A Cloud-Based Venue Recommendation Framework on MobiContext

Ambika L G , Anitha T N,Bharathi M
PG scholar[1], Associate professor [2,3], Department of Computer Science and Engineering, S.J.C Institute of Technology, Chickballapur -562101.
ambikalg1991@gmail.com

ABSTRACT-In this paper demonstrate MobiContext, a hybrid cloud-based Bi-Objective Recommendation Framework(BORF).The MobiContext utilizes multi-objective optimization techniques to create modified recommendations.To address the issues pertaining to cold start and datasparse,the BORF performs data preprocessing by using the Hub-Average(HA) inference method and the Weighted Sum Approachis implemented for scalar optimization and vector optimization to provide finest suggestions to the users about a venue.The results of complete experiments on a large-scale real data set verify the accuracy of the proposed recommendation framework.

Index Terms—Multi-objective optimization, Collaborative Filtering(CF).

1. INTRODUCTION

In recent year, on going fast development of the Internet and simple accessibility of various e-commerce and informal organizations services,such as Amazon,Foursquare,and Gowalla,have sheer volume of information gathered by the administration suppliers on consistent schedule. The persistent gathering of huge volumes of information has moved the center of examination group from the fundamental data recovery issue to the separating of appropriate information[1], there fore, most research is currently coordinated towards the planning of more perceptive and self-sufficient data recovery frameworks, known as Recommendation Systems.

In late years,mobile social networking services, such as,google latitude,facebook has essentially picked up the fascination of countless.A portable informal community administrations permits a client to perform vast number of"check-ins" based on every day registration aggregate a huge volumes of data.Based on the information stored,several venue reccomendation system(VRS) were developed.So that VRS are intended to perform proposal of venues to users that most nearly match with users preferences.

A. PROBLEMS

The VRS are suffer with numerous limitations and challenges.A major challenges for such system is to process data at a real time and extract preferred venues from a huge dataset of user‘s historical checkins[3][1].The solution for VRS applied collaborative filtering(CF).The CF-based approache generate recommendation based on the similarity in actions and routines of users.

Later the CF-based recommendation system suffers from several limitations.The following are the most common problems in many existing CF-based recommendation systems:

B. CONTRIBUTIONS

To solve this problems we propose MobiContext,a hybrid cloud based Bi-objective recommendation framework(BORF).To address the cold start problem, it utilizing model-based Hub-average inference method,The HA method comptes and assignes popularity ranking to venues and users at various geographical location.

To address data sparseness,it utilize a metric known as confidence measure.confidence measures define the conditional probability.confidence measure is utilized to compute link waight between two users.This way,it helps replacing among zero similarity entries in user-to-user to matrix by alternate non-zero entries,to improving recommendation quality.

To improve scalability performance the cloud based MobiContext framework follows the Software as a Service(SaaS).The proposed framework can scale on demand as additional virtual machines are created and deployed.

2. SYSTEM OVERVIEW

The existing recommendation systems utilize centralized architectures that are not scalable enough to process large volume of geographically distributed data.

Therefore, to address the scalability issue, we introduce the cloud-based MobiContext BORF framework.

In terms of functionality,the proposed system architecture has main phases:a)A pre-processing phase b)A recommendation phase.Preprocessing phase is divided into a)Ranking module b)Mapping module.

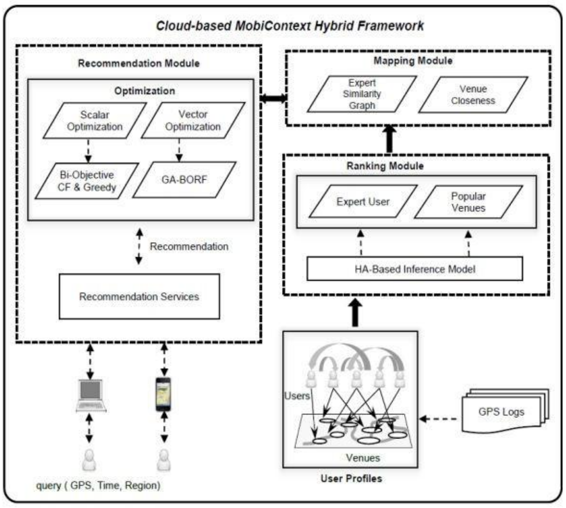

Fig 1:Cloud based MobiContext BORF framework

a)In ranking module the HA inference model is applied on user profiles to compute ranking for users and venue check-ins that is utilized to compute popularity ranking scores for users and venues.Which user visited more popular venues that user is called expert user.The all expert user visited venues that venue called popular venues.b)The mapping module computes the similarity among the expert users.It also computes the geographical distance of the current user from the popular venues.The user will gives query(GPS,location of user time and region)through mobile or desktop the recommendation service recives user queries.The recommendation service passes user recommendation to optimization module.The optimization utilizes the both scalar and vector optimization,the scalar optimization utilizes the Bi-objective CF,the vector optimization utilizes the GA-BORF.

3. IMPLEMENTATION

This framework contains the 4 main modules:

- **User Profiles**

As reflected in Fig.1,the MobiContext structure keeps up records of users' profiles for each geographical region.The arrows from clients to venues at lower right of Fig.1indicate the quantity of registration performed by every user at different venues.A user's profile comprises of the user's identification,venues went to by the user,and registration time at a venue.

- **Ranking Module**

On top of users' profiles, the positioning module performs usefulness amid the pre-handling period of information refinement.The pre-preparing can be performed as occasional group occupations running at month to month or week by week premise as arranged by framework administrator.The positioning module applies model-construct HA derivation technique with respect to users profiles to allocate positioning to the arrangement of users and venues in light of shared fortification relationships.The thought is to extracta set of famous venues and master users.We call road as popular,if it is gone by numerous master users,and a user as master if(s)he has gone to numerous prevalent venues.The users and venues that have low scores are pruned from the dataset amid disconnected from the net pre-preparing stage to decrease the online calculation time.

- **Mapping Module**

The mapping module figures comparability diagrams among master users for a given district amid pre-handling stage. The reason for comparability chart calculation is to produce a system of similarly invested individuals who share the comparative inclinations for different venues they visit in a land district. The mapping module additionally processes venue closeness in light of geological separation between the present client and prevalent venues.

- **Recommendation Module**

Fig. 1 delineates the online proposal module that runs a support of get suggestion questions from users. A user's solicitation comprises of: (a) present setting, (for example, GPS area of client, time, and locale), and (b) a limited district encompassing the user from where the top N venues will be chosen for the present client (N is number of venues). The proposal administration passes the user's question to enhancement module that uses scalar and vector streamlining procedures to produce an ideal arrangement of venues. In our proposed structure, the scalar streamlining method uses the CF-based methodology and eager heuristics to produce user favored suggestions. The vector improvement strategy, to be specific GA-BORF.

4. RELATED WORK

Previously, most work concentrated on direction based methodologies for venue suggestion frameworks [1]–[3]. The direction based methodologies record data around a user's visit design (as GPS directions) to different areas, the courses taken, and stay times. The creators in [3] connected information mining and machine learning on direction information to prescribe most prominent spots. In spite of the fact that, direction based methodologies prescribe areas to clients in view of their past directions, a noteworthy downside of such methodologies is that they can't at the same time consider other compelling variables separated from straightforward GPS follow that makes them deliver less ideal proposals. To address such lack, we used multi-target streamlining in our proposed structure. Another issue is that the direction based methodologies experience the ill effects of information inadequacy issue as for the most part a man does not every now and again visits numerous spots, which brings about meager client venue lattice. Also, the direction based methodologies experience the ill effects of versatility issues as enormous volumes of direction information should be handled bringing on extensive overhead.

A percentage of the methodologies, for example, [3], [5] depend on the online evaluations gave by the clients to the went to puts. The creators in [7] consolidate the accessible venue appraisals with clients' social binds to suggest venues that are high-positioned and in addition most favored by a client's companions. Nonetheless, the creators did not contrast their methodology and any of the standard methodologies, and does not talk about many-sided quality of their work. The previously stated methodologies perform distinctive displaying to clients' inclinations, yet they are not considering different destinations that we particularly considered in our study. In addition, they likewise experience the ill effects of information meager condition issues because of set number of sections inside of the client rating framework.

Aside from rating based methodologies, few of the strategies have their models based on registration based methodologies where the clients give little criticisms as registration about the spots they went to [2]–[4], [7], [14]. For instance, the creators in [6] connected arbitrary stroll with-restart on a client venue registration grid to produce customized suggestions. The majority of the aforementioned approaches have their outlines based on memory-based CF that empowers such ways to deal with give suggestions to clients on the premise of their past sections. Be that as it may, such methodologies experience the ill effects of regular disadvantages of memory-based CF (e.g. cool begin and information sparsity) which decrease their execution. Also, substantial number of likeness calculations on client to-venue lattice makes such methodologies less versatile. There has been some restricted work performed on applying multi-objective optimization on proposal frameworks. One such commitment is by Ribeiro[15] where creators performed a weighted blend of various suggestion calculations and connected improvement to discover proper weights for the constituent calculations. In any case, their methodology is calculation concentrated and no time unpredictability was talked about.

To address the issues refered to above, we proposed a half and half approach over a cloud design that joins the advantages of memory-based and model-based synergistic separating alongside multi-target enhancement to acquire an ideal rundown of venues to be suggested. Besides, our proposed structure shows an answer for adaptability, information meager condition, and frosty begin issues.

5.CONCLUSION

The proposed a cloud-based structure MobiContext cap produces upgraded recommendations by at the same time considering the exchange offs among genuine physical variables, for example, individual's geographical area and area closeness. The noteworthiness and curiosity of the proposed structure is the adjustment of collaborative filtering and bi-objective streamlining methodologies, such as, scalar and vector. In our proposed approach, information inadequacy issue is tended to by incorporating the user to user comparability calculation with certainty measure that evaluates the measure of comparable hobby showed by the two users in the venues ordinarily went to by them two. Besides, an answer for cold start issue is examined by presenting the HA inference model that allots positioning to the users and has a precompiled set of well known unvisited venues that can be prescribed to the new client.

REFERENCES

[1].A.Majid,L.Chen,G.Chen,H.Turab,I.Hussain,and J.Woodward,–A Context-aware Personalized Travel Recommendation System based on Geo-tagged Social Media Data Mining,‖International Journal of Geographical Information Science,pp.662-684, 2013.

[2]. M.Ye,P.Yin,and W.Lee,–Location recommendation for location-based social networks,‖ In Proceedings of the 18th SIGSPATIAL International Conferenceon Advances in Geographic Information Systems,ACM,pp.458-461,2010.

[3].Y.Zheng,L.Zhang,X.Xie,andW.Y.Ma,–Mining interesting locations and travel sequences from gps trajectories,‖In Proceedings of the 18th international conference on Worldwideweb,ACM,pp. 791-800,2009.

[4]. C.Chow,J.Bao,andM.Mokbel,–Towards Location-Based Social Networking Services,‖In Proceedings of the 2nd ACMSIGSPATIAL International Workshop on Location Based Social Networks,ACM,pp.31-38, 2010.

[5].P.G.Campos,F.Díez,I.Cantador,–Time-aware Recommender Systems: A Comprehensive Survey and Analysis of Existing Evaluation Protocols,‖User Modeling and User-Adapted Interaction,vol.24,no.1-2,pp. 67-119, 2014.

[6].A.Noulas,S.Scellato,N.Lathia,and C.Mascolo,–A Random Walk around the City:New Venue Recommendationin Location-Based Social Networks,‖In Proceedings of International Conferenceon Social Computing (SocialCom),pp.144-153, 2012.

[7].Y.Doytsher,B.Galon,andY.Kanza,–Storing RoutesinSociospatial Networks and Supporting Social-based Route Recommendation,‖In Proceedings of 3rd ACMSIGSPATIAL International Workshopon Location-Based Social Networks,ACM,pp.49-56, 2011.

1. [8].S.Seema,andS.Alex,–Dynamic Bus Arrival Time Prediction,using GPS Data,‖In Proceedings of the Nat. Conference Technological Trends(NCTT),pp.193-197,2010.

2.

3. [9].B.Chandra,S.Bhaskar,–Patterned Growth Algorithmusing Hub-Averaging without Pre-assigned

Weights,‖In Proceeding of IEEE International Conferenceon Systems, man, and Cybernetics(SMC), pp.3518-3523,2010.

4.

[10].B.Hidasi,andD.Tikk,–InitializingMatrixFactorizationMethodsonImplicitFeedbackDatabase,‖JournalofUniversalComputerScience, vol. 19,no.12,pp.1835-1853,2013.

[11].C.ChitraandP.Subbaraj,–Anon dominated Sorting Genetic Algorithm for Shortest Path Routing Problem in Computer Networks,‖Expert Systems with Applications, vol.39,no.1,pp.1518-1525, 2012.

[12].Y.Wang,S.Wang,N.Stash,L.Aroyo,andG.Schreiber,–Enhancing Content-Based Recommendation with the Task Model of Classification,‖In Proceedings of the Knowledge and Management,pp.431-440,2010.

[13].J.Bobadilla,F.Ortega,A.Hernando,A.Gutiérrez,–Recommender Systems Survey,‖ Knowledge-Based Systems, vol.46, pp.109-132,2013.

[14].J.Bao,Y.Zheng,M.F.Mokbel,–Location-based and Preference Aware Recommendation using Sparse Geo-Social Networking Data,‖In Proceeding of 20th International Conference on Advancesin Geographic Information Systems,ACMNewYork, pp.199-208,2012.

[15].M.Ribeiro,A.Lacerda,A.Veloso,and N.Ziviani,―Pareto-Efficient Hybridization for Multi-objective Recommender Systems,‖In Proceeding of 6th ACM Conferenceon Recommender Systems,pp. 19-26,2012.