Mobile Based Location Recommendation System Using Cloud Approach

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Abstract- *Now a day, recommendation system provides different recommendation services for large scale Location-based social networks, with including the social and geographical characteristics of users and locations. Using that concepts recommender system where users can easily search their related location but it does not provide rating facility to those users. so, users can easily get the popular places in that their current user location. With that utilizes multi-objective optimization techniques to generate personalized recommendations. In FCF, only friends are used as references in collaborative filtering with using concepts of precision and recall for the performance evaluation and this approach used for location recommendation based on collaborative ratings of places made by the social friend. Non-dominated Sorting Genetic Algorithm (NSGA II) is applied for vector optimization to provide optimal suggestions to the users about a venue.*

Keywords- Recommender System, Collaborative Filtering (CF), Friend-based Collaborative Filtering (FCF), Non-dominated Sorting Genetic Algorithm (NSGA II).

I. INTRODUCTION

Now a day, rapid development smart phone with provides a number of location-based social networking services. This location-based social networking services used for users to connect with friends, native places (e.g., restaurants, stores, hospitals, colleges etc.), Moreover, as the users and locations. In location-based social networking services are rapidly growing, it is essential to adopt efficient techniques for realizing Location recommendation. Particularly, particularly, provides both social and geographical characteristics of relationships between users and places to support the location recommendation services. This has two implications:

First, while recommender systems have proven to excel in web settings [7], they have historically operated with ordinal Rating data where spatial properties tend to not matter and users have the ability to provide negative feedback. Instead, check-in data only counts users' visits to venues, which are also inherently spread over a geographic space. Second, recommender systems have traditionally operated under the sole assumption of like-mindedness (i.e., historically similar users will continue to have shared preferences). Instead, there is a wide range of reasons why mobile users may want to visit a place (e.g., visiting friends, attending an event, touring culturally significant locations); applying the state-of-the-art in web recommendation to this new context will inexorably exclude a host of features that this data contains [7].Friend-based collaborative filtering (FCF) approach for location recommendation based on collaborative ratings of commonly visited places made by social friends. Collaborative Filtering methods (CF) are able to provide an accurate recommendation if enough feedback is available.

Various following problem came into the previously unvisited venues from behavioral, social, spatial data are as follow:

i) How often do people tend to visit?

New places ? Though that we can check-in services datasets. We found that between 60-80% of user's check-ins are to the venue that has not been visited in the previous month: these datasets contain granular representations of irregular beyond daily routines.

II. LITERATURE SURVEY

In Paper [1], propose a new method for recommending tourist locations that are relevant to users (i.e., personalization) in the given context (i.e., context awareness). We obtain user-specific travel preferences from his/her travel history in one city and use these to recommend tourist locations in another city.

In Paper [2], mainly focused on the research issues in realizing location recommendation services for large-scale location-based social networks, by exploiting the social and geographical characteristics of uses and location/places. Accordingly, we develop a friend-based collaborative filtering (FCF) approach for location recommendation based on collaborative ratings of places made by social friends.

In paper [3], Exploiting temporal context has been proved to be an effective approach to improve recommendation performance. Time-aware recommender system (TARS).In the literature, however, reported results and conclusions about how to incorporate and exploit time information within the recommendation process seem to be contradictory in some case.

In paper [4], the popularity of location-based social networks available on mobile devices means that large, rich datasets that contain a mixture of behavioural (users visiting venues), social (links between users), and spatial (distance between venues) information are available for mobile location recommendation system. With that provide the 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 the other models.

In paper [5], Cellular phones and GPS navigation system allow recording the location history of users, to places the users frequently visit and routes along which the users frequently travel. This provides associations between users and geographical entities. Considering this association as edges that connect users of a social network to geographical entities on a spatial network yields integrated socio-spatial networks.

In this paper, also presents a graph model for socio-spatial networks that stores information on frequently travelled routes. With that a query language that consists of graph traversal operations, aiming at facilitating the formulation of queries, and show how queries over the network can be evaluated anciently.

III. ALGORITHM

i). NSGA based Venue Selection:-

NSGA is used to provide the set of the candidate solution called a population And also find out the preferred recommendation venues.

Input: R: set of recommendations.

Output: top-N Recommendations based on bi-objective optimization.

Definitions: Pop=set of population, Epop=set of population after evaluation, gen= number of generations,

Qt = Set of top-N optimized recommended venues,
$psize$= total size of population**.**

1: $a \leftarrow c;\ \delta \leftarrow 1;$
2: $G_c \leftarrow getSimGraph(C,R)$
3: $K_a \leftarrow \{x: G_c | sim(a,x) > 0\}$
4: $visitedlist \leftarrow a$
5: Sort K_a in terms of $[Sim\,(a,j) \times \eta(i,j)]$, $j \in K_a$ (descending)
6: **for each** $e \in K_a$ **do**
7: $S \leftarrow \{v: V_e | v \notin V_a\}$
8: $M \leftarrow M.append(e,S)$
9: $visitedlist \leftarrow visitedlist \cup \{e\}$
10: **end for**
11: **if** $venueCount(M) \geq N$ **then**
12: go to Line 23
13: **else**
14: $\forall j \in K_a$, set $a \leftarrow j$, such that we have $\arg\max\left[Sim(a,j) \times \eta(i,j) \times \frac{z_j}{N}\right] \wedge\ K_j \neq \emptyset \wedge\ \forall g \in K_j |\ g \notin visitedlist$
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: $D' \leftarrow computeDist(l_c, M)$
23: $V' = aggregateranking(M, D')$
24: **return** V'

IV. PROPOSED SYSTEM

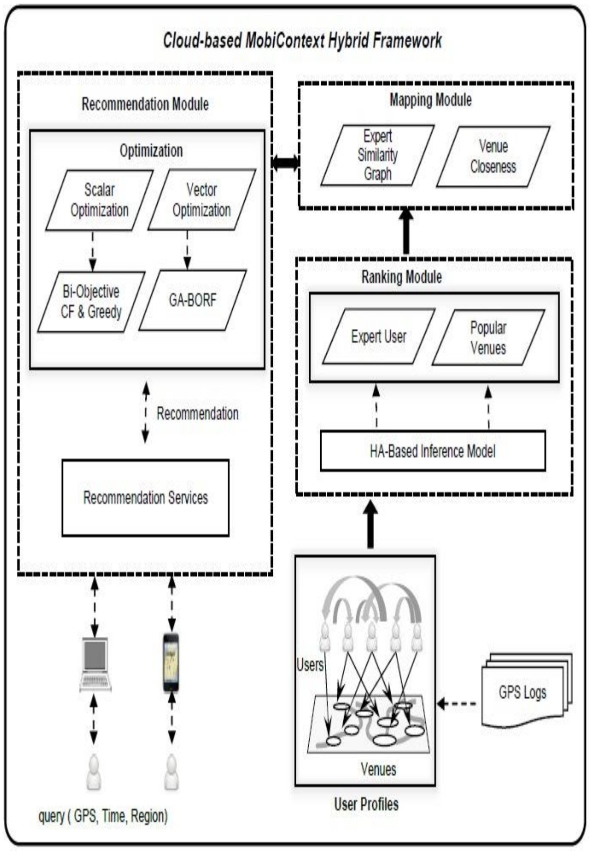

Fig1. System architecture [1]

V. MATHEMATICAL MODEL

<u>Mathematical Model:-</u>

Let S be the whole System,
S= {I, P, O}
Where,
I-input,
P-procedure,
O- Output.
Now,

Input (I):

I= client triggers query for upload and download files (F) = {F1, F2, F3 … Fn} from server.

Procedure (P)-

P= {R, M, R1, SO, VO}
Where,
R- Ranking,
M-Mapping
R1- Recommendation,
SO- Scalar Optimization,
VO- Vector Optimization,

Stage 1- Ranking-

$$e_u^{<n>} = (M_c \times M_c^T) \times e_u^{<n-1>} \times \frac{1}{\partial}$$

e_u – Expert users,
M_c - Check in matrix,
∂ – A Total number of popular venues checked in by expert users.
n - No of iterations.

Stage 2- Mapping

$$s_r(c,c') = \frac{\sum_{v \epsilon S_{cc'}} (r_{cv} - \bar{r}_c)(r_{c'v} - \bar{r}_{c'})}{\sqrt{\sum_{v \epsilon S_{cc'}} (r_{cv} - \bar{r}_c)^2 \sum_{v \epsilon S_{cc'}} (r_{c'v} - \bar{r}_{c'})^2}},$$

Where,

$$S_{cc'} = \{v \epsilon V \mid r_{cv} \neq 0 \wedge r_{c'v} \neq 0\}.$$

S_r (c,c') - Similarity matrix of user c and c',
$r_{c,v}$, $r_{c',v}$ - Number of check in at venue v performed by the user c and c',
V - Set of all venues
E-Set of expert user in a region
∂-Total number of popular venues checked in by expert users
$\bar{rc}$ - Average number of check-ins of user c[1].

Stage 3- Recommendation-

$$max\ f(o_i)\ \forall\ o_i \in \{p_v, v_c\},$$

Where,
$f_{(o_i)}$ - The maximized objective function, in terms of popular venues, visited.
p_v -expert users
v_c - Venue closeness

Stage 4- Scalar Optimization

$$f(u) = \sum_{i=1}^{n} \alpha_i \times f_i(u),$$

Where,
(u) is the aggregate objective function
a_i - The weight
n – the number of objective functions

Stage 5- Vector Optimization

$$f_2 = \frac{1}{\sum_{i=1}^{n} cost\ (l_u, v)_i \times\ t}.$$

n- Represents the total length of an individual,
$(vd\ ,\ lu\ )$ - calculates the geospatial closeness between the current location of the user lu and the consecutive venues *v* (genes),
$f2$ - Overall fitness for the venue closeness of a single individual in a population [1].

Output (O)-

Proposed system implementation presents a solution for scalability, data sparseness, and cold start issues [1].

VI. CONCLUSION

This paper has examined the modern problem related to that recommendation services for the location-based social networking systems, with that we also observe that their subsist strong social and geospatial ties among users and their visited locations in the system. A part from that we also study the Friend based collaborative filtering (FCF) approach for location recommendations based on collaborative filtering of locations among social friends[7] and also provides rank and classify the new venues for each user. With providing NSGA algorithm for the purpose of selecting particular venues and to achieve suitable venues from a network of like-minded people who share the similar preferences for various venues they visit in a geographical region [1].

In terms of future work, we can provide more users' friendly and new venue recommendation system to the user through the cloud-based approach.

ACKNOWLEDGMENT

We would like to thank Mr. Suhas Patil Assistant professor Computer engineering department, in K.J College of engineering and management research, Pune, Maharashtra, India for their useful guidelines.

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