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Analytical study on Collaborative Filtering techniques for Location-based Recommendation

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Abstract— The popularity of location-based social networks provides us with a new platform to understand users' behavior and preferences based on their location histories. Social networking applications have become very important web services that provide Internet-based platforms for their users to interact with their friends. With the advances in the location-aware hardware and software technologies, location-based social networking applications have been pro-posed to provide services for their users, taking into account both the spatial and social aspects. Location as one of the most important components of user context implies extensive knowledge about an individual's interests and behavior, thereby providing us with opportunities to better understand users in a social structure according to not only online user behavior but also the user mobility and activities in the physical world. Under many such circumstances, a location recommender system is a valuable but unique application in location-based social networking services, in terms of what a recommendation is and where a recommendation is to be made. Collaborative filtering (CF) technique for recommendation becomes one of the popular recommendation techniques for location recommendation. This analysis presents a comparative study on different collaborative filtering methods like Hypertext Induced Topic Search (HITS) based model, CF with Collaborative Location and Activity Recommendations (CLAR) and candidate selection method used for location recommendation.

Index Terms— Collaborative Filtering, Location and Activity Recommendations, Location Recommendation, Location-based Social Networks, Social Networks, User Preferences, Weighted Category Hierarchy

1 Introduction

THE popularity of location-based social networks provides us with a new platform to understand users' behavior and preferences based on their location histories. Social networking applications have become very important web services that provide Internet-based platforms for their users to interact with their friends. With the advances in the location-aware hardware and software technologies, location-based social networking applications have been pro-posed to provide services for their users, taking into account both the spatial and social aspects [1]. Recommender systems have been developed to help fill the gap between information collection and analysis, by filtering all available information and presenting the most relevant items to the user. The recommender system helps enhance the capacity and efficiency of this process. The biggest challenge of this type of system is finding the perfect match between those recommending and those receiving the recommendation that is, defining and discovering the relation between their interests [2].

A location recommender system is a valuable but unique application in location-based social networking services, in terms of what a recommendation is and where a recommendation is to be made. The most used techniques employed in recommender systems are the collaborative filtering and content-based systems. The collaborative filtering does not take into account the type of items, nor their attributes. It takes exclusively into account the expressed opinion about the other items, location rating inference in order to make recommendations [2]. In Location Based Social Networking systems (LBSNs) offers a particular user a set of venues (such as restaurants and shopping malls) within a geospatial range with the consideration of User personal preferences and Social opinions of other users. The dimension of location brings social networks back to reality, bridging the gap between the physical world and online social networking services. Location as one of the most important components of user context implies extensive knowledge about an individual's interests and behavior, thereby providing us with opportunities to better understand users in a social structure according to not only online user behavior but also the user mobility and activities in the physical world [3].

2 Concepts in Location-Based Social Networks (LBSN)

2.1 Social Networks

A social network is a social structure made up of individuals connected by one or more specific types of interdependency, such as friendship, common interests, and shared knowledge. Generally, a social networking service builds on and reflects the real-life social networks among people through online platforms such as a website, providing ways for users to share ideas, activities, events, and interests over the Internet.

2.2 Location

A location can be represented in absolute (latitude-longitude coordinates), relative (100 meters north of the Space Needle), and symbolic (home, office, or shopping mall) form. By the meantime, a location usually has three kinds of geospatial representations: A point location, a region, and a trajectory.

A LBSN does not only mean adding a location to an existing social network so that people in the social structure can share location-embedded information, but also consists of the new social structure made up of individuals connected by the interdependency derived from their locations in the physical

world as well as their location-tagged media content, such as photos, video, and texts.

Here, the physical location consists of the instant location of an individual at a given timestamp and the location history that an individual has accumulated in a certain period. Further, the interdependency includes not only that two persons co-occur in the same physical location or share similar location histories but also the knowledge, e.g., common interests, behavior, and activities, inferred from an individual's location (history) and location-tagged data [3],[5].

Location recommendations provide a user with some venues (e.g., an Italian restaurant or a fancy movie theater) that match her personal interests within a geospatial [2]. Such applications should also recommend high quality recommendation results when people travel to an unfamiliar area, where they have little knowledge about the neighborhoods. A high quality location recommendation has to simultaneously consider the following three factors; user preferences, the current location of a user, the opinions of a location given by the other users.

User preferences are extracted according to user interest's For Example; artistic users are more interested in art galleries and museums, while the shoppingaholics would pay more attentions to nearby shopping malls. For more accurate recommendations system need to know the current location of the user as the users prefers the nearby locations, this location indicates the spatial range of the recommended venues and may affect the ratings of these recommendations. And the last factor social opinions of nearby users are valuable resource for making high quality recommendations [4].

The system offers a particular user a set of venues (such as restaurants and shopping malls) within a user specified geospatial range with the consideration of the three factors as user's preferences are learned from user's location history and the preferences are modeled with a (WCH). To computing the similarity between the two users' WCHs we need to estimate the similarity between two users' preferences. This method infers handling the data `ness problem and user preference modeling problem for location recommendations. By pre-computing and extracting the local expert for each location category in a city using an iterative inference model over the available users' location histories, which improves the efficiency of our online recommendation process. Online recommendation model infer the rating to a venue with the local experts selected by a preference-aware candidate selection algorithm and a collaborative filtering based model. This approach enables a real-time location recommendation by simultaneously considering an individual's location, preferences granularities, and opinions from local experts [4].

3 Literature Survey

In this section, we present some of previous studies done by different authors on location based recommendation based on social networking data using collaborative filtering methods. There are many sources available to write literature on analysis of the location based recommendation systems based on different recommendation techniques and collaborative filtering methods that try to address one or another issues in such recommendation systems, but collaborative filtering technique with Weighted Category Hierarchy (WCH) and candidate selection algorithm guarantees that it gives better recommendation results than the existing recommendation surveys as per my observation. Some of the related works are mentioned here.

Chi-Yin Chow, Jie Bao, and Mohamed F. Mokbel [1] proposed system architecture of GeoSocialDB; which is also a location-based social networking database System. The proposed system delivers location-based news feeds, location-based news ranking and location-based recommendation services to its users based on their personalizes spatial and social preferences. They have implemented these services as query operators inside a database engine to optimize the query processing performance. Their framework directs towards the realization of scalable and practical query processing for location based social networking services. For designing location and rank-aware query operators, materializing query answers, supporting continuous query processing, and providing privacy-aware query processing for these three location based social networking services

Jie Bao, Yu Zheng, Mohamed F. Mokbel [4] proposed a preference-aware location based recommender system, which provides a user with location recommendation over the specified geo-region on the user's personal preferences learnt from her location history and social opinions mined from the local experts who could share similar interests. This system projects a user's location history into the category space and models a user's preferences using a WCH. This method handles the data sparseness problem and enables the computing of similarity between users who do not share any physical location histories, e.g., living in different cities. This system facilitates people's travel not only near their living areas but also to a city that is new to them. The proposed candidate selection algorithm improves the efficiency of this approach tremendously while maintaining the effectiveness that enables an online recommendation scenario.

Tzvetan Horozov, Nitya Narasimhan, and Venu Vasudevan [6] proposed a novel extension to the well-known memory-based collaborative filtering algorithm, optimizing it for its application to location-based items. They proposed a model that achieves the optimization by employing personalized location-based data partitioning method that allow the system to scale even for very large datasets. For testing the utility and performance of optimizations, they developed and deployed GeoWhiz, a practical restaurant recommender system that uses traditional user-based collaborative filtering techniques coupled with location-based partitioning. GeoWhiz observe real-world usage of such recommender systems, and the collected voting data provided data-mining fodder for interesting observations on potential categorization of such points of interest (POIs).

In paper, Y. Zheng, L. Zhang, Z. Ma, X. Xie [7], and W.Y. Ma effectively introduced a location-history-based recommender system which uses a particular individual's visits on a

geospatial location as their implicit ratings on the location and tries to predict a particular user's interest in an unvisited location in terms of their location history and those of other users. In their system, each user will be recommended a group of potential friends who might share similar tastes of travel, sports, or entertainment, and a list of geospatial locations which might match the user's interests [7]. Therefore, a user can organize some social activities in a community and expand their geographical knowledge with minimal effort. Hierarchical-graph-based similarity measurement (HGSM) is proposed this recommender to uniformly model various users' location histories and infer the similarity among users. The sequence property of user movement, hierarchy property of geographical spaces and visited popularity of a location, these are the features of this system and also considered in this similarity measure. So this system is able to reduce the cold start problem of recommender systems and offer users a better location recommendation to some extent.

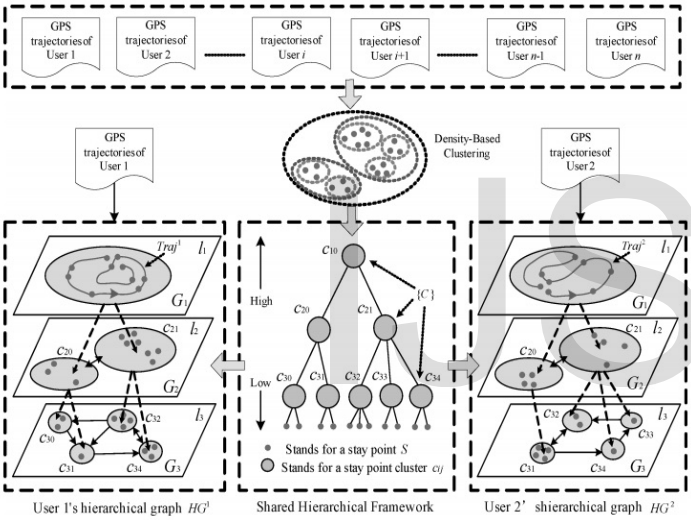


Figure 1.1: Hierarchical graph modeling individual location history [7]

Y. Zheng, L. Zhang, X. Xie, and W.Y.Ma. [8], in their paper they have proposed a recommendation model that gives generic and personalized travel recommendations from a large number of user-generated GPS traces. Generic recommendation, modeled multiple users' location histories with tree-based hierarchical graph (TBHG), and mined the top *n* interesting locations and the top *m* popular travel sequences in a given geospatial region based on the TBHG and a Hypertext Induced Topic Search (HITS)-based inference model [8, 15]. Figure 2.1 shows how tree based hierarchical graph is formulated using tree based hierarchy. This system gives personalized recommendation, by calculating the correlation between locations by employing the user travel experiences and the sequence of locations visited and incorporated this correlation into an item-based Collaborative Filtering model, which predicts a user's interest in an unvisited location in terms of other users and the user's location history.

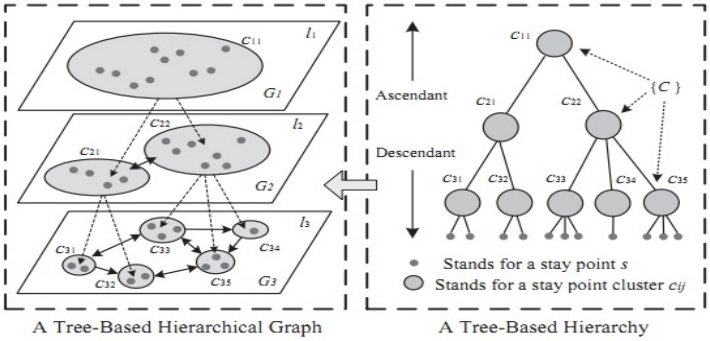


Figure 1.2: Building a tree-based hierarchical graph [8]

V.W. Zheng, Y. Zheng, X. Xie, and Q. Yang [9] proposes a model that uses the location data based on GPS and users' comments at various locations using this information they have discovered interesting locations and possible activities that can be performed for recommendations. They model the users' location and activity histories that take as input. Then they mine knowledge, such as the location features and activity-activity correlations from the geographical databases and the Web, to gather additional inputs. Finally, they apply a collective matrix factorization method to mine interesting locations and activities, and use them to recommend to the users where they can visit if they want to perform some specific activities and what they can do if they visit some specific places. They exploit other information such as including the location features and the activity-activity correlations from various information sources that enhances the performance. They also provided a collaborative filtering approach based on collective matrix factorization to take these information sources as inputs and train a location and activity recommender.

M. Ye, P. Yin, W.C. Lee, and D.L. Lee [10] proposed a model that facilitates a POI recommendation service in location-based social networks. The proposed model incorporates user preferences, social influence and geographical influence in the recommendation. In addition they have derived user preference by user-based collaborative filtering and captured social influence from friends, they have also model the geographical influence among POIs by incorporating the user preference and social influence in the collaborative recommendation techniques by employing power law distribution to uncover the spatial clustering phenomenon in user check-in activities. They also propose a unified POI recommendation framework, which fuses user preference to a POI with social influence and geographical influence. As the results shown in the paper geographical influence shows a more significant impact on the effectiveness of POI recommendations than social influence; the strength of social ties do not reflect the similarity of check-in behavior among users in LBSNs and Item-base CF is not an effective approach in our application due to insufficient number of visitors to many locations at the current state of LBSNs.

This literature survey shows that the location-based social networks provide a new platform to understand users' behavior and preferences based on their location histories. The sur-

vey shows that location based recommendation are carried out using collaborative filtering technique with different methods provides recommendation results with some pros and cons. As per the survey we can say that among all the methods mentioned above, collaborative filtering with WCH and candidate selection technique gives better recommendation results.

Our recommendation is based on location and user preference system that offers a particular user a set of venues (such as Hotels and shopping malls) within a user specified geospatial range with the consideration of user preferences, current location of a user and opinions of a location given by the other users . By modeling a user's preferences based on the category information of her location history (instead of physical locations) in a LBSN, our recommender system facilitate people's travel not only near their living areas but also to a city that is new to them.

Therefore method offers more effective recommendations than all existing recommender systems, while having a good efficiency of providing better location recommendation results. The detailed description is given in the next section.

4 Recommendation System

4.1 Introduction

The explosive growth of the World Wide Web (www), the emerging popularity of e-commerce and social networks have provided access to a large quantity of information, which was previously inaccessible. Gathering data is not a problem anymore, but the extraction of useful information and its presentation to the user in a relevant way is. Recommender systems have been developed to help fill the gap between information collection and analysis, by filtering all available information and presenting the most relevant items to the user [8],[15]. The recommender system helps enhance the capacity and efficiency of this process. The biggest challenge of this type of system is finding the perfect match between those recommending and those receiving the recommendation; that is, defining and discovering the relation between their interests.

Information systems that filter relevant information for a specific user based on his/her profile are known as Recommender Systems. A recommender system usually compares the user profile with some reference characteristic and attempts to predict the evaluation a user would provide of a particular item that has not yet been considered. E-commerce websites are currently the main interest group of recommender system usage, employing different techniques to find more appropriate products for their clients and to raise sales volume.

Recommender system belongs to personalized information filtering techniques that suggests which items or products available which might be of a particular user's interest. These systems make recommendations using three steps: acquiring preferences (acquiring preferences from the user's input data), recommendation computation (computing recommendations using proper methods) and recommendation presentation (presenting the recommendation to the user) [11], [16].

4.2 Recommendation System Approaches

Recommendation systems are usually classified on the basis of their approach to rating estimation:

- Collaborative Filtering System
- Content-based System
- Hybrid System

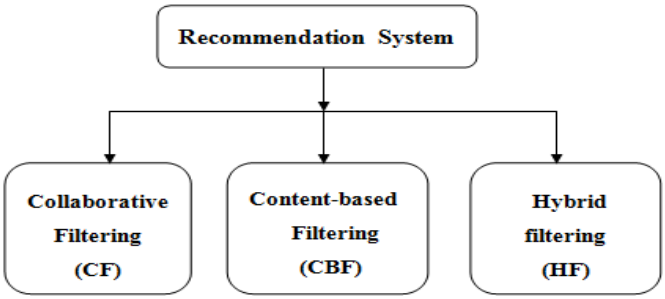


Figure 1.3: Classification of Recommendation System

The above figure 1.3 shows the classification of Recommendation System. In content-based approach, similar items to the ones the user preferred in past will be recommended to the user while in collaborative filtering, items that other people with similar tastes and preferences like will be recommended. In order to overcome the limitations of both approach hybrid systems are proposed that combines both approaches in some manner.

4.2.1 Collaborative filtering

Collaborative filtering (CF) systems work by collecting user feedback in the form of ratings for items in a given domain and exploiting similarities in rating behavior amongst several users in determining how to recommend an item. CF systems recommend an item to a user based on opinions of other users. For example, in a movie recommendation application, CF system tries to find other like-minded users and then recommends the movies that are most liked by them [12].

Collaborative filtering computes the similarity of user's interests rather than computing the similarity of items,. This means that subjective data about items can be incorporated into recommendations. These interesting items from other users can extend the current user's scope of interest beyond his already seen items. In addition, collaborative Filtering techniques can be used to recommend both textual articles and audio and video Files [13].

4.2.2 Content-based filtering

Content based recommendation systems recommend an item to a user based upon a description of the item and a profile of the user's interests. Such systems are used in recommending web pages, TV programs and news articles etc. All content based recommender systems has few things in common like means for description of items, user profiles and techniques to compare profile to items to identify what is the most suitable recommendation for a particular user [12].

A user's selection is often based on the subjective attributes such as the quality, style or point-of-view of items of the item, whereas content-based approaches are based on objective attributes such as the text content of a document about the items and do not take the user's perceived valuation of such subjective attributes into account. For example, these methods cannot distinguish between a well written and a badly written article if both happen to use the same terms [13].

4.2.3 Hybrid filtering

Hybrid recommenders are systems that combine multiple recommendations techniques together to achieve a synergy between them. Several researchers have attempted to combine collaborative filtering and content- based approaches in order to smoothen their disadvantages and gain better performance while recommendations. Depending on domain and data characteristics, several hybridization techniques are possible to combine CF and CB techniques which may generate different outputs. Some of the techniques are weighted, feature augmentation, feature combination, mixed, switching, cascade etc. [12].

4.3 Problems in Recommendation Systems

Various techniques used in a recommender system experiences some of the hurdles that may be described in terms of basic problems.

4.3.1 Sparsity Problem

In any recommender system, the number of ratings already obtained is usually very small compared to the number of ratings that need to be predicted. Effective prediction of ratings from a small number of examples is important. Also, the success of the collaborative recommender system depends on the availability of a critical mass of users. For example, in the movie recommendation system, there may be many movies that have been rated by only few people and these movies would be recommended very rarely, even if those few users gave high ratings to them. Also, for the user whose tastes are unusual compared to the rest of the population, there will not be any other users who are particularly similar, leading to poor recommendations. Stated simply, most users do not rate most items and hence the user ratings matrix is typically very sparse. This is a problem for Collaborative Filtering systems, since it decreases the probability of finding a set of users with similar ratings. This problem often occurs when a system has a very high item-to-user ratio, or the system is in the initial stages of use. This issue can be mitigated by using additional domain information or making assumptions about the data generation process that allows for high-quality imputation [14].

4.3.2 Cold-Start Problem

New items and new users pose a significant challenge to recommender systems. Collectively these problems are referred to as the cold-start problem. The first of these problems arises in Collaborative Filtering systems, where an item cannot be recommended unless some user has rated it before. This issue applies not only to new items, but also to obscure items, which is particularly detrimental to users with eclectic tastes. As such the new-item problem is also often referred to as the first-rater problem. Since content-based approaches do not rely on ratings from other users, they can be used to produce recommendations for all items, provided attributes of the items are available. In fact, the content-based predictions of similar users can also be used to further improve predictions for the active user. The new-user problem is difficult to tackle, since without previous preferences of a user it is not possible to find similar users or to build a content-based profile. As such, research in this area has primarily focused on effectively selecting items to be rated by a user so as to rapidly improve recommendation performance with the least user feedback. In this setting, classical techniques from active learning can be leveraged to address the task of item selection [14].

4.3.3 Scalability

With the growth of numbers of users and items, the system needs more resources for processing information and forming recommendations. Majority of resources is consumed with the purpose of determining users with similar tastes, and goods with similar descriptions. This problem is also solved by the combination of various types of filters and physical improvement of systems. Parts of numerous computations may also be implemented offline in order to accelerate issuance of recommendations online [14].

5 Location Based Social Networking Services (LBSN)

Location-based social network integrates two of the most popular service: location-based services and social networking services. The newly added location dimension bridges the gap between the physical world and the cyber world. Also, the rich data generated in location-based social networks provides us with a new platform to understand user behavior and preferences according to their physical locations.

The location information brings many new challenges for us to extend the traditional social networking services with location-awareness from: efficiency, to take advantage of the location information to prune the unnecessary computational effort when providing the service and effectiveness, to take advantage of the implicit information contained in the user's location history to study the user's behavior and preferences.

Location recommendation offers a particular user a set of venues (such as a restaurant or shopping mall) around her present location in terms of the user's personal preferences learned from her location history and social opinions mined from the local experts who could share similar interests with the user. The dimension of location brings social networks back to reality, bridging the gap between the physical world and online social networking services. Location as one of the most important components of user context implies extensive knowledge about an individual's interests and behavior, thereby providing us with opportunities to better understand users in a social structure according to not only online user behavior but also the user mobility and activities in the physi-

cal world [4].

5.1 Algorithm Used In Collaborative Filtering

In Location based recommendation system we are mainly consternate on Collaborative Filtering techniques. In collaborative filtering many methods and algorithms are used for computation of recommendation system. As stated in L. Zhang et.al.[8] they have used a collaborative filtering technique based on Tree-Based Hierarchical Graph (TBHG) and Hypertext Induced Topic Search (HITS) based inference model. In V.W. Zheng et.al.[9] they used the collaborative filtering technique with collective matrix factorization method. Also in Yu Zheng et.al [4] paper they used Collaborative filtering with weighted category hierarchy (WCH) and Preference aware Candidate selection algorithm. Here we analyze all the above stated papers with the different Collaborative Filtering methods.

5.1.1 CF With TBHG And HITS Based Model [8]

Using Tree based hierarchical graph they model the multiple users individual history, based on TBHG they proposed an HITS based model that models the individual's access on a location as a directed link from the user to that location.

Interest of location depends on the three factors as Interest of users that refers to number of users visiting the locations, user's travel experiences and also by mining classical travel sequences that is by considering interests of these locations and users' travel experiences. Based on multiple users' GPS trajectories, they mine the top n interesting locations and the top m classical travel sequences in a given geospatial region, by taking into account users' different travel experiences as well as the correlation between locations. At the same time,

Algorithm LocationInterestInference ($TBHG$, $LocH$)

Input: A tree-based hierarchy graph $TBHG$=(H, G), and collection of users' location histories $LocH$
Output: the collection of users' hub scores, $\boldsymbol{h}$, and the collection of locations' authority scores, $\boldsymbol{a}$.

1. $\boldsymbol{h} = \boldsymbol{a} = \emptyset$;
2. **For** $i = 1$; $i < L$; i++ //for each level
3. **For** $j = 1$; $j \leq C_i$; j++ // for each cluster on this level
4. **For** $x = i+1$; $x \leq L$; x++ //search the descendant levels
5. C_x' = LocationCollecting (x, c_{ij}, H);
6. M = MatrixBuilding (C_x',$LocH$);
7. ($\{h^k_{ij}\}$,$\{a^x_i\}$) = HITS-Inference (M);
8. $\boldsymbol{a} = \boldsymbol{a} \cup a^x_i$;
9. $\boldsymbol{h}=\boldsymbol{h} \cup h^k_{ij}$;
10. Return ($\boldsymbol{h}$, $\boldsymbol{a}$);

Figure 1.4: The algorithm for inferring the authority and hub scores [8]

they are able to infer the most k experienced users in a geo-related community. In HITS-based model, a geospatial region corresponds to a topic; an individual's hub score stands for their travel experiences, and the authority score of a location represents the interest of the location. So by considering a user's experience of travel and the interest of a location, they mine the classical travel sequences from people's GPS logs.

Figure 1.4 depicts an off-line algorithm for inferring each user's hub scores and the authority scores of each location conditioned by the different regions. Here C_x is the collection of clusters on xth level. $C_x' \subset C_x$ denotes the collection of c_{ij}'s descendant clusters on the xth level. A $TBHG$ is the integration of H and G, $TBHG$ = (H, G). H is define H denotes collection of stay point-based clusters C with a hierarchy structure L *where* $L = (l1, l2, \ldots, ln)$ denotes the collection of levels of the hierarchy and C means the collection of clusters on different levels. Here, cij represents the jth cluster on level $li \in L$, and Ci is the collection of clusters on level li and $G = \{gi = Ci , Ei , 1 < i \leq |L|\}$. On each layer $li \in L$, $gi \in G$ includes a set of vertexes Ci and the edges Ei connecting $cij \in Ci$. Also h^k_{ij} denotes u_k's hub score conditioned by the region of c_{ij} .

5.1.2 Collaborative Location And Activity Recommendtion (CLAR) [9]

The location data based on GPS and users' comments at various locations, they discover interesting locations and possible activities that can be performed there for recommendations. They first model the users' location and activity histories that are taken as inputs. Then they mine knowledge, such as the location features and activity-activity correlations from the geographical databases and the Web, to gather additional inputs. Finally, by applying a collective matrix factorization method that mine interesting locations and activities, and use them to recommend to the users where they can visit if they want to perform some specific activities and what they can do if they visit some specific places. With the available user comments to the GPS trajectories, they got the statistics about what kinds of activities the users performed on some location, and how often they performed these activities. By organizing this statistics' data in a matrix form, they form a location-activity matrix, with rows as locations and columns as activities. An entry in the matrix denotes the frequency for the users to perform some activity on some location. By extracting the location features with the help of POI category database they form a location-feature matrix, with rows as locations and columns as features. Each entry of the matrix denotes some feature value on that location. They also extract knowledge from World Wide Web, to get the knowledge about the activity correlations.

This knowledge is better to infer that if a user performs some activity on a location, then it is likely that she will also perform another activity. By organizing the data in a matrix form, they form an activity-activity matrix, with rows and columns both as activities. Each entry of the matrix denotes the correlation between a pair of activities. Having the knowledge of location-activity matrix, location-feature matrix and activity-activity correlation matrix, they trained a recommender system. Using a collaborative filtering model under the collective matrix factorization framework and manage to fill the missing entries in the location-activity matrix. Based on the filled location-activity matrix, they rank and retrieve the top k locations/activities for recommendations to the users.

Algorithm CLAR

Input: Incomplete Location - activity matrix $Xm{\times}n$,
Location - feature matrix $Ym{\times}l$ and
Activity - activity matrix $Zn{\times}n$.
Output: Complete location-activity matrix $Xm{\times}n$.
1. $t = 1$;
2. **While** ($t < T$ and $L_t - L_{t+1} > \epsilon$) **do** // T is #(max iterations)
3. Get the gradients ∇_{Ut} , ∇_{Vt} and ∇_{Wt} by Eq.(6);
4. $\gamma = 1$;
5. **While** ($L(U_t - \gamma\nabla_{Ut}, V_t - \gamma\nabla_{Vt}, V_t - \gamma\nabla_{Vt}) \geq L(U_t, V_t, W_t)$) do
6. $\gamma = \gamma/2$; // search for the maximal step size
7. $U_{t+1} = U_t - \gamma\nabla_{Ut}$, $V_{t+1} = V_t - \gamma\nabla_{Vt}$ and $W_{t+1} = W_t - \gamma\nabla_{Wt}$;
8. $t = t + 1$;
9. **Return** X;

Figure 1.5: Algorithm description of CLAR [9]

Figure 1.5 depicts the algorithm for Collaborative Location and activity recommendation (CLAR). Here a gradient is denoted as ∇, matrix U used to shares the location information, and matrix V used to shares the activity information.

5.1.3 CF with WCH and Preference Aware Candidate Selection Algorithm [4]

Here recommender system offers a particular user a set of within a geospatial range with considering User personal preferences, which are automatically learned from her location history and Social opinions, which are mined from the location histories of the local experts. This recommender system can facilitate people's travel not only near their living areas but also to a city that is new to them. They model each individual's personal preferences with a weighted category hierarchy (WCH) and infer the expertise of each user in a city with respect to different category of locations according to their location histories using an iterative learning model. By selecting candidate local experts in a user specified geospatial range that matches the user's preferences using a preference-aware candidate selection algorithm and then infer a score of the candidate locations based on the opinions of the selected local experts. Finally, the top-k ranked locations are returned as the recommendations for the user.

The social knowledge learning infers each user's expertise in each category city-by-city according to their location histories. Then they model each category group of location histories using a user location matrix, in which each entry denotes a user's number of visits to a physical location. By applying an iterative inference model to each user-location matrices, we calculate a score w.r.t. a category for each user, indicating a user's expertise in that category in that city. By ranking the users in terms of the score corresponding to a category, they discovered the local experts of different categories in the city. The Personal preference discovery component models each user's personal preferences using a WCH by taking advantage of the location category information lying her location history, which help to overcome the data sparsity problem. Specifically, a WCH is a sub-tree of the predefined category hierarchy, where each node carries a value denoting the user's number of visits to a category. Taking inputs as user with a list of venues, considering the user's preferences, current location, and social opinions from the selected local experts, Preference-aware candidate selection component selects a set of local experts who visited the venues within a user's recommendation range R and have a high expertise in the categories preferred by the user.

Algorithm Preference Aware Candidate Selection

Input: (1) Spatial Region R,
(2) A user's $u.wch$, and
(3) Total number of location recommendations N.
Output: (1) A set of selected local experts E and
(2) A set of candidate locations V
1. Retrieve venues V' in R
2. $U \leftarrow$ users who have visited V'
3. **while** *True* **do**
4. **for** level l from bottom to the root-1 in $u.wch$ **do**
5. $w_{min} \leftarrow$ minimum preference weight at l
6. **for *each*** category c in user's $u.wch$ at level l **do**
7. $k \leftarrow | u.w_c / w_{min} |$ //*Calculate the number of users*
8. $e \leftarrow$Top(k, U, c) // *Select top-k users based on u'c.h*
9. **for *each*** $u' \in e$ **do**
10. $V \leftarrow V \cup u'.V$ located in R
11. $E \leftarrow E \cup e$
12. **if** enough candidate venues $|V| \geq N$ ***or*** $E == U$ **then**
13. **Return** local experts E and candidate locations V

Figure 1.6: Algorithm for Preference aware Candidate selection [4]

A preference-aware candidate selection algorithm properly chooses these local experts from different categories according to a user's different preference weights in her WCH. This algorithm also improves the efficiency of our approach significantly while maintaining the effectiveness, making our system really location-aware. Location rating calculation component computes the similarity between each selected local expert and the user using a similarity function based on their WCHs. The calculated similarity score is further fed into a CF-based model to infer the rating that the user would give to an unvisited candidate venue. Later, the venues with relative high predict ratings are returned as the location recommendations.

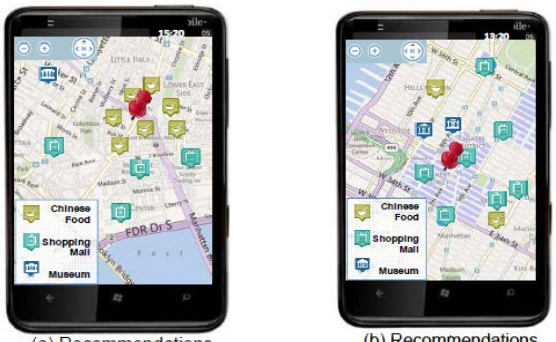
Figure 1.6 depicts the algorithm for preference aware candidate selection. Here *u.wch* denotes the user's weighted category hierarchy (WCH), k denotes number of user's, e denotes the top-k users based on *u'c.h* i.e. user's category hierarchy. C indicates the category information of user.

As above mentioned collaborative filtering methods used in Location based recommendation system for recommending locations depends on different parameters used in the system. In CF technique with WCH and candidate selection algorithm, if the larger range is specified by a user there is a chance that the more inexperienced users are present and also low quality locations our candidate selection algorithm removes this problem. In short, the candidate selection algorithm improves the

efficiency of our system significantly while maintaining the effectiveness.

The CF based technique with WCH and Candidate selection performs best among all the above mentioned methods. As even this method overcomes the problems of CF based technique i.e. data sparsity and cold start problem which are very critical problems when we are dealing with CF technique for recommendation system. The detailed analysis and comparison of above three mentioned methods of CF technique are described in the next section.

5.2 Application Scenario



(a) Recommendations near Chinatown (b) Recommendations near 7th Ave

Figure 1.7: Example of an Application Scenario in NYC [4]

Figure 1.7 demonstrates an application scenario of system presented by Yu Zheng [4], where the top N venues matching a user's preferences are recommended based on the geo-region of the current view. Here, the number of recommendations and the geo-region's scale are determined by a user based on the location history of the user and the opinions from the other people. Here the number of locations belonging to a category in the recommendations follows the distribution of the categories in the user's preferences.

For example, the user (whose location is represented by the push-pin in Figure 1.7) has "Chinese restaurants" as users most preferred location category and "Shopping malls" as the second. Then, as demonstrated in Figure 1.7a), "Chinese restaurants" have the biggest presence and shopping malls are the second in the recommendations, when user is near the Chinatown. However, when we change the map view to the 7th Ave, as shown in Figure 1.7b), the presence of malls could become the majority of the recommendations though Chinese restaurants is her first interest. The reason is that the malls have much higher quality than the Chinese restaurants, according to people's location histories in that particular area [4].

6 Comparison Of Collaborative Filtering Methods

6.1 Location Recommendation Using CF

Social network based-recommendation uses for improve recommendation systems because of its benefits. For example, as long as cold-start users are connected to the social network, it can deal with them. Main goal of some articles in recommendation system is omitting the cold start problem for new users. (Nabizadeh Rafsanjani, Salim, Mohammadhossein, & Bagheri Fard, 2013) purpose a new framework that omitted the cold start problem for new user that helps to increase the accuracy of results of recommendation system. Social network based recommendation systems are more robust to fraud, in particular to profile attacks (Jamali & Ester, 2011). Also (Sinha, 2001) compare quality of recommendation systems with friends' recommendation. Their results show that users prefer friends' recommendation against generated recommendation from system.

In our system we use collaborative filtering based location recommender system which creates personalized recommendations by combining the knowledge of similar users in the system. In collaborative Filtering (CF) technique, the recommendation process is automated by building on users' opinions of items in a community. Collaborative Filtering (CF) is based on the principle that the finest recommendations for an individual are given by people who have similar flavor. Collaborative filtering identifies users with choice similar to the target user and then computes predictions based on the score of the neighbors. Collaborative filtering considerably progresses recommendation system.

6.2 Comparison

The comparison of various Collaborative filtering algorithms on behalf of the different parameters is shown in Table 1.

Table 1
Comparison of three CF methods based on Location Based Recommendation System

Methods / Parameters	TBHG and HITS based model	Collaborative Filtering with CLAR	Collaborative Filtering with WCH and Candidate selection
Location history	Yes	Yes	Yes
Social opinion	No	Yes	Yes
Category of Location	No	Yes	Yes
User's preference	Yes	Yes	Yes
Preference hierarchy	Yes	No	Yes
Local experts	No	No	Yes
Candidate selection	No	Yes	Yes
Effectiveness	Less Effective Recommendation	Effective Recommendation	More Effective Recommendation
Computation	More	More	Less

Note :
HITS : Hypertext Induced Topic Search
TBHG : Tree based Hierarchical graph
WCH : Weighted Category Hierarchy

CLAR : Collaborative Location and Activity Recommendation

From above parametric comparison Collaborative Filtering technique with WCH and Candidate selection algorithm gives more effective and better recommendation results then the other two stated algorithms. Candidate selection algorithm considers the parameters like Local experts, category hierarchy, and preference hierarchy because of these parameters algorithm gives better recommendation results. Here Local expert is the one who visited the venues within a user's recommendation range R and have a high expertise in the categories preferred by the user.

Candidate selection algorithm computes a user's expertise in each category in different cities based on category information encapsulated in the user's location history. Local experts of a category can find high quality venues of the category as compared with the regular users, resulting in more valuable location histories for a reference. Using the local experts we are able to ignore some random users who have little data and knowledge in a category of locations, thereby reducing unnecessary computation during the online recommendation [4].

Paper 1 uses TBHG and HITS based model retrieve data from GPS trajectories and it also considers the user's history, its preferences and modulates these preferences into preference hierarchy and accordingly selects the locations and recommends the results. GPS data with TBHG and HITS model requires more computation than the CF with WCH and Candidate Selection algorithm. So system using TBHG an HITS model gives less effective recommendation results. Paper 2 uses the Collaborative filtering technique with CLAR that considers the parameters like user's history, social comments, and user preferences and also according to category locations are divided. That is one of the advantages when we are dealing with recommendation systems. Depending on all these parameters using CLAR algorithm it finds the candidate locations that are recommend to the user as the recommendation result. As in this algorithm CLAR algorithm combines location-activity matrix, location-feature matrix and activity-activity correlation matrix to produce the proper recommendation result. To combine all three matrices system has to gone through many computations to produce the proper recommendation to the user. Because of these it gives effective recommendation result than paper1 but it is less effective than paper 3 recommendation results.

From above parametric comparison collaborative filtering technique with WCH and candidate selection algorithm give better performance and also gives more effective recommendation results then the other two techniques. This algorithm also removes the data sparsity and cold start problem which is an advantage of this technique.

7 Conclusion

Many researches have been done on location based recommendation systems. Recommendation system with collaborative filtering technique also has many researches done and many systems are implemented. Collaborative filtering technique has many disadvantages and problems. To give the better recommendation results to the user many methods are used under collaborative filtering. Some of the methods are compared in the above section. Among the three techniques that is TBHG and HITS model, CF with CLAR and CF with WCH and candidate selection methods outperforms the weakness of collaborative filtering methods such as Data sparsity problem and cold start problem.

We analyzed that the from above mentioned algorithms of collaborative filtering technique CF with WCH and Candidate selection algorithm performs well and also gives better recommendation results than the other two techniques. The main parameters as social opinion, preference hierarchy, candidate selection, local expert are used for more effective recommendation. Because of all the above mentioned parameters system has less computation load than the other two methods.

So we are concluding here that the CF with WCH and Candidate Selection method overcomes the problems of CF technique and also gives the better recommendation results than the two techniques.

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