ISSN: 0975-766X
CODEN: IJPTFI
Research Article

Available Online through
www.ijptonline.com

LOCATION BASED PREFERENCE AWARE RECOMMENDATION USING SPARSE GEO SOCIAL NETWORKING DATA

[1]M.Janarthanan, [2]Dr.Meera Gandhi
[1]Master of Computer Applications, [2]Professor, Faculty of Computing.
Email: Mjanarthanan07@gmail.com

Received on 03-03-2016 *Accepted on 26-03-2016*

Abstract

During the recent past, studies about services that are location-based have been attracting extensive attentions because of the huge number of applications. Amid these, one among the highly active topics happens to be Cloud-oriented Trip Planning that meets personal needs of users. A lot of studies have been proposed related to this topic in literatures. But major portion of them regard only user-specific limitations as certain filtering conditions toward planning a trip. In reality, it is desired on the part of users to immerse the restrictions on to travel suggestion systems for providing a trip that is personalized. Moreover, time complication with trip planning from a given set of enticements is responsive to scalability of travel zones. Most of presently existing suggestion systems have based their patterns on correlative filtering methods which render them easy to implement. Nonetheless, the performance of major portion of existing correlative filtering-oriented suggestion systems are affected by challenges like (a) scalability, (b) data sparseness, and (c) cold start. Furthermore, the problem of recommendation is frequently marked with presence of several decision variables or contradictory objectives like venue closeness and users' preferences. In this study, we introduced MobiContext which is one hybrid cloud-oriented Bi-Objective Recommendation Framework (BORF) related to mobile social grids. In this study, we have also put forward a duration time and feedback value that is recommended always to produce quality results. The MobiContext makes use of multi-goal optimization methods for generating personalized suggestions. For addressing the problems concerning data sparseness and cold start, BORF carries out preprocessing of data by making use of Hub-AVERAGE (HA) deduction model. Furthermore, Weighted Sum approach (WSA) has been Implemented toward scalar optimizing and an Evolutionary Algorithm (NSGA-II) has been applied toward vector optimizing for providing optimal recommendations about a venue to users. In this analysis, we give position-aware suggestion systems in the

scenario of mobile computing. The comprehensive experiment results on large scale actual dataset validate the precision of the introduced suggestion framework.

Keywords: MobiContext, Bi-Objective Recommendation Framework (BORF), Hub-Average (HA), Weighted Sum Approach (WSA), evolutionary algorithm (NSGA-II).

1. Introduction

Suggestion systems have achieved acceptance on a widespread level and they have enticed the increased recognition by masses for more than a decade. Recommender systems tend to alleviate complications in services and product selection tasks and they are meant for overcoming the problems of data overload [1].

Recommender systems gather data about user preferences, sift through large volume of the data that has been scattered along the web, and choose the particular information which best suits preferences of users. In general, recommender systems get information either implicitly or explicitly from users [2, 3].

In modern society, traveling happens to be one among the most crucial entertainments. Conventionally, prior to traveling to some city which is unfamiliar, one of the possible ways to plan a trip is through tourists asking travel agencies for scheduling their trip or by directly buying some tour package. Nonetheless, everyone may not be satisfied with such popular trips [7],[8].

Advancement in intelligent mobile digital devices and Web 2.0 strategies, several types of applications pertaining to Position-oriented services and web services, Universal Positioning System (GPS) has become more and more popular and sophisticated, and has started to get integrated with users' mobile digital terminal units such as PDA, smart phone, laptop, and so on.

Taking a look at existing position-oriented services, their data are being extracted from individual content suppliers like telecommunication amenity providers and map makers. Therefore, there exist certain significant constraints. [4]. This forms one independent and known research region called Location-oriented Services (LBS0 [5, 6]. Multimedia of the new generation such as iPhone has started integrating online LBS like Google maps is for helping users in accessing their required destinations along with information about traffic and conditions of road. Moreover, makers of GPS maps, vendors of GPS software, and producers of GPS chips also have slowly started attempting mobile terminal digital application development [9].

2. Related Work

In the tourism field, existing suggestions systems emulate typically services provided by tourist agents in whom potential tourists are referring to searching guidance on tourist destinations under some given budget and time constraints [13]. Normally, the suggestion systems compare the factors of user's profile to some properties which act as threshold attributes for predicting how the user may possibly 'feedback' the content factors (for example, time, rank, like, place, and so on) that one user has yet not considered [14].

These properties may be related with the informative content (methods that are content-based) or with particular social environment pertaining to the user. From a technical perspective, suggestion systems make use of content-oriented methods in which users will state their interests, requirements, and also their constraints on the basis of chosen parameters.

The system will then collaborate choices of users with the catalogued destination places that are described by making use of same set of parameters. Just like in electronic tourism, the personalized amenities depict a vital factor toward further infiltration, adoption, and success of digital mobile tourism [15].

The specific properties belonging to mobile tourism promotes vital opportunities and new challenges toward evolution of novel personalized amenities that do not have any meaning in electronic tourism field. For example, knowledge about the location of user establishes suitable grounds toward provision of position-oriented services (LBS).

Cold start:

The cloud start is collecting some of the issues over the recommendation system for suggesting the venue of the users. The insufficient information of the check-in is producing the similar zero user result in process for degrading the performance of recommendation system [11].

Data sparseness:

There are many existing recommendation system is suffering within the problem of data sparseness when users are visiting the limited venues [13]. Result over the venuecheck-in matrix producing the sparsely filled information within data.

Scalability: The traditional majority of recommendation functions to cover the scalability issues within dynamic and fast expansion for the recommender system over parsing the millions of record for check-in to find the similar users [10], [12].

3. Proposed System

3.1 Overview

The proposed technique over the recommendation is providing user feedback and time aware review for the trip travel details. The proposed technique is considering over the GABORF and Bi-Obj algorithm.

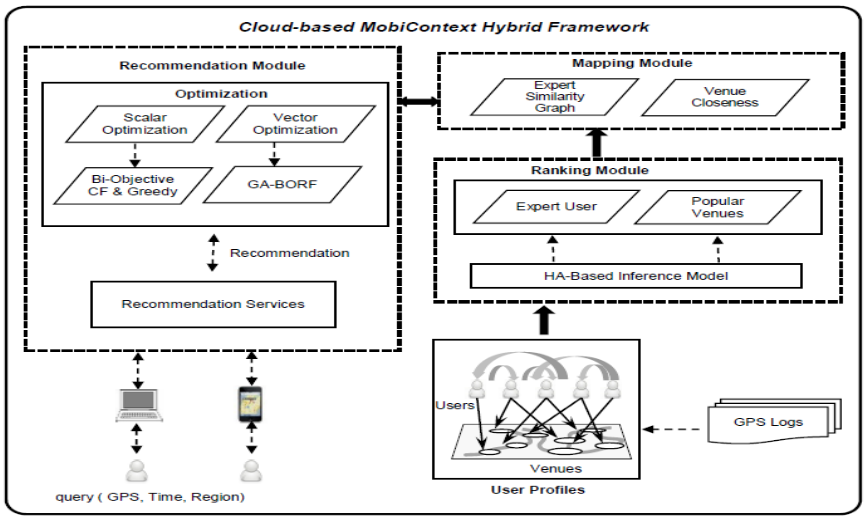

Figure-1: Overall Architecture.

3.2 Pre-Process and List of Time Ware

The top part of the user's profile is performing a module ranking functionality within the data refinement pre-processing step. The operation of pre-processing could perform a periodic form for running the weekly or monthly configuration through system administrator. The profile of the user consist the identification of users, user's venue and venue in time. The home agent inference the user's profile for rank the user venue and set on the basis of mutual relationship reinforcement. The extraction idea is for collecting the expert users and popular set. It known as the popular venue, if many users are visiting the venue or place, it's producing very low score and pruning the offline dataset over the phase of pre-processing for reducing the computation time online.

3.3 Detection of Popular Venue and Users

The computation over the expert users by a similarity graph and it is providing a specific region at the pre-processing phase. The purposes of computation for similarity graph are for generating a like-minded network for sharing the various preferences for visiting the geographical region and several venues. The module of mapping is computing distance based on the geographical purposes within popular venues.

3.4 Recommendation and Feedback

The module for online recommendation runs over the recommendation service for receiving the queries through users. The user request is containing some of the metrics:

a) Surrounded bounded region for the top of user

b) Current context (Location of GPS, feedback, region and time).

The services over recommendation are passing the optimization of user's query that utilizing the technique of vector and scalar for generating optimal venue set. Te proposed framework utilizing a technique scalar optimization within greedy heuristic and CF-based technique for generating the user recommendation. The technique of vector optimization (GA-BORF) is utilizing the evolutionary technique as NSGA-II for producing the recommendation optimization.

3.5 CF-Based Recommendation Process

The recommendation system based on the collaborative filter is making a filtration based on the transaction histories of user abundant and popular content. The system of collaborative filtering is showing the interest individually for predicting the similar users group. The collaborative filter system is obtaining the consumption of enough historical feedback and record. The prediction at other side, feedback implicit, and classification technique of opinion must have to get adopted for solving the user's problems. The collaborative filter is producing rating for grouped clusters for the determination of social community. The user's similarity is finding the group for recommendation and prediction.

3.6 Algorithm

Input: Location_ID, User_ID, Time, Device_Profile

Output: Download the relevant application

1. Function(Location_ID, User_ID, Time, Device_Profile);
2. App_Initialization=[]
3. If Location_ID contains application(M) then,
4. For each m ¡ô M do
5. Initialize_matchm=0;
6. Initialize_ratingm=0; //m has open access
7. m=Max_Score();
8. matchm=1
9. end
10. else

```
matchm=matchm+F();
end
m=0.5 matchm + 0.5 ratingm//m relevant to APP
App=App+m
end
return
```

4. Result and Discussion

4.1 Experimental Setup

The proposed system implements with following system configuration such as Intel(R) Pentium (R) processor, G2020 CPU with 2.90 GHz clock speed, Windows 7 Professional operating system and 4 GB RAM

Search Page and Recommendation

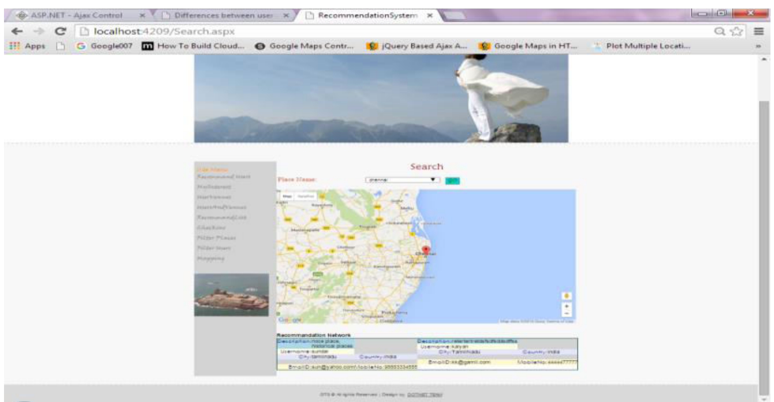

Figure 2: Search page with recommendation.

The above mentioned figure is describing searching criteria, within location and displaying the recommended option based on the query. The search criteria are displaying the output based on the location and user's venue.

User's Feedback and Behavior

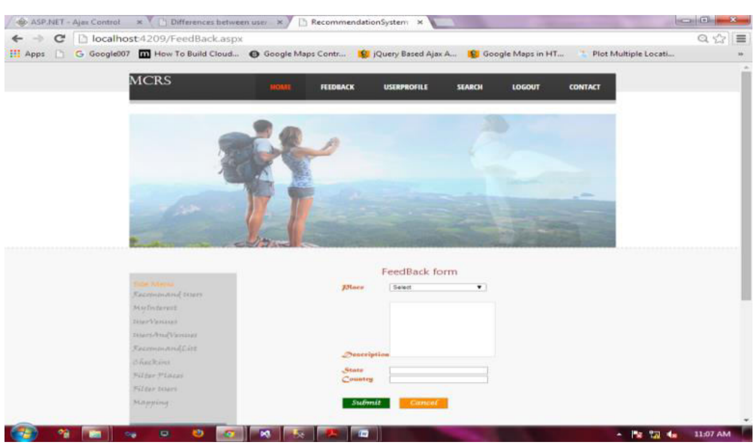

Figure 3: Feedback form for user behavior activity.

The above mentioned figure is presenting the user's feedback and behavior log. The user could provide the feedback over the recommendation service based on their defined criteria.

Accuracy and Efficiency

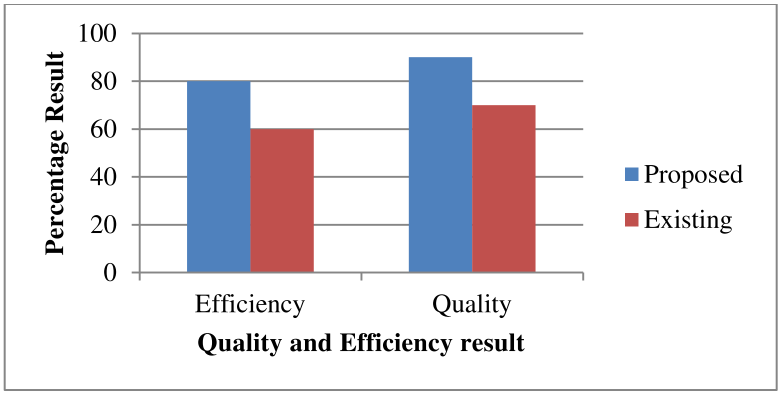

Figure 4: Comparison for Quality and Efficiency.

This figure 4 is showing the comparison between existing and proposed system, the proposed system is producing more accuracy over efficiency and quality.

5. Conclusion and Enhancement

The proposed system is producing a better enhancement over the recommendation system within proposed technology Collaborative Filtering. The collaborative filter is proposing the venue system and venue check-in system for performing over the recommendation system. The user behavior is being counted for proposing and presenting the recommendation as well the user has an option to provide the feedback for their query and recommendation. The GABORF and Bi-Obj algorithm is proposing a better enhancement and providing better recommendation by considering venue or location within the check-in matrix.

Reference

1. L. Lü, M. Medo, C. H. Yeung, Y.C. Zhang, Z. K. Zhang, and T. Zhou, "Recommender systems," Physics Reports 519, no. 1, 2012, pp. 1-49.

2. Jiang, B., Yao, X. B, "Location-based services and GIS in perspective", Computers, Environment and Urban Systems,Vol.30, No.6, 2006, pp. 712-725.

3. Shiode, N., Li, C., Batty, M., Longley, P., & Maguire, D. "The impact and penetration of location-based services", In H. A. Karimi & A. Hammad (Eds.), Telegeoinformatics: location-based computing and services, 2004, pp. 349–366, CRC Press.

4. B. Mobasher, R. Burke, R. Bhaumik, C. Williams, “Towards trustworthy recommender systems: an analysis of attack 3. J. Bobadilla, F. Ortega, A. Hernando, A. Gutiérrez, “Recommender systems survey,” Knowledge-Based Systems, vol. 46, July 2013, pp. 109-132.

5. Koeppel, I, “What are location services? From a GIS Perspective”, ESRI white paper.2000.

6. E. H.-C. Lu, W.-C. Lee, and V. S. Tseng, “A Framework for Personal Mobile Commerce Pattern Mining and Prediction,” IEEE TKDE, 24 (5), pp. 769-782, 2012.

7. Gowalla, http://gowalla.com

8. Foursquare, https://foursquare.com/

9. Facebook, https://www.facebook.com

10. J. J.-C. Ying, E. H.-C. Lu, W.-C. Lee, T.-C. Weng and V. S. Tseng, “Mining User Similarity from Semantic Trajectories”, In Proceedings of LBSN' 10, San Jose, California, USA, November 2, 2010.

11. J. J.-C. Ying, E. H.-C. Lu, W.-C. Lee, T.-C. Weng and V. S. Tseng, “Mining User Similarity from Semantic Trajectories”, In Proceedings of ACM SIGSPATIAL International Workshop on Location Based Social Networks, San Jose, California, USA, November, 2010.

12. Berka T., Plößnig M. (2004), “Designing Recommender Systems for Tourism”, Proceedings of the 11th International Conference on Information Technology in Travel & Tourism (ENTER’2004).

13. Ricci F. (2002), “Travel Recommender Systems”, IEEE Intelligent Systems, 17: 55-57.

14. Scharl A., Dickinger A., Murphy J. (2004), “Diffusion and Success Factors of Mobile Marketing. Electronic Commerce Research and Applications”, 4(2): 159-173.

Corresponding Author:

M. Janarthanan*,

Email: *Mjanarthanan07@gmail.com*