# A POINT OF INTEREST RECOMMENDATION ENGINE FOR SUGGESTING SIGHTSEEING SPOTS BY USER REVIEWS AND RATINGS

# Geetha.G<sup>1</sup>, Kanniga.M<sup>2</sup>, Kavithaa.V<sup>3</sup>, Megha.R.Nair<sup>4</sup>, PRIYANKA.S.V<sup>5</sup>

B.E, (Computer Science and Engineering, T.J.S Engineering College, Tamilnadu, India.

# ABSTRACT

Tourism has become an important industry for most of the economies, especially for non-industrialized countries where it represent the main source of income. Recommendation systems are defined as the techniques used to predict the rating one individual will give to an item or social entity. These items can be places, books, movies, restaurants and things on which individuals have different preferences. These preferences are being predicted using two approaches first content-based approach which involves characteristics of an item and second collaborative filtering approaches which takes into account user's past behavior to make choices. Point of interest (POI) recommendation, which provides personalized recommendation of places to users. However, quite different from traditional interest-oriented merchandise recommendation, POI recommendation is more complex due to the timing effects: we need to examine whether the POI fits a user's availability. With increasing adoption and presence of Online services, designing novel approaches for efficient and effective recommendation has become of paramount importance. In existing services discovery and recommendation approaches focus on keyword-dominant Web service search engines, which possess many limitations such as poor recommendation performance and heavy dependence on correct and complex queries from users. Recent research efforts on Online service recommendation center on two prominent approaches: collaborative filtering and content-based recommendation. Unfortunately, both approaches have some drawbacks, which restrict their applicability in Web service recommendation. In proposed system for recommendation we will be using Agglomerative Hierarchal Clustering or Hierarchal Agglomerative Clustering for effective recommendation in this system.

**Keyword:** - BIG Data, Networking, Internet Protocol, JAVA, J2EE, JAVA Servlets, My Sql, Modules, Testing, Use Case Diagrams, Database, Clustering, Net Beans, etc...

# **1. INTRODUCTION**

BIG data has emerged as a widely recognized trend, attracting attentions from government, industry and academia. Generally speaking, Big Data concerns large-volume, complex, growing data sets with multiple, autonomous sources. Big Data applications where data collection has grown tremendously and is beyond the ability of commonly used software tools to capture, manage, and process within a "tolerable elapsed time" is on the rise. The most fundamental challenge for the Big Data applications is to explore the large volumes of data and extract useful information or knowledge for future actions. Spurred by service computing and cloud computing, an increasing number of services are emerging on the Internet. As a result, service-relevant data become too big to be effectively processed by traditional approaches. In view of this challenge, a Clustering-based Collaborative Filtering approach (Club CF) is proposed in this paper, which aims at recruiting similar services in the same clusters to recommend services collaboratively.

Recommender systems in location based social networks mainly take advantage of social and geographical influence in making personalized Points-of-interest (POI) recommendations. The social influence is obtained from social network friends or similar users based on matching visit history whilst the geographical influence is obtained from the geographical footprints users' leave when they check-in at different POIs. However, this approach may fall short when a user moves to a new region where they have little or no activity history. We propose a location aware

POI recommendation system that models user preferences mainly based on; user reviews and categories of POIs. We evaluate our algorithm on the Yelp dataset and the experimental results show that our algorithm achieves a better accuracy.

Cluster-based recommendation is best thought of as a variant on user-based recommendation. Instead of recommending places to users, places are recommended to clusters of similar users. This entails a pre-processing phase, in which all users are partitioned into clusters. Recommendations are then produced for each cluster, such that the recommended items are most interesting to the largest number of users. The upside of this approach is that recommendation is fast at runtime because almost everything is pre computed.

#### 1.1 Existing System

- ▶ In the Existing technique, we utilize a content based recommendation approach to convey the ratings to the particular user. Instead of explicitly providing a rating for a given program.
- In traditional algorithms, to compute similarity between every pair of users or services may take too much time, even exceed the processing capability of current RSs.
- ➤ In the traditional paradigm, places are recommended to the user by highly rated places by people and trending places it not based on user's taste.
- The family sizes chosen are fairly small. This limits the amount of confusion that occurs where preferences are assigned to the wrong user.
- Existing system is content based recommend the locations to each users.

#### 1.2 Objective

Point-of-interest (POI) recommendation that suggests new places for users to visit arises with the popularity of location-based social networks (LBSNs). Due to the importance of POI recommendation in LBSNs, it has attracted much academic and industrial interest. In this paper, we offer a systematic review of this field, summarizing the contributions of individual efforts and exploring their relations. We discuss the new properties and challenges in POI recommendation, compared with traditional recommendation problems. First, we categorize the systems by the influential factors check-in characteristics, including the geographical information, social relationship, temporal influence, and content indications. Second, we categorize the systems by the methodology, including systems modelled by fused methods and joint methods. Third, we categorize the systems as general POI recommendation and successive POI recommendation by subtle differences in the recommendation task whether to be bias to the recent check-in. For each category, we summarize the contributions and system features, and highlight the representative work. Moreover, we discuss the available data sets and the popular metrics. Finally, we point out the possible future directions in this area.

#### **1.3 Contribution**

In this project, it achieves high efficiency because of two clustering methods which are user based and item based clustering. In order to find same similarity tastes between the users, the algorithms have been proposed accordingly. As we all know that in present system, the system will not be able to produce useful recommendations for most of the users until there are a sufficient number of people whose interests are known as well as the large set of rated places. So in order to overcome the need of the users, user based and item based clustering is used and it is high efficiency.

# 2. LITERATURE SURVEY

This paper presents an overview of the field of recommender systems and describes the current generation of recommendation methods that are usually classified into the following three main categories: content-based, collaborative, and hybrid recommendation approaches. This paper also describes various limitations of current recommendation methods and discusses possible extensions that can improve recommendation capabilities and make recommender systems applicable to an even broader range of applications. These extensions include, among others, an improvement of understanding of users and items, incorporation of the contextual information into the recommendations. Point-of-interest (POI) recommendation has become an important way to help people discover attractive and interesting places, especially when they travel out of town. However, the extreme sparsity of user-POI matrix and cold-start issues severely hinder the performance of collaborative filtering-based methods. Moreover,

user preferences may vary dramatically with respect to the geographical regions due to different urban compositions and cultures. To address these challenges, we stand on recent advances in deep learning and propose a Spatial-Aware Hierarchical Collaborative Deep Learning model (SH-CDL). The model jointly performs deep representation learning for POIs from heterogeneous features and hierarchically additive representation learning for spatial-aware personal preferences. To combat data sparsity in spatial-aware user preference modeling, both the collective preferences of the public in a given target region and the personal preferences of the user in adjacent regions are exploited in the form of social regularization and spatial smoothing. To deal with the multimodal heterogeneous features of the POIs, we introduce a late feature fusion strategy into our SH-CDL model. The extensive experimental analysis shows that our proposed model outperforms the state-of-the-art recommendation models, especially in outof-town and cold-start recommendation scenarios. In recent years, a variety of review-based recommender systems have been developed, with the goal of incorporating the valuable information in user-generated textual reviews in to the user modeling and recommending process. Advanced text analysis and opinion mining techniques enable the extraction of various types of review elements, such as the discussed topics, the multi-faceted nature of opinions, contextual information, comparative opinions, and reviewers' emotions. In this article, we provide a comprehensive overview of how the review elements have been exploited to improve standard content-based recommending, collaborative filtering, and preference-based product ranking techniques. The review-based recommender system's ability to alleviate the well-known rating sparsity and cold-start problems is emphasized. This survey classifies stateof-the-art studies into two principal branches: review-based user profile building and review-based product profile building. In the user profile sub-branch, the reviews are not only used to create term-based profiles, but also to infer or enhance ratings. Multi-faceted opinions can further be exploited to derive the weight/value preferences that users place on particular features. In another sub-branch, the product profile can be enriched with feature opinions or comparative opinions to better reflect its assessment quality. The merit of each branch of work is discussed in terms of both algorithm development and the way in which the proposed algorithms are evaluated. In addition, we discuss several future trends based on the survey, which may inspire investigators to pursue additional studies in this area. The availability of user check-in data in large volume from the rapid growing location-based social networks (LBSNs) enables a number of important location-aware services. Point-of-interest (POI) recommendation is one of such services, which is to recommend POIs that users have not visited before. It has been observed that: (i) users tend to visit nearby places, and (ii) users tend to visit different places in different time slots, and in the same time slot, users tend to periodically visit the same places. For example, users usually visit a restaurant during lunch hours, and visit a pub at night.

# **3. PROPOSED SYSTEM**

- > We proposed an Agglomerative Hierarchal Clustering or Hierarchal Agglomerative Clustering.
- Clustering are such techniques that can reduce the data size by a large factor by grouping similar services together.
- A cluster contains some similar services just like a club contains some like-minded users. This is another reason besides abbreviation that we call this approach Club CF.
- This approach is enacted around two stages. In the first stage, the available services are divided into small-scale clusters, in logic, for further processing. At the second stage, a collaborative filtering algorithm is imposed on one of the clusters.
- This similarity metric computes the Euclidean distance d between two such user points this value alone doesn't constitute a valid similarity metric, because larger values would mean more-distant, and therefore less similar, users. The value should be smaller when users are more similar.

#### 3.1 Advantages of Proposed System

- > The optimal weight is different depending on the situation. Second, application proposes an approach for estimation of the appropriate weight value based on collected rating.
- > User-side virtualization reduces the complexity of managing the computers. Enhanced user experience.
- > The recommend places are most probably user's liking or user's similar taste places.

# 4. RESULT

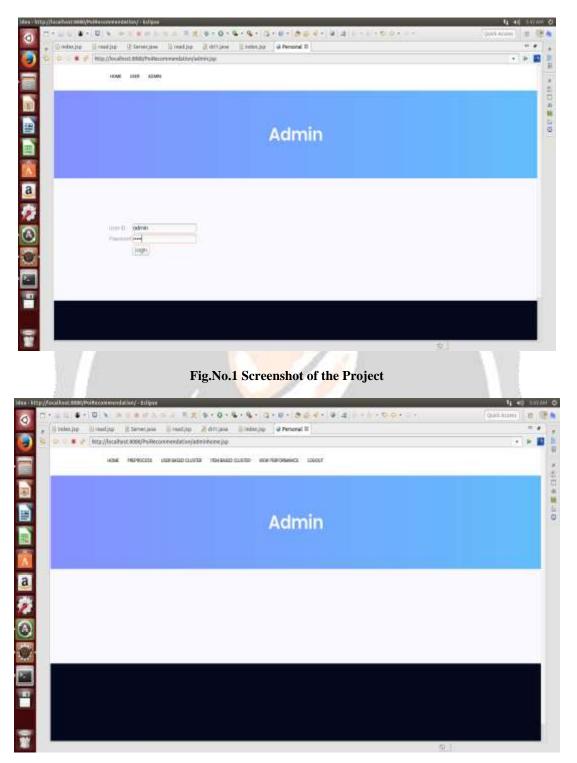


Fig.No.2 Screenshot of the Project

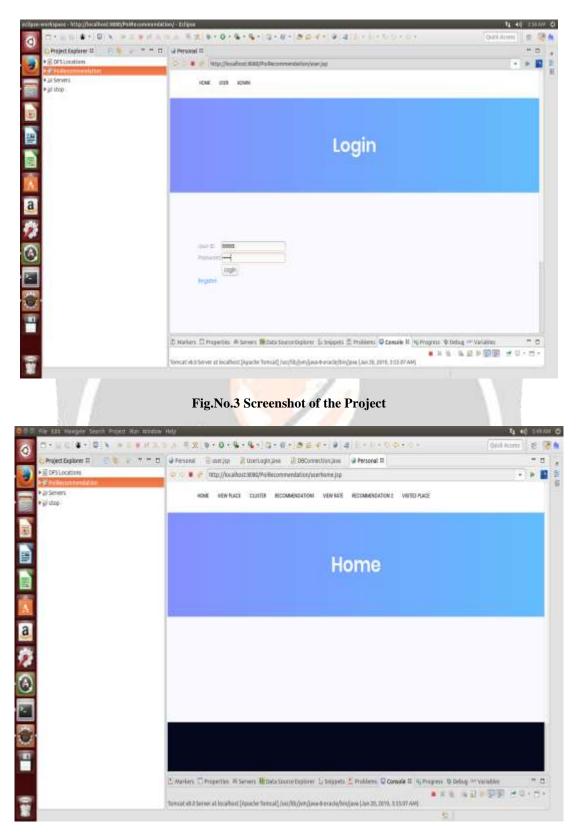


Fig.No.4 Screenshot of the Project

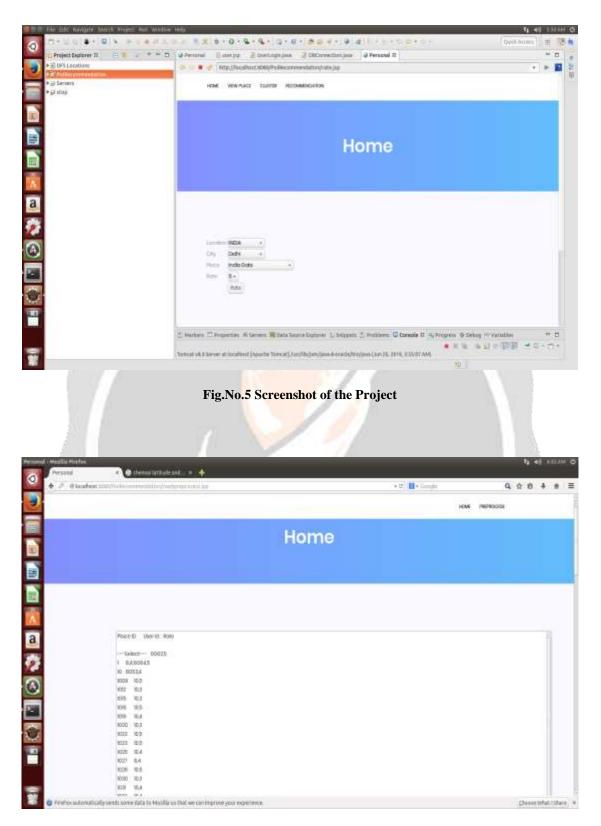


Fig.No.6 Screenshot of the Project

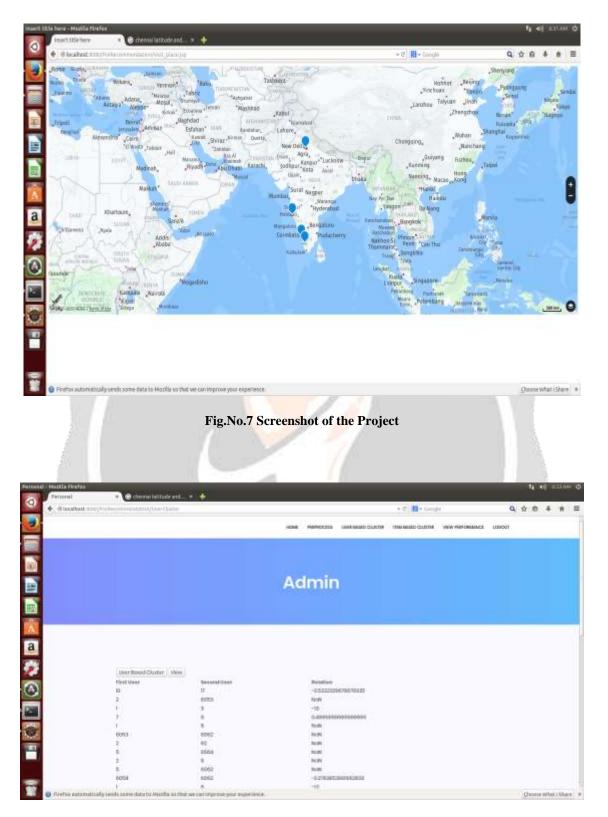


Fig.No.8 Screenshot of the Project

tie bare - Mozella Firefox Intertilite bare 🔹 😨	merenilatikakenet. • 🔶		14 48 100M
• @lacabant story to increase	dallari/koallik, genilijarri-milli	+ 17 / III + Groups	Q 🖄 8 🗍 9
Z Babrit			
	NORTH		
*			
1	· · · · · · · · · · · ·		
and and a second			
A State of S			
Piraftex automatically sends tome	date to Merilla to that we can improve your experience		Choose What I She
L			
Sec. 1.			

# Fig.No.9 Screenshot of the Project

#### **5. CONCLUSIONS**

We present an Agglomerative Hierarchical clustering approach for big data applications relevant to service recommendation. Before applying CF technique, services are merged into some clusters via an AHC algorithm. Then the rating similarities between services within the same cluster are computed. As the number of services in a cluster is much less than that of in the whole system, Club CF costs less online computation time. Moreover, as the ratings of services in the same cluster are more relevant with each other than with the ones in other clusters. If we want, add the new places with name, city and country.

#### 6. REFERENCES

1) H. Yin, W. Wang, H. Wang, L. Chen, and X. Zhou, "Spatial-aware hierarchical collaborative deep learning for POI recommendation," IEEE Trans. Knowl. Data Eng., vol. 29, no. 11, pp. 2537-2551, 2017.

2) G. Adomavicius and A. Tuzhilin, "Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions," IEEE Trans. Knowl. Data Eng., vol. 17, no. 6, pp. 734–749, 2005.

3) L. Chen, G. Chen, and F. Wang, "Recommender systems based on user reviews: the state of the art," User Modeling and User-Adapted Interaction, vol. 25, no. 2, pp. 99–154, 2015

4) Q. Yuan, G. Cong, and A. Sun, "Graph-based point-of-interest recommendation with geographical and temporal influences," in CIKM, 2014, pp. 659–668.

5) M. Aliannejadi, I. Mele, and F. Crestani, "Personalized ranking for context-aware venue suggestion," in SAC, 2017, pp. 960–962.

6) J. Bao, Y. Zheng, D. Wilkie, and M. F. Mokbel, "Recommendations in location-based social networks: a survey," GeoInformatica, vol. 19, no. 3, pp. 525–565, 2015.

7) V. W. Zheng, Y. Zheng, X. Xie, and Q. Yang, "Collaborative location and activity recommendations with GPS history data," in WWW, 2010.

8) B. M. Sarwar, G. Karypis, J. A. Konstan, and J. Riedl, "Item-basedcollaborative filtering recommendation algorithms," in WWW,2001, pp. 285–295.