International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol.-7, Special Issue-14, May 2019 E-ISSN: 2347-2693

User Centric Recommendation System for Location Promotion in LBSNs

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DOI: https://doi.org/10.26438/ijcse/v7si14.284287 | Available online at: www.ijcseonline.org

Abstract—Aim of this paper is to propose a user-centric location recommendation service for the rapidly increasing LBSN (location-based social network). Our idea is to consider three important influencing factors i.e. client predilection, social impacts and distance influence for point-of-interest recommendations. Also, the influence factors i.e. client predilection, social impact are predicted via user-based collaborative filtering and friend-based collaborative filtering, we propose a technique to focus more on distance factor impacts because of the spatial clustering recorded in user visiting locations in LBSNs. Our research shows that the distance influence among locations plays a vital role in user check-in practices which is implemented by power law distribution. Likewise, we build an agglomerative location recommendation system, which combines client predilection to a location with social effect and distance influence. Our result shows that the proposed fusion framework performs better than the already proposed recommendation techniques.

Keywords—LBSN,point-of-interest recommendation system,power-law

I. INTRODUCTION

The quick advancement of cell phones, remote networks and Web innovation, various LBSN administrations, e.g., Foursquare and Gowalla, have developed as of late. These LBSNs enable users to build up digital connects to their companions or different clients, and offer encounters of their visits to a location of interest e.g., eateries, film, and so forth. In LBSNs, a POI recommendation service, going for prescribing new point-of-interests to users so as to enable them to explore new nearby places and realize the urban communities, is critical usefulness that has received many momenta recently.[4][5]

However, to recommend a location in the recommendations system in location-based social network is an interesting issue to explore in light of the fact that important data, for example, the computerized information of users just as the physical connections among clients and locations have been recognized in the frameworks. [4][5] This data has not been completely depicted in earlier research [1] contemplates important to POI recommendations.
The traditional recommendation methods [1][6][7] are based on user inclination and the social effect is by all accounts appropriate for the point-of-interest recommendation. In particular, incorporating the distance influence between locations has not been found already.

In our proposed method, we develop a recommendation model for location recommendation in LBSN by the means of fusion framework which combines the three crucial influencing factors: 1) user predilection [7][8] 2) social impact[6][7] and 3)distance influence through user-based collaborative filtering, friend-based collaborative filtering and the power law distribution respectively, which explores users' point-of-interest. It shows that the users' understood predilection of locations can be achieved from their visiting patterns on different locations. Considering two users who have visited at many basic locations as comparative users, we may find the certain preference of a client based on the past visiting records of comparative users. Finally, we propose a model which combines location-distance factor in our recommendation agglomerated with the user's social influence and personal preferences

Organization of the paper is a follow, Section I contains the introduction of the paper, Section II contains the related work in the research domain, Section III contains the methodology used for implementation, Section IV consists of the Results obtained and Section V concludes the research work followed by the future scope in this research.

II. RELATED WORK

Point-of-interest Recommendation in Location-based Social Networks [1]. Two generally embraced methodologies for recommender frameworks are content-based and collaborative filtering strategies. A substance-based framework chooses elements for a recommendation based on the comparability between thing substance and user profile.
In earlier investigation, the influence boost is dependent on the number of users in the social network (LBSN) which

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increases the social impact eventually. This assumption doesn't affect our location recommendation system.

Earlier researched location recommendation systems [7] are based on three factors: 1) users' personal taste and preference of locations 2) users' social group preference of locations influencing the user. 3) Balance between the above two mention factors to achieve better accuracy.
The proposed technique works fine unless two friend users are notgeographically apart. In case of geographically separated friends, the recommended location is irrelevant to the user since the distance between the user and the location is very high.

Other proposed methods[9] consider only the GPS dataset with respect to the users' current location and recommend the point-of-interests. This technique helps the users to explore the nearby locations, by creating a correlation between the users' preference and the nearby point-of-interests. By following this approach, the uses' social influence is not taken in consideration which results in recommendation not likely to the users' preference.

Discussing about the social networking architecture, social friendship is playing a major role in collaborative filtering recommendation system such as random walk [9,10,11] and memory based [9,10]. These concepts show the similarity between two social friends i.e. they exhibit common interest and their social relationship can be considered in collaborative filtering. Social friendship is already researched in model-based systems [12,13], which is mainly used in conventional recommendation models.
Through the point by point investigation above, we came to a conclusion that the existing POI recommendation systems are: 1) Doesn't consider the user's' social influence conventional and geographical influence together. 2) purely business oriented and works business biased

III. Methodology

In this section, we will discuss about the architecture and three different influencing factors of this recommendation system.

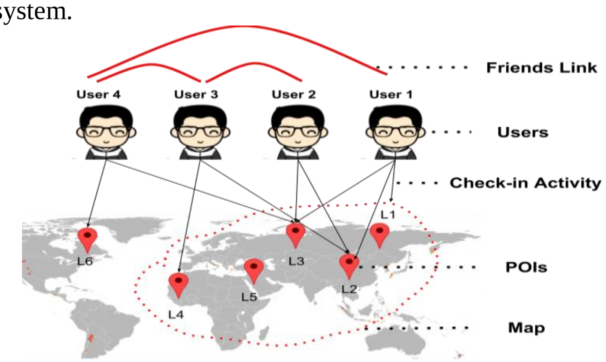

Figure 1: Graphical representation of users in a LBSN

As represented in Figure 1, users of location-based-social-network, signified as user1, user2, user3, user4, are connected through social network In addition, point-of-interest, meant as loc1, loc2, ..., loc6, are associated with various users through their "check-in" exercises. Finally, as additionally outlined in the figure, the point-of-interest are bounded on map.

A. User-based Collaborative Filtering
As indicated by collaborative filtering, it is a technique for making programmed filtering about the preferences of a client by gathering inclinations from comparative clients. Considering U be the clients and L be the locations, both these parameters monitor the check-in behaviour. The user a check-in behaviour represented as $u_a$belongs to set U at a location lbbelongs to set Value of ya,b= 1 represented user ua has check-in at location lb.whereas, ya,b= 0 shows that u_a has never visited to location lb. To calculate the probability of an unvisited user at a particular location using ya,b is given as:

$$\hat{Y}_{a,b} = \frac{\sum u_p X_{a,p} \times Y_{p,b}}{\sum u_p X_{a,p}}$$

where xa,p - similarity weight within [us,ub].
To calculate the similarity weights xa,p of users ua and uk, cosine similarity can be used, which is represented as:

$$X_{a,p} = \frac{\sum_{l_{b\in L}} Y_{a,b} \times Y_{k,b}}{\sqrt{\sum_{b\in L} {Y_{a,b}}^2}\sqrt{\sum_{b\in L} {Y_{a,b}}^2}}$$

B. Friend-based Collaborative Filtering
Companions will, in general, have comparative conduct since they are companions and may share many regular interests, consequently prompting related registration practices. For instance, two companions may hang out to see a movie together here and there, or a client may go to an eatery suggested by her companions.[15] Every one of those conceivable reasons proposes that companions may give a great recommendation to a given client because of their potential corresponded registration conduct. Likewise, in simple words, recommendation of client's friends is called as recommendation based social impact from companions. Location recommendations based on social impact is given as:

$$\hat{Y}_{a,b} = \frac{\sum_{u_{k\in F}} SI_{k,a} \cdot Y_{k,b}}{\sum_{u_{k\in F}} SI_{k,a}}$$

where $y_{a,b}$- probability of check-in of user u_a at location l_b. F_a is the friends set of u_a, and $SI_{k,a}$is the social influence weight u_k has on u_a.
Social connection and similarity of two users' check-in activities plays a major role in defining the social influence weight, which is given as:

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$$SI_{k,a} = \eta . \frac{|F_k \cap F_a|}{|F_k \cup F_a|} + (1-\eta) . \frac{|L_k \cap L_a|}{|L_k \cup L_a|}$$

F_k denotes the friend set and L_k denotes the location set and η is defined as turning parameter value between 0 to 1.

C. Geographical Influence

Two major factors can be considered for distance influence (1) individuals will be in general visit location near their homes or offices; (2) individuals are interested in exploring close-by locations of their attraction, regardless of whether of the distance from their place. So, our research considers impact of social influence and distance influence on location recommendation.[6]

The distance between two locations is affects the user check-in based on the similarities of user's visited location. In order to achieve this value, the distances between all sets of locations that a client has visited is calculated. Power law distribution is used to calculate the probability of a user has checked-in to a location based on the distance between two locations checked-in earlier by the same user as follows:

$q = x \times p^y$

Here, x and y represent the parameters used in power-law, and the distance between two locations checked-in by a similar user is represented by p and q.

D. Fusion Framework

We built a combined framework to perform recommendation, which combines different influencing parameters of customer preference, social impact and distance influence in POI recommendation. In our approach, $S_{a,b}$ is taken as the check-in probability of user u_a at location l_b,. Also, $S^u_{a,b}$ represents the the check-in probability of users u_a at location l_b based on user preference, $S^s_{a,b}$ be the the check-in probability of users u_a at location l_b based on social impact and $S^g_{a,b}$ are the check-in probability of users u_a at location l_b based on geographical influence as mentioned above. $S_{a,b}$ is given as:

$$S_{a,b} = (1 - \alpha - \beta)S^u_{a,b} + \alpha . S^s_{a,b} + \beta . S^{\mathbf{g}}_{\mathbf{a,b}}$$

where α and β are the tuning parameters, sum (α + β) ranging from (0,1). Considering α = 1, only the social impact is taken into prediction whereas, β = 1 takes only the geographical influence is taken for prediction. And, α = β = 0 calculates $S_{a,b}$ only on user preference.

IV. RESULTS

We tried to build a recommendation system from users point of interest. The model hyperparameters 'alpha' and 'beta' were evaluated and set as 0.1 as they resulted in better prediction. The model could score a precision score of 49% with 0.5% tolerance and recall score of 67% ± 0.8%

Table 1: Precision and recall score comparison

	Precision@5		Recall@5	
	α= 0.1	β= 0.1	α= 0.1	β= 0.1
w/ fusion framework(Our model)	49% ± 0.5		67% ± 0.8	
w/o fusion framework(Earlier)	24.5%		64%	

We can get N number of recommendations where N can be provided as an argument. Results could be considered as very promising as such complex predictions involve imbalance and biasing. In the previous studies [6], data preprocessing played an important role in the performance of the recommendation model. Using the foursquare dataset, 0.2 precision was achieved with the α and β value of 0.1 at N=5 and recall value smaller than 0.05.

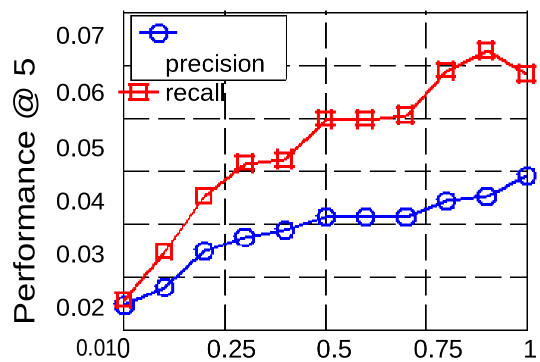

Figure 2. Performance @5 – Gowalla (w/ Fusion framework)

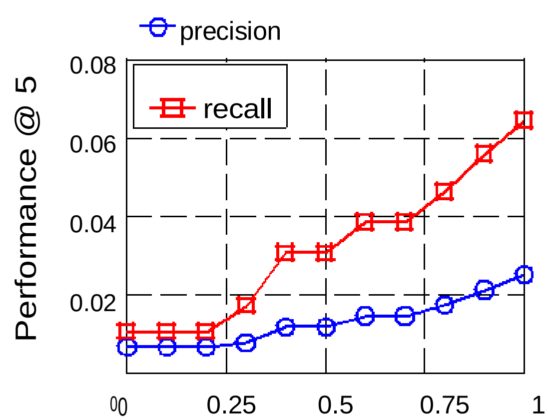

Figure 3. Perfomance@5 – Gowalla (w/o fusion framework)

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Figure 3 shows the performance of the model at N set as 5(number of recommendations). The precision and recall score obtained in earlier studies are 24.5% and 64% which islesser as compared to our model. This significant change in scores is mainly due to the influencing factors which we have taken in our recommendation model. There is a secondary factor of data preprocessing also.

Figure 2. shows the performance of the model at N set as 5(number of recommendations). We can see the precision and recall score better than the earlier recommendation models.[1]This clearly shows the significant impact of grid selection used for data cleaning in this research as well as the choice of fusion framework combined of three essential factors i.e. user predilection, social impact and distance influence made a significant impact on the performance of the recommendation system proposed in this paper.

V. CONCLUSION

This research is an attempt to build a user-centric location-based point-of-interest recommendation system. Our approach is to agglomerate customer predilection (user preference), social impact and distance influence. Also, we build a combined user-centric POI recommendation system, which combines customer preference to a POI with social impact and distance influence. Our proposed recommendation system exhibits the precision value of 49% with ±0.5% error rate and recall value of 67% with ± 0.8% tolerance.Results could be considered as very promising as such complex predictions involve imbalance and biasing. Also, the computational time of training the model is the bottleneck in the process. In future scope of improvement, Optimization of the recommendation system can be conducted to improve the accuracy and precision and to optimize the results. After the optimization of the model, it can be implemented on real time applications.

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