed tasks. The slaves TaskTracker execute the tasks as directed by the master and provide task-status information to the master periodically. The JobTracker is a single point of failure for the Hadoop MapReduce service which means if JobTracker goes down, all running jobs are halted.

### Hadoop Distributed File System

Hadoop can work directly with any mountable distributed file system such as Local FS, HFTP FS, S3, FS, and others, but the most common file system used by Hadoop is the Hadoop Distributed File System (HDFS). The Hadoop Distributed File System (HDFS) is based on the Google File System (GFS) and provides a distributed file system that is designed to run on large clusters (thousands of computers) of small computer machines in a reliable, fault-tolerant manner. HDFS uses a master/slave architecture where master consists of a singleNameNode that manages the file system metadata and one or more slaveDataNodes that store the actual data. A file in an HDFS namespace is split into several blocks and those blocks are stored in a set of DataNodes. The NameNode determines the mapping of blocks to the DataNodes. The DataNodes takes care of read and write operation with the file system. They also take care of block creation, deletion and replication based on instruction given by NameNode. HDFS provides a shell like any other file system and a list of commands are available to interact with the file system. These shell commands will be covered in a separate chapter along with appropriate examples.

### Hadoop YARN

This is a framework for job scheduling and cluster resource management.

### Hadoop Common Utilities

These are Java libraries and utilities required by other Hadoop modules. These libraries provide file system and OS level abstractions and contains the necessary Java files and scripts required to start Hadoop.

## 4.0 PROPOSED WORK

In this work, the geographical based information on user-items and item-pairs and the recommendation engine is built was implemented. When the geo-social data through smart phone is given by step 1, as shown in Fig 5, the model is built up combining geo-social factors to learn user and item latent features. User and item latent feature matrices can be calculated by machine learning methods for rating prediction. Once the ratings are predicted, the items can be ranked by the ratings and provided as TopN recommendation.

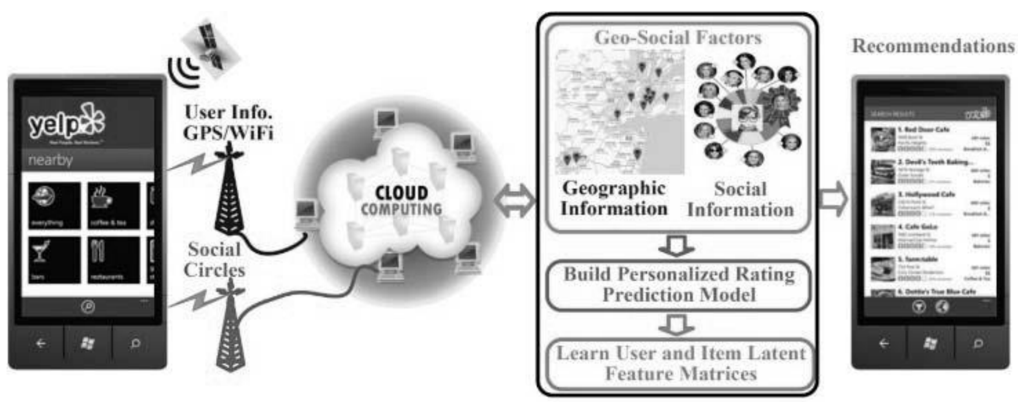



**Fig.5 Recommendation Engine based user-item Location**

The overall process will be carried out by analyzing the customers liking between the products and the location is an major task. The following Fig 6 depicts the overall process in the recommendation engine and their operations based on user - item based geographical location.

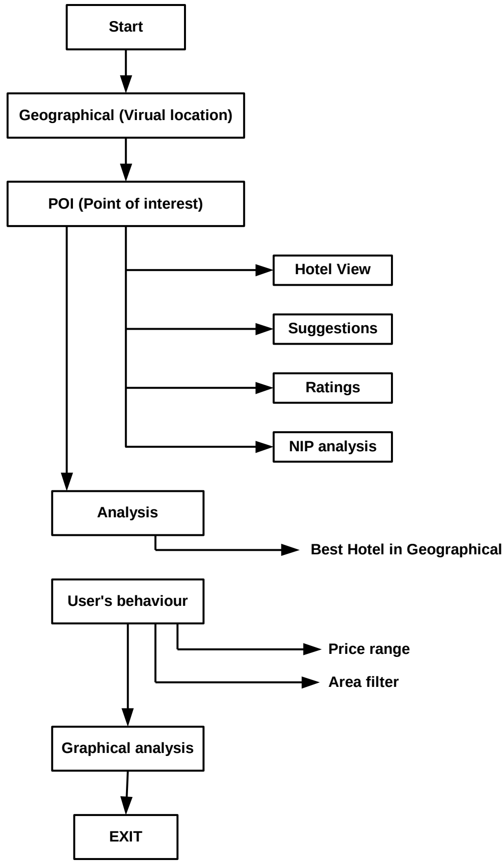



**Fig 6 Overall Process based on Geographical Location**

## Geographical based user performance analysis

In this module based on the yelp data set three important factors are analyzed. 1) the importance between user's ratings and user-item geographical location distances, called as user-item geographical connection, 2) the importance between users' rating differences and user-user geographical location distances, called as user-user geographical connection.3) Interpersonal skills between the users and location.

## Rating Prediction Module

The rating prediction module predicts the rating of products by combination of three important factors namely users, items and geographical locations to predict their number of products purchased in the location. In this module matrix M is created by number of products purchased by the customers and the total number of purchases performed in the location. By applying the gradiant decent approach to work with the user profiles and analyze their purchasing patterns.

$$Y_{um}^{\wedge} = \hat{Y}_{um}^{baseline} + \frac{\sum_{f \in S^k(m)} S_{mj}\,(Y_{uj} - \hat{Y}_{um}^{baseline})}{\sum_{f \in S^k(m)} S_{mj}}$$

### Recommendation Engine

Based on the prediction module important factors are analyzed and recommendation engine is built based on the user previous experience. It is necessary to discuss the impact of discrete predicted ratings. Therefore, decimal ratings we predicted are rounded to discrete integers. We conduct experiments with 5-fold cross validation based on Yelp Restaurants, Nightlife, and Shopping datasets.

### Performance Evaluation

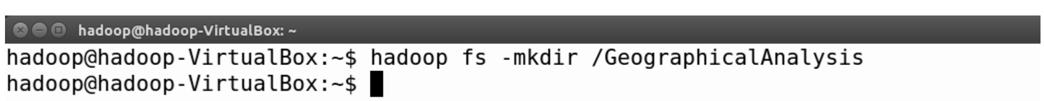
In this module consists of the impact of the amount of user information, the impact of the three factors, the impact of geographical location distances, the impact of different curve fitting methods, and the impact of predicted integer ratings on performance.

### DATASET Information

For this work the datasets are collected from Yelp local directory service with social networks and user reviews. It is the largest review site in America. Users rate the businesses, submit comments, communicate shopping experience, etc. It combines local reviews and social networking functionality to create a local online community. Moreover, it is proved by the data of Yelp that users are more willing to visit places or to consume items that his/her friends have visited or consumed before. For each rating of a user, if the item has been rated by his/her friends, we call it rating intersections. It is obvious that the more rating intersections are, the users are more influenced by their friends. In can be discovered that there are many rating intersections between users and their friends. Therefore, it can be concluded that users' mobility and consuming behaviors may be easily influenced by their social relationships. We have crawled nearly 80 thousand users' social circles and their rated items.

## 5.0 RESULTS AND DISCUSSION

The service rating prediction based on the social users in mobile for location is performed in map reduce architecture using big data framework. The experiment is carried out with the yelp datasets around 15,000 of products based on user likes. The graphs are plotted through R programming. The following Fig 7 represents the directory creation in hadoop named geographical analysis and input file is loaded into corresponding directory.



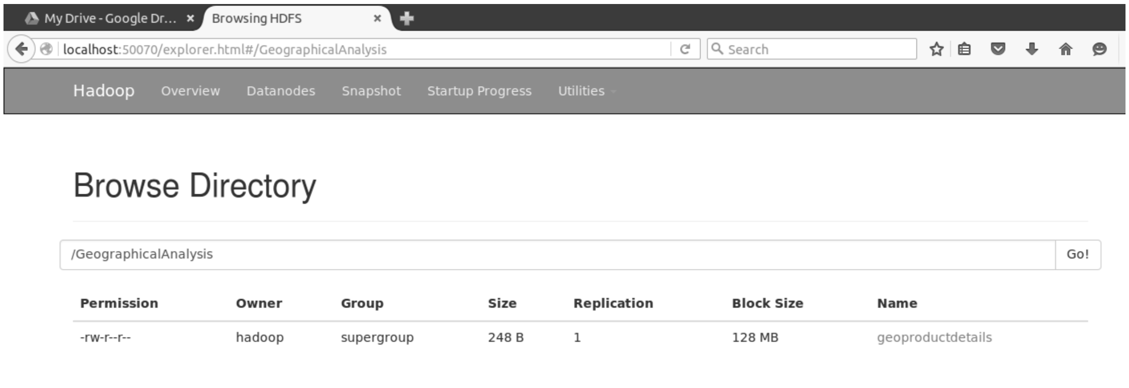



**Fig.7 Directory Creation in Hadoop**

Fig 8 represents the input file of geographical based analysis of service ratings from the mobile social users

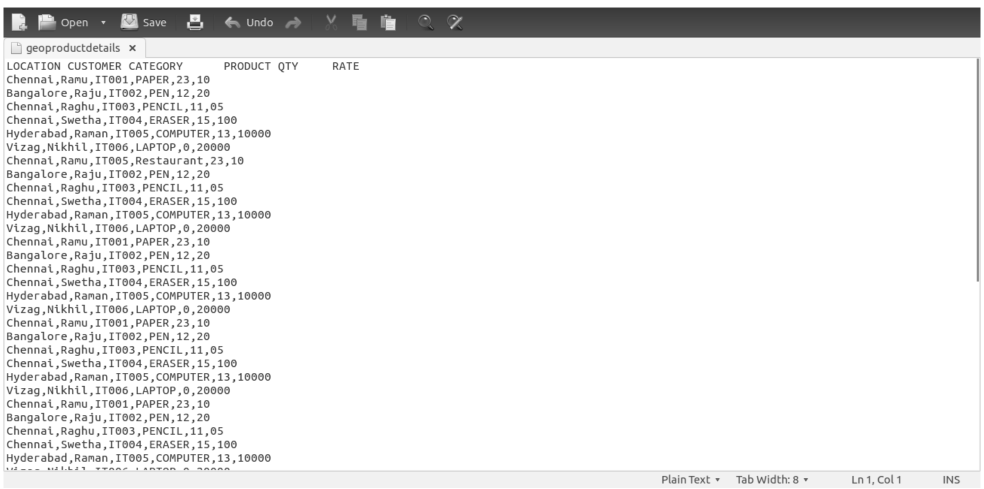

```
LOCATION CUSTOMER CATEGORY      PRODUCT QTY     RATE
Chennai,Ramu,IT001,PAPER,23,10
Bangalore,Raju,IT002,PEN,12,20
Chennai,Raghu,IT003,PENCIL,11,05
Chennai,Swetha,IT004,ERASER,15,100
Hyderabad,Raman,IT005,COMPUTER,13,10000
Vizag,Nikhil,IT006,LAPTOP,0,20000
Chennai,Ramu,IT005,Restaurant,23,10
Bangalore,Raju,IT002,PEN,12,20
Chennai,Raghu,IT003,PENCIL,11,05
Chennai,Swetha,IT004,ERASER,15,100
Hyderabad,Raman,IT005,COMPUTER,13,10000
Vizag,Nikhil,IT006,LAPTOP,0,20000
Chennai,Ramu,IT001,PAPER,23,10
Bangalore,Raju,IT002,PEN,12,20
Chennai,Raghu,IT003,PENCIL,11,05
Chennai,Swetha,IT004,ERASER,15,100
Hyderabad,Raman,IT005,COMPUTER,13,10000
Vizag,Nikhil,IT006,LAPTOP,0,20000
Chennai,Ramu,IT001,PAPER,23,10
Bangalore,Raju,IT002,PEN,12,20
Chennai,Raghu,IT003,PENCIL,11,05
Chennai,Swetha,IT004,ERASER,15,100
Hyderabad,Raman,IT005,COMPUTER,13,10000
Vizag,Nikhil,IT006,LAPTOP,0,20000
Chennai,Ramu,IT001,PAPER,23,10
Bangalore,Raju,IT002,PEN,12,20
Chennai,Raghu,IT003,PENCIL,11,05
Chennai,Swetha,IT004,ERASER,15,100
Hyderabad,Raman,IT005,COMPUTER,13,10000
```


**Fig.8 Input File**

Fig 9 represents the map reduce process of geographical based service ratings for the mobile social users**.**

```
hadoop@hadoop-VirtualBox:~/bigdata/geographicanalysis/jar$ hadoop jar geographic.jar GeoGraphicAnal
ysis.ItemMain /GeographicalAnalysis/geoproductdetails /GeographicalAnalysis/out
```

```
                Reduce shuffle bytes=183
                Reduce input records=5
                Reduce output records=5
                Spilled Records=10
                Shuffled Maps =1
                Failed Shuffles=0
                Merged Map outputs=1
                GC time elapsed (ms)=96
                CPU time spent (ms)=0
                Physical memory (bytes) snapshot=0
                Virtual memory (bytes) snapshot=0
                Total committed heap usage (bytes)=335290368
        Shuffle Errors
                BAD_ID=0
                CONNECTION=0
                IO_ERROR=0
                WRONG_LENGTH=0
                WRONG_MAP=0
                WRONG_REDUCE=0
        File Input Format Counters
                Bytes Read=248
        File Output Format Counters
                Bytes Written=160
hadoop@hadoop-VirtualBox:~/bigdata/geographicanalysis/jar$
```

**Fig.9 MapReduce Process**

Fig 10 represents the sample map-reduce output from the analysis of user-item product pairs and the total number of products purchased by users based on location.

```
Open  Save  Undo
part-r-00000(16)
Bangalore       IT002  PEN      12      240.0
Chennai  IT001  PAPER  23      230.0
Chennai  IT003  PENCIL  11      55.0
Chennai  IT004  ERASER  15      1500.0
Hyderabad       IT005  COMPUTER        13      130000.0
```

**Fig.10 Sample MapReduce**

Fig 11 represents the distribution of business categories represent in yelp dataset for location based social users.

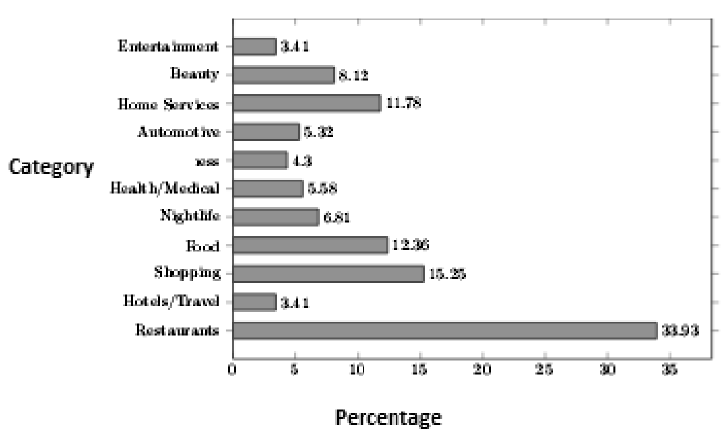



**Fig.11 Distribution of Business Categories**

Fig 12 represents the distribution of reviews for each categories represent in yelp dataset for location based social users.

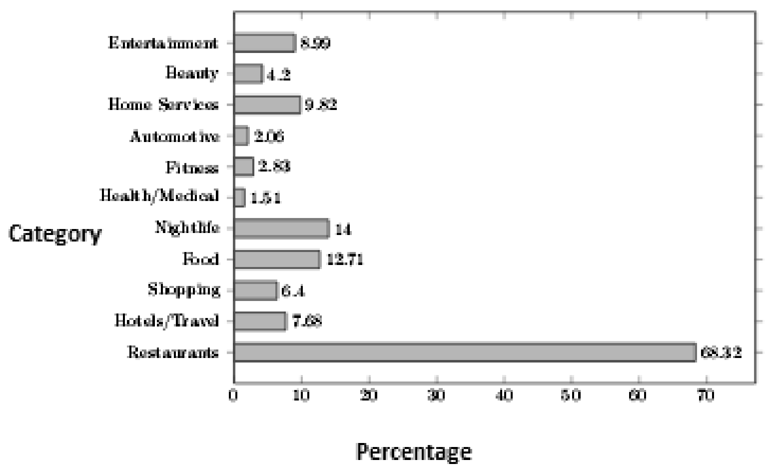



**Fig.12 Distribution of Business Categories**

Fig 13 represents the analysis of user - item based collaborative filtering approach based on locations.

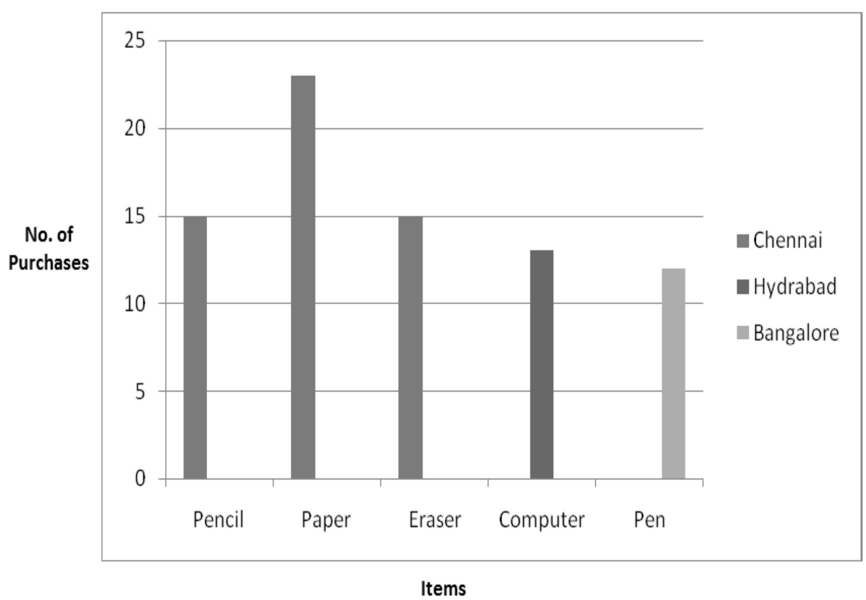



**Fig.13 Collaborative Filtering Approach**

## 6.0 CONCLUSION AND FUTURE WORK

In this work, it consists of the relevance between users' ratings and user-item geographical location distances, the relevance between users' rating differences and user-user geographical location distances. It is discovered 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, especially when users travel to new cities, and these factors are fused together to improve the accuracy and applicability of recommender systems. In our future work, check-in behaviors of users will be deeply explored by considering the factor of their multi-activity centers and the attribute of POI's.

# REFERENCES


[1] G. Adomavicius, and A. Tuzhilin, "Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions," *IEEE Transactions on Knowledge and Data Engineering*, pp. 734-749, Jun. 2005.

[2] B. Sarwar, G. Karypis, J. Konstan, and J. Reidl, "Item-based collaborative filtering recommendation algorithms," *World Wide Web*, pp. 285-295, 2001.

[3] Y. Koren, "Factorization meets the neighborhood: a multifaceted collaborative filtering model," *KDD'08*, 2008.

[4] Y. Koren, "Collaborative filtering with temporal dynamics," *KDD'09*, pp. 447-456, 2009.

[5] J. Wang, A. P. d. Vries, and M. J. T. Reinders, "Unifying userbased and item-based collaborative filtering approaches by similarity fusion," *SIGIR'06*, 2006.

[6] N. N. Liu, M. Zhao, and Q. Yang, "Probabilistic latent preference analysis for collaborative filtering," *CIKM'09*, pp. 759-766, 2009.

[7] Q. Liu, E. Chen, H. Xiong, C. Ding, and J. Chen, "Enhancing collaborative filtering by user interest expansion via personalized ranking," *IEEE Transactions on Systems, Man, and Cybernetics- Part B*, pp. 218-233, Feb.2012.

[8] Y. Chen, and J. Canny, "Recommending ephemeral items at web scale," *SIGIR*, pp. 1013-1022, 2011.

[9] M. Harvey, M. J. Carman, I. Ruthven, and F. Crestani, "Bayesian latent variable models for collaborative item rating prediction," *CIKM'11*, pp. 699-708, 2011.

[10] M. Jamali, and M. Ester, "A matrix factorization technique with trust propagation for recommendation in social networks," *ACM RecSys*, 2010.

[11] H. Feng, and X. Qian, "Mining User-Contributed Photos for Personalized Product Recommendation," *Neurocomputing*, 2014.

[12] G. Zhao, X. Qian, and H. Feng, "Personalized Recommendation by Exploring Social Users' Behaviors," In *Proc. MMM*, 2014.

[13] X.-W. Yang, H. Steck, and Y. Liu, "Circle-based recommendation in online social networks," *KDD'12*, pp. 1267-1275, 2012.

[14] M. Jiang, P. Cui, R. Liu, Q. Yang, F. Wang, W.-W. Zhu, and S.-Q. Yang, "Social contextual recommendation," *CIKM'12*, pp. 45-54, Oct.2012.

[15] J. Bao, Y. Zheng, and M. F. Mokbel, "Location-based and Preference- Aware Recommendation Using Sparse Geo-Social Networking Data," *ACM SIGSPATIAL GIS'12*, Nov. 2012.

[16] Y. Zheng, L. Zhang, Z. Ma, X. Xie, and W. Y. Ma, "Recommending friends and locations based on individual location history," *ACM Transactions on the Web*, 2011.

[17] J. Liu, Z. Huang, L. Chen, H. Shen, Z. Yan, "Discovering areas of interest with geo-tagged images and check-ins," *ACM Multimedia*, pp. 589-598, 2012.

[18] Hadoop(The Definitive Guide) By Tom White, 2012.

[19] Book Analytics with R and Hadoop By Vignesh Prajapati, 2013.