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# Venue Recommendation Based on User Location

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**ABSTRACT:** In this paper, we have concentrated on the efficient and effective use of venue recommendation system. For this purpose we have presented an idea of an android application which will recommend venues to users. We prefer MobiContext framework, which is used for mobile social networks. The MobiContext is a hybrid cloud-based Bi-Objective Recommendation Framework (BORF). Above framework will contain venue selection based on users' personal preference and venue closeness on geographical information. We have implemented collaborative filtering (CF) before using BORF, because CF will make more ideal choices in real life practical application. There are challenges such as cold start, data sparseness and scalability are overcame in proposed system i.e. venue recommendation system. In proposed system two users with similarity in interest might get same outcome but if there similarities change the confidence measure changes and different satisfactory results are achieved. Cold start is conquered using Hub Average (HA) interface model which will find the importance of venue if it is unvisited by user. A hybrid approach over the cloud architecture is used to combine model based and memory based collaborative filtering. Multi-objective optimization will produce venues' optimal collection without repetition of venues which are visited or far away from users' location. We propose this kind of system because recommendation provides some undesired outputs, sometimes location might be far or more difficult to reach. Algorithms like BORF, HA interface model and multi-objective optimization makes above tasks easier to overcome.

**KEYWORDS**: Bi-Objective Recommendation Framework (BORF), Collaborative Filtering (CF), Hub Average (HA), MobiContext.

## I. INTRODUCTION

In every aspect of our lives we try to spend less time and expenses on selecting anything that will suit our lifestyles and spend more time and expenses to use that thing. In today's world this situation occurs everywhere, so we have selected the field of recommendation systems that will provide venues based on the user location and user preferences. General idea behind this system is to provide a mobile application that will recommend the user nearby places which can be visited in user's spare time. We are going to use cloud computing methods for storing user's historic data and venue information. The main goal is to find a proper venue from cloud dataset that will match user's preferences.

### A. *MOTIVATION*

We get the idea for creating such system from travelling at unknown places. We have recommendation systems like Google maps recommendation, but the problem is that, the system shows any kind of recommendation of any type of venue regardless of user's liking. Sometimes user might end-up with navigating a bad venue. Recent work in recommendation systems includes intelligent aides for filtering and choosing places and information of user interest. As a result, it seems applicable to have personalized intelligent systems that process, filter, and display available information in a manner that suits each individual. Our system is a small prototype but it can be implemented as vast project in order to get globalized. For this purpose MobiContext framework is proposed in our system.

### B. *LITERATURE SURVEY*

The idea of providing venues to the user based on their historical check-ins using photo sharing app. In this paper authors proposed a recommendation system based on user's shared geotagged photos [1]. System is designed to recommend venues based on a popular location-based social networking system which will provide location recommendation based on collaborative ratings of places made by social networking friends. For these they have used

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*friend-based collaborative filtering* (FCF) more specific *Geo-MeasuredFCF* (GM-FCF) [2]. Time aware recommendation systems (TARS) can be made more efficient to use. A methodological description framework aimed to make the evaluation process fair and reproducible. They also present an empirical study on the impact of different evaluation protocols on measuring relative performances of well-known TARS [3].

Authors propose a new model based on personalized random walks over a user-place graph that, by seamlessly combining social network and venue visit frequency data, obtains between 5 and 18% improvement over other models. Their results pave the way to a new approach for place recommendation in location-based social systems [4]. Authors present a query language that consists of graph traversal operations, aiming at facilitating the formulation of queries, and they show how queries over the network can be evaluated anciently. They also show how social-based route recommendation can be implemented using their query language [5].

Authors present a general initialization framework that preserves the similarity between entities (users/items) when creating the initial feature vectors, where similarity is defined using e.g. context or metadata information. They demonstrate how the proposed initialization framework can be coupled with MF algorithms. They show that the initialization significantly improves the performance of the MF algorithms by most ranking measures [6]. Authors define reusable inference steps for content based recommender systems based on semantically-enriched collections. They show an instantiation in the case of recommending artworks and concepts based on a museum domain ontology and a user profile consisting of rated artworks and rated concepts. The recommendation task is split into four inference steps: realization, classification by concepts, classification by instances, and retrieval. Their approach is evaluated on real user rating data. They compare the results with the standard content-based recommendation strategy in terms of accuracy and discuss the added values of providing serendipitous recommendations and supporting more complete explanations for recommended items [7].

Authors modify the definition of dominance in order to solve constrained multiobjective problems efficiently. In this paper they suggest a non-dominated sorting-based MOEA, called NSGA-II (Non-dominated Sorting Genetic Algorithm II) [8]. Authors propose the weighted sum method of vector objective secularization is known to generate points on convex Pareto front whose distribution cannot be controlled. This work presents a method of improving the distribution of Pareto points generated by weighted sum method by nonlinear weight selection [9].

By surveying all above papers we come to conclude to reference, that is more effective in terms all aspects. In recent years, recommendation systems have seen significant evolution in the field of knowledge engineering. Most of the existing recommendation systems based their models on collaborative filtering approaches that make them simple to implement. However, performance of most of the existing collaborative filtering-based recommendation system suffers due to the challenges, such as: (a) cold start, (b) data sparseness, and (c) scalability. Moreover, recommendation problem is often characterized by the presence of many conflicting objectives or decision variables, such as users' preferences and venue closeness. In this paper, author proposed MobiContext, a hybrid cloud-based Bi-Objective Recommendation Framework (BORF) for mobile social networks.

The MobiContext utilizes multi-objective optimization techniques to generate personalized recommendations. To address the issues pertaining to cold start and data sparseness, the BORF performs data preprocessing by using the Hub-Average (HA) inference model. Moreover, the Weighted Sum Approach (WSA) is implemented for scalar optimization and an evolutionary algorithm (NSGA-II) is applied for vector optimization to provide optimal suggestions to the users about a venue. The results of comprehensive experiments on a large-scale real dataset confirm the accuracy of the proposed recommendation framework [10].

### C. *PROBLEM DEFINITION*

Earlier systems having venue recommendation framework mostly face the problem regarding data insufficiency, new users facing the problem finding the location and making the system more scalable. The problems regarding the data insufficiency is more difficult to solve because to do the process on users query there should be a sufficient amount of data regarding the user's current location. The cold start that is the problem regarding the new users signing up for the system suffers due to the lack of profile information. System is implemented in a smaller scale in order to maintain the data of a small geographical location.

- Data Insufficiency

The problem occurs at the start of the new system. Because until and unless the new users and venues are not added to system, the system is not capable for working efficiently.

- Cold Start

This problem occurs because user is new to the system. He/she does not have sufficient data to represent his/her preferences for the system, so venues visited most are only source for recommendation for the new users.

- Scalability

The system face this problem more often because system's data start to increase as new users and new venues are get added to the system. It becomes difficult to handle vast amount of data with normal structure.

### D. *BACKGROUND*

The existing system contains algorithm such as BORF and NSGA-II. The system filters all the dataset using collaborative filtering so that the strong dataset will be available for performing query operations. The challenges in the CF such as data sparseness, cold start and scalability is solved using Mobicontext BORF. The Weighted Sum Approach (WSA) is implemented for scalar optimization and an evolutionary algorithm (NSGA-II) is applied for vector optimization to provide optimal suggestions to the users for visiting a venue.

For proposed system we prefer collaborative filtering that will create a dataset with purity. This dataset is further used for BORF algorithm which will create a mobile social network of users. The HA based system is to get venues ranked as per their popularity. By far collecting all we get cloud dataset with BORF algorithm which will provide each user a ranked venue based on users preference. Collaborative filtering will resolve the problem of cold start. The system framework is hybrid MobiContext so it is easy to scale the system to large size. The problem regarding data insufficiency is solved using ranking module which is discussed further. The insufficient data is filled by ranking each venue as it is added to the system.

### E. *THEORY*

The proposed system is CF-based which will provide the recommendations list which builds dataset. This dataset is provided to new signed-up user. That is if new user uses the system CF will provide a previous list of historical data at specific location. The Multi-Objective Optimization is done in this system so as to make the system faster while doing multiple tasks such as getting user preferences and popular venues linked, getting nearby venue to user's location. If there are multiple venues nearby to user's location that will be difficult to choose appropriate venue for user. This task is mainly done by Multi-Objective-Optimization.

The BORF will be implemented as an optimizer while selecting the venues. To improve scalability performance the cloud based MobiContext framework follows the Software as a Service (SaaS). The venues which are visited most are taken in account for gathering confidence measure of particular location. If similar set of visited venues occurs two or more times visited by many users then that venues are considered as a chain via checking for their confidence measure. For example an user is travelling from place A to place E the number of possible venues user can visit in between A to E are B, C and D. User might visit all or not but if user does visit all and other user with the same travelling arrangement does also visit the all, the pattern is stored in the system and it becomes easier to get optimized venues for popular routes.

## II. ALGORITHMS

### A. *COLLABORATIVE FILTERING*

Input: Current User: c, region: R

Output: $Toprec$= A set $S'$ of top-N venues.

Definitions, $Ve$= set of venues visited by expert user e, $Nc$= set of recommended venues, lc=location of current user c, $Vc$ = set of venues visited by current user, $Sr$ =set of expert users similar to the current user c, $\varsigma ce$ = closeness measure of the expert user e with the location of current user c, $sce$ is similarity of the user c with the expert user e.

1: $Nc \leftarrow \emptyset$; $zagg \leftarrow \emptyset$;
2: $Sr \leftarrow computsimset$ (c, E)
3: for $each\ e \in Sr$ do
4: S $\leftarrow \{v: Ve\ |v \notin\ \}$
5: $\varsigma ce \leftarrow m(computsimD(lc\ , \text{S}))$
6: $za$[e] $\leftarrow computeagg(sce\ , \varsigma ce\ )$

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7: end for
8: $Nc \leftarrow computRec$(c, $zagg$)
9: $Toprec \leftarrow sort$ ( )

Collaborative filtering algorithm is used to select venues from given content of dataset. That is if user wants to visit a place P from the region R that is in which he/she is currently located, where user's location is O then user must be accessible to all the possible outcomes in region R and places such as P, where O is the centre of the users location.

B. *Greedy-BORF approach for Venue Recommendation*

Input: Current user: $s$, Type: $\mathcal{C}$, region: R
Output: A set $V'$ of top-$N$ venues visited by expert user similar to current user.
Definitions: Kj= neighbor set of node j, $\delta ij$ = edge count between i and j,
$(i, j)$ = 1/$\delta ij$ and, $\mathcal{Z}j$= number of required venues found at a node j, visited list=∅.

1: $a \leftarrow c$; $\delta \leftarrow 1$;
2: $Gc \leftarrow getSimGraph(\mathcal{C}, R)$
3: $Ka \leftarrow \{x: Gc\ |s(a, x) > 0\}$
4: $visitedlist \leftarrow a$
5: Sort $Ka$ in terms of $[Sim\ (a, j) \times (i, j)]$, $j \in Ka$ (descending)
6: for each $e \in Ka$ do
7: $S \leftarrow \{v: Ve\ |v \notin\ \}$
8: $M \leftarrow M.append(e, S)$
9: $visitedlist \leftarrow visitedlist \cup \{e\}$
10: end for
11: if $venueCou(M) \geq N$ then
12: go to Line 23
13: else
14: $\forall j \in Ka$, set $a \leftarrow j$, such that we have
$arg\ max\ [Sim(a, j) \times \eta(i, j) \times \mathcal{Z}j/N] \wedge Kj \neq \emptyset \wedge \forall g \in Kj\ |\ g \notin visitedlist$
15: if $No\ any\ such\ node\ found\ in\ Step$ 15 then
16: go to Line 22
17: else
18: $\delta \leftarrow \delta + 1$;
19: go to Line 6
20: end if
21: end if
22: $D' \leftarrow computeDi(lc\ , M)$
23: $V' = aggregateranki(M, D')$
24: return $V'$

Venues are selected using collaborative filtering algorithm and the recommendation of top ranked venues near by the user location done by the Greedy BORF algorithm. If number of venues are N then top ranked venues are denoted by top-N is descending order. The ranked places are then shown as recommendation to user so that user is able to find between them according to his preference.

## III. IMPLEMENTATION

### A. *SPECIFICATION OF SYSTEM*

Each user is given a unique identity number at the time of sign-up and that identity number has unique combination with user's password. This dataset is stored on cloud and can be recalled at any location user wants. After sign-up user can login to the system and using current location of user the ranked venues are shown. The GPS connection should be ON while doing the task. While ranking venues user is getting data from the same cloud used for storing user's username and password. The actual implementation of system is done over here, the user's required location should be

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shown in this phase as well as the recommended venues for the user. The historical check-ins of user shows the field of interest of user and how many places he have visited. On the basis of this data user is able to generate his profile that is the user side is clear. User can get proper recommendation now, but only if the venues near user are having potential of user's requirement. The users' login and check-ins on various location will build up this dataset. The each user should login and check-in at the recommended location. Considering this time of visit the location gets ranked and is recommended to users' of similar preferences as that of previous visits by the multiple users.

B. ***MODULE OF SYSTEM***

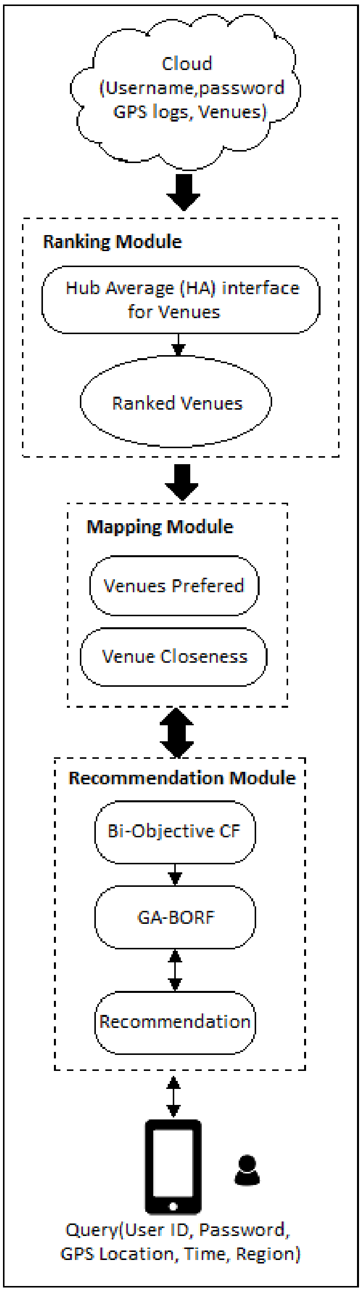


Fig. 1 Hybrid MobiContext Architecture for Venue Recommendation

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Fig. 1 shows how the system will work at each level. The architecture is general idea of lifecycle of processing of system. Each module in the architecture has specific task assigned as per discussed earlier. The recommendation module is bi-directional so that the data stored in the system is always get updated time to time.

- Cloud Dataset

Cloud is used to store data of each user as in one, so as to find each users rating and each venues popularity. Dataset is globally accessed by each user there is no restriction to any user or any venue. Users' data such as usernames and password is also stored at the cloud dataset.

- Ranking module

The ranking module will contain Hub-Average (HA) interface that will be applied to each new checked-in venue for making the venue as a strong recommendation if multiple users visit the same. The HA method computes and assigns popularity ranking to venues and users at various geographical locations. With such ranking available, the new user can be recommended with venues that have highest ranking in a geographical region. From HA method all the venues are get ranked according to their popularity.

- Mapping Module

User's previous history is monitored in mapping that is what kind of places user intended to visit, which place user prefer most. The next thing is how close the venue is from user's location because if venue is not close as per user's convenience then that venue should be neglected. Both the user's preference and venue preferred is close to user's location are the things which are considered during mapping.

- Recommendation Module

As discussed above the recommendation module will use to main algorithms for searching venues near user's location as per user's convenience. Bi-Objective CF algorithm will form cluster of user's preference with the venues and Genetic Algorithm based BORF (GA-BORF) utilizes optimization among venues which are preferred by the mapping module. The situation such as number of venues preferred are so many then at that time user must spend time at proper venue and also be able to visit more number of venues.

## IV. EVALUATION

### A. *RELATED WORK*

Previous systems we have referred are using historical check-ins of users' on social networking sites and their collaborative friend circle. This kind of architecture is more useful if there are more number of user's are connected to your profile. System with geographical location gives accurate location but recommending exact location to users profile and users preferences is difficult in such systems. Our system combines the users' profile data as well as users' geographical location and also users' venue closeness for the purpose of recommendation. Venue closeness is optimized on basis of distance and time taken by previous users to travel there. So combination of all make a suitable venue for user to visit in less consumption of time

### B. *FUTURE WORK*

Proposed system contains are mainly focussed on recommendation and the data provided from the cloud. We can add contains in future such as user profile linked with user's social network so that user's profile made stronger. User will automatically without entering his preferences in the system will be able to operate system. We can also add contains such as what venue user prefer that is if any user is handicapped user should be able to visit only such venues where handicapped people are allowed. The users' having problems with venue such as the venue is too crowded then he/she is not intended to visit there. That is adding a special module for checking at what time location user intended to visit is full of people, user may or may not visit such place based on his/her nature. Our system is more specialized only for the purpose of visiting new places we can generalize it for more things like coffee shops, food places, hospitals, places with parking, supermarket, etc.

## V. CONCLUSION

We propose a cloud based framework that produces streamlined recommendations at the same time considering the geographical location of user and recommended venue closeness. The significance and oddity of the proposed framework is the adjustment of collaborative filtering and bi-objective streamlining approaches, such as scalar and

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vector. In our proposed approach, data sparseness issue is tended to by incorporating the client to client comparability computation with confidence measure that evaluates the measure of comparative interest indicated by the two clients in the venues commonly went to by both of them. In addition, an answer for cold start issue is discussed by introducing the HA inference display that relegates positioning to the clients and has a precompiled arrangement of prevalent unvisited venues that can be recommended to the new client. We are intended to insert more functionalities in our framework such as contextual data of user that is users' check-ins time interval, users' modified profile, users' hobbies. Besides, we mean to incorporate different approaches, such as machine learning, content mining, and artificial neural systems to refine our current framework.

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