Effective Generation of Location-Sensitive Recommendations in Social Network Environments using Enhanced SSU Approach

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Abstract –Today, the Social network environment is trending with the recommendation generation among various applications like products recommendation, online sharing and shopping services. The users of the applications are allowed to rate the products with comments. To make the rating prediction and recommendation of items, social graph and bipartite graph are widely used. These recommendations are known as social recommendations. The recommendations are generated without the consideration of the spatial features. As the location-based social networks has an information that gradually affects rating and recommendation qualities and correlation of items, the proposed approach called enhanced Spatial Social Union (SSU) is used to predict the similarity measurement among group of users. This integrates the relation among users and also interaction among items locations. The SSU-aware location based recommendation algorithm is proposed with respect to time interval. To measure the performance, proposed work is compared with other algorithms in terms of precision and recall.

Keywords—*social network, spatial social union, recommendations, bipartite graph*

I. INTRODUCTION

Services computing refer to a flexible computing architecture that packages functionality as a suite of routines that can be used within multiple, separate systems from several business environments. All the Service computing requires loose coupling of services with operating systems, and other technologies that support online applications. Working operations are separated into distinct self-describing and autonomous units, or services, which developers make accessible through interfaces that are already defined over a network in order to allow users to combine and reuse them in the production of applications. These services communicate with each other by passing data in a well-defined, shared format, or by coordinating an activity among services. Services computing include the concepts of mashups, Service Oriented Architecture, Software as a Service, and Cloud Computing.This value of Services Computing covers the entire progress of services innovation research that includes business componentization, as well as services management. The target of Services Computing is to enable IT services and computing technology to perform business services more efficiently and effectively. The rise of Services Computing technology family intends to create, operate, monitor and generalize these processes in a well-defined architecture for higher flexibility facing future business dynamics. Therefore, it is time that we look Inside the services to establish the foundation of Services science, technologies. Furthermore, the introduction of Services Computing into a traditional industry may add new values and innovative functions and improve the internal and external integration of industry-specific applications. For example, the introduction of SOA may help integrating the diagnosis and prescription processes within a hospital and the medicine pick-up process within Pharmacies, which can greatly simplify the medical treatment process for patients.With the emergence of Service-Oriented Architecture (SOA) and Web services technology, more companies have been exposing their business applications through well-defined interfaces in a platform-independent manner to increase the interoperability with partners' applications to streamline the whole business collaboration chain. Wireless mobile ad hoc networks are self-configuring, dynamic networks in which nodes are free to move. This proposed work shows the history of the ad-hoc networks and its development and its applications based on its decentralized nature of networks and it shows how the routing algorithms are used for routing. First, three types of similarity matrices derived from user-item bipartite graph, user-user social graph, and user-location bipartite graph are provided and analyzed. Second, the similarity identification approach, spatial social union that combines the three similarity matrices together is proposed. Third, Friend TNS algorithm and featured the SSU-aware location-sensitive recommendation algorithm for items, location and items. Last, the proposed SSU-aware location-sensitive recommendation algorithm is evaluated using data set, which is a very popular product recommendation service. The proposed works predict the rating of products candidates and provide the top-15 recommended products for the newly added user. This proposed work proposes an approach called spatial social union (SSU) with time interval, to predict the similarity measurement among group of users and age of users are considered for recommendations. The SSU-aware location-sensitive recommendation algorithm is then devised with respect to time interval.

II. RELATED WORKS

Generating the location-sensitive recommendations by rating prediction of items in adhoc social network environments and propose spatial social union (SSU), an approach that combines multiple similarity matrices derived from user-item bipartite graph, user-user social graph, and user-location bipartite graph (UL-BG).The online Social Rating Networks (SRNs) such as Epinions and Flixter, allow users to form several implicit social networks, through their daily interactions like co-commenting on the same products, or similarly co-rating products. In location recommendation services in location-based social networks (LBSNs) makes recom-mendations without considering where the targeted user is currently located. The collaborative recommendation framework [2], called User Preference, Proximity and Social-Based Collaborative Filtering (UPS-CF), to make location recommendation for mobile users in LBSNs. The work propose the User Preference, Proximity and Social-Based Collaborative Filtering (UPS-CF) recommendation framework.The basic idea of UPS-CF follows the user-based CF algorithm to explore the implicit preferences of top similar users in making a location recommendation.The majority of work in Rating Prediction and Recommendation of products such as Collaborative Filtering [3] have been researched for over a decade as a tool to deal with information overload. When an active user would like a recommendation, the system finds users with similar taste and uses their opinions to generate a recommendation mainly takes into account ratings of users on products.a new Belief Distribution Algorithm[3] that overcomes these flaws and provides substantially richer user modeling . Probabilistic factor analysis framework [4], which naturally fuses the users' tastes and their trusted friends' favors together. In this framework, the term Social Trust Ensemble to represent the formulation of the social trust restrictions on the recommender systems.The complexity analysis indicates that our approach can be applied to very large datasets since it scales linearly with the number of observations.Social-Union[5], a method which combines similarity matrices derived from heterogeneous (unipartite and bipartite) explicit or implicit SRNs. The novel algorithmic approach to content recommendation based on adaptive clustering [6] of exploration-exploitation ("bandit") strategies. The work provide a sharp regret analysis of this algorithm in a standard stochastic noise setting, demonstrate its scalability properties, and prove its effectiveness on a number of artificial and real-world datasets where the main idea is to use confidence balls of the users' models to estimate both user similarity, and to share feedback across (deemed similar) users.User profiles

[7] that contain compact descriptions of users' interests and personal preferences provide a method for selecting from an increasing amount of multimedia content and for reducing information overload . A user profile can be (a) filterinput content, so that programs or items that the user has shown interest in are presented to the user, and/or (b) request from a content distribution service the programs of interest.The novel algorithms for (i) automatically determining a user's profile from his/her usage history (profiling agent), and (ii) automatically filtering content according to the user's profile (filtering agent) is proposed [6]. To enhance similarity matrices under sparse data ,the prediction algorithm [8] which computes the final transition probability matrix,used as an item similarity matrix in typical item-oriented approaches. The recent emergence of location-based social networking services is revolutionizing .The web-based social networking allowing users to share real-life experiences via geo-tagged user-generated multimedia content. Inorder to Investigate the possibilities of managing trust between the users of a based social network while recommending items to the members of the network, novel framework [9] is proposed to integrate trust among community members and public reputation of items to recommend the most appropriate items to a user of the network. networking services allow users to connect with friends, explore places (e.g., restaurants, stores, cinema theaters, etc),share their locations, and upload photos, video, and blogs. The research issues in realizing location recommendation services for large-scale location-based social networks, by exploiting the social and geographical characteristics of users and locations/places is dealt with friend-based collaborative Filtering (FCF) approach for location recommendation [10] based on collaborative ratings of places made by social friends. Moreover, a variant of FCF technique, namely Geo-Measured FCF (GM-FCF) [10] based on heuristics derived from observed geospatial characteristics in the Foursquare dataset. G.Adomavicius et al [11] discusses various limitations of current recommendation methods and possible extensions that can improve recommendation capabilities and make recommender systems applicable to an even broader range of applications. These extensions include, among others, an improvement of understanding of users and items, incorporation of the contextual information into the recommendation process, support for multcriteria ratings, and a provision of more flexible and less intrusive types of recommendations. In large online social rating networks (e.g., Epinions, Blippr) the identification and analyzation on array of features that exert effect on product affinity the method called AffRank[12], that utilizes these features to predict the future rank of products according to their affinities. Evaluated on two real-world datasets,demonstrate the effectiveness and superior prediction quality of AffRank compared with baseline methods. The Private Buddy Search (PBS) [13], a framework to enable private evaluation of spatial queries predominantly used in social networks, without compromising sensitive information about its users. Utilizing server side encrypted index structures and client side query processing, PBS enjoys both scalability and privacy. The traditional recommender systems assume that all the users are independent and identically distributed; this assumption ignores the connections among users.

III. PROBLEM DEFINITION

A. Location –Sensitive Recommendations

The problem of suggesting new location to users who participate in location-based social networks as an increasingly huge number of users partake in LBSNs, the recommendation problem in this setting has attracted significant attention in research and in practical applications. The literature about previous user behavior that is indentified by the LBSN distinguishes the problem significantly from its traditional setup. The spatial feature in the previous user behavior and also the information about the user social interaction with other users, provide a higher background to construct a more preemptive and expressive recommendation model. There have been extensive studies on recommender systems working with user-item ratings, GPS trajectories, and other types of data, there are very few approaches that exploit the unique characteristics of the LBSN user check-in data. In location-based social networks (LBSNs), users share information about their locations with other social information. Visits are reported explicitly (by user *check-ins* in known venues and locations) or implicitly by allowing smart phone applications to report visited locations to the LBSN. This information is then shared with other users who are socially related (e.g., friends). The same information can be exploited by the LBSN operator to propose new points of interest to users. Recommending new locations is an important issue; it allows efficiently advertising companies with a physical presence (theaters, bars, restaurants, etc.) and creating revenue for the LBSN. The most popular approach in recommender systems is that of collaborative filtering.

B. Spatial social union

Spatial social union (SSU), an approach that integrates various similarity matrices derived from user-item bipartite graph, user-user social graph, and user-location bipartite graph (UL-BG). SSU differs from the Social union because it takes into account not only the interaction between user and item as well as the social relationships between users, but also the relationships between users with location. Both item and location an SSRN is associated with a community. The proposal is binding the user-location network with user-item network in order to recommend and predict the rating for living-items efficiently The improvisation is based on social on among the user-item network and user-user relationship

network. The main difference between social suggestion and location-sensitive suggestion in ad-hoc social networks is that the user-location network and age similarity among the users are considered. To overcome the demerits of items recommendation and rating prediction in social networks, the proposed work integrate the location features into generalized social networks for the spatial social union.

C. Collaborative Recommendations

Content based system and collaborative filtering are the two types of collaborative recommendation. The content-based system usually selects items based on the correlation between the content of the items and the users' preferences.

Collaborative filtering systems are divided into two categories: memory-based and model-based. The similarity between all users is calculated in memory based which is fully based on their ratings of items using cosine similarity and the Pearson correlation score. K nearest neighbors of the user who needs the recommendations is mainly used for missing rating. The model-based filtering systems assume that the users build up clusters based on their similar behavior of rating the items. But collaborative filtering methods have not been used to support database queries for spatial objects matrix factorization which has become the dominant technique for recommendation system. It has ability to handle latent factors and also to accommodate additional information like biases, temporal dynamics and confidence level. LibFM is an algorithm proposed for matrix factorization model.

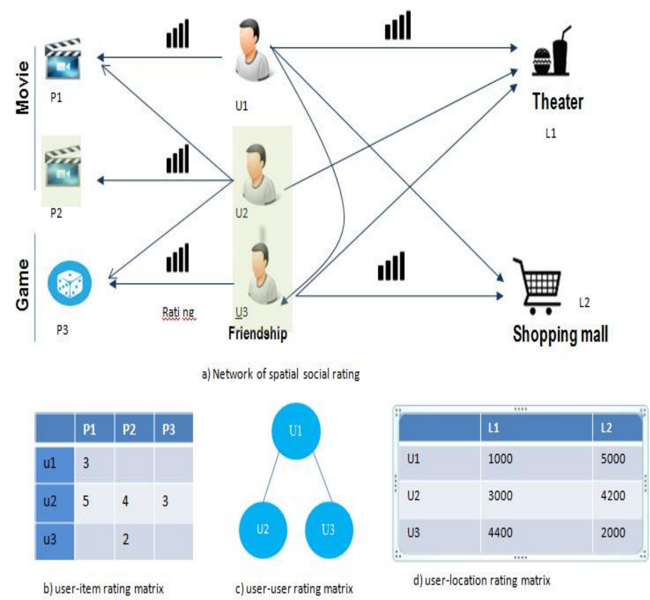

Fig.1 Network of Spatial social union

IV. SOLUTION FRAMEWORK

A. Location-Based Ad-Hoc Social Networks Recommendations

A location-based ad-hoc social network mean adding a location to the people in the social structure can share location embedded information by their mobile devices, consists of the new social structure made up of individuals connected by the interdependency derived from their locations and the location-tagged media contents. The emergence of location-based social networking services offered by providers such as Facebook, Foursquare, Gowalla are allowing users to share real-life experiences, to see where their friends are, to search location-tagged content within their social graph, and to meet others nearby. Most of the existing location-based social networking systems focus on specific services: sharing geo-tagged message and supporting privacy-preserving buddy search considered the spatial features of the recommended items and proposed SSU, a location-aware recommender system that uses location-based ratings to produce recommendations. In the proposed work the items recommendation in a limited geographical area is within a given time interval.

B. Enhanced SSU Framework

To overcome the demerits of items recommendation and rating prediction in social networks, the proposed work integrates the spatial property into generalized social networks and proposes the spatial social union. The detailed working process of the SSU solution framework includes the following steps:

1. Input data tensorization
2. Projection of input data
3. Similarity measurement
4. Similarity aggregation
5. Rating prediction and recommendation.

1. The SSRN as an input can be tensorized as a kind of tensor with three dimensions.

2. Projection of input data:

Then, we make two projections on tensorized SSRN and derive the user-item bipartite graph and user-location bipartite graph, respectively. Besides, the user-user social graph (G) from the social networks is derived.

3.Similarity measurement:

Based on these derived graphs, similarity matrices between users can be constructed as simR, simA and simD.

4.Similarity aggregation:

The similarity calculation approach, spatial social union that combines the three similarity matrices together is proposed. Further, it proposes an aggregation union, namely SSU which combines the various similarity matrices simR, simA and simD together and returns the similarity matrix between any two users.

5. Rating prediction and recommendation:

At last, it adopts the finalized similarity matrix to predict the missing ratings and provide the recommendations.

V. GENERATION OF RECOMMENDATIONS

A. M-Fast Floyd Algorithm

Modified-Fast Floyd (M-Fast Floyd) algorithm presents an efficient way to process the matrix of high dimensional and also the vector elegantly. This involves in generating the matrix of higher dimensional from the graph. It compares all possible paths through the graph and help in measuring similarity.

Algorithm 1 Modified-Fast-Floyd Algorithm

Input:
matrix M
Output:
matrix D
1: n row number of M
2: **for** k =1 to n
3: i2k →**replicate** the matrix
4: k2j→ **replicate** the matrix n times
5: D = max(M, i2k multiply element-wise k2j)
6: **end for**
7: **return** D

B. Enhanced Friend TNS Algorithm

In ad-hoc social networks, the users can share their opinions or attitudes for the items. The user oriented algorithm design is critical to devise the appropriate recommendation that matches the users' requirement. Each individual has his or her own ratings and recommendations, the algorithm should take account of those implicit valuable information. Hence the proposed work applies the Modified-Friend TNS (M-Friend TNS) algorithm. This algorithm is to find the users who are directly connected or have the relationship of first connection in the ad-hoc social network. Then based on the assumption, symmetric and undirected graph are to store the corresponding row and column index for the users who have direct first connection. This also calculates the maximum value from the user-user similarity matrix. The matrix simA is flipped up from the lower triangular matrix to the principal diagonal.

C. **Enhanced SSU Approach to Provide Location Sensitive Recommendations**

The locations information such as area name, distance are considered for suggestions of items to the users. The input of the algorithm includes the user-item rating matrix R, user-user relationship matrix A, user-location metric matrix D, and the number of users N which involves the newly added user, property between item and location. C_{il}, is considered as a given targeted location which features item and location, and type of recommendation Z. The output is the rating prediction and recommendations for the new user as well as a group of users adopt the classical cosine similarity calculation and our proposed M-Friend TNS algorithm. The algorithm is used for following purposes:

1. It has the procedure of adapting where the parameters can be tuned manually or automatically.
2. It applies our SSU model to solve the predicted rating scores.
3. It make the prediction based on the hypothesis that the new user who really wants some recommendations.
4. It recommends the items for group of users by taking the property C_{il} into account.

VI. EXPERIMENTS AND PERFORMANCE ANALYSIS

The evaluation of the proposed work SSU-aware location sensitive recommendation algorithm. study how to collect the data set and configuration the experiment setup. Hence, the analysis and discussion of the experimental results are presented.

A. Data Set Collection

Shopping items are typical in our daily life, the data set consists of:(1) various products (2) each user has rated at least 20 different products and some profile information for the users, e.g. age, gender, occupation, zip etc. The users and products are numbered consecutively from 1, and the original data is ordered randomly as the format of user_id|item_id|rating_score. The product information includes the original format of Product_name|product_id|date|type. However, the above data set does not provide the user social relationship graph. As mentioned before, w take into account the properties between item and location, i.e, C_{il} inorder to evaluate the performance of the proposed location-sensitive recommendation for a group of users in social network environments. Distance between product and user location C_{il} is done according to the traffic situation, with integer level C_{il} ={1; 2; 3; 4; 5}

B. Prediction Analysis

The first module is to tensorize the input and second module is to calculate user similarity and user-item similarities. Using the user-item matrix we calculate the ULI-BG similarity matrix and get the top K average ratings to the new user. The ratings based on user hits and general hits the links are experimentally analysed and the resulted graph is shown in Fig.2

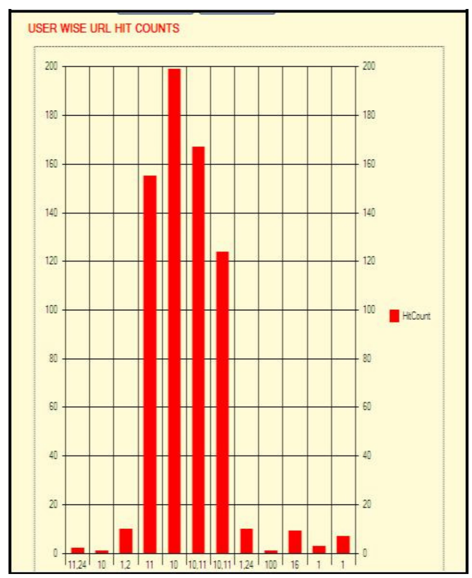

Fig.2 User wise Hit Count

After those similarity matrix generations the following works are to be proceeded to generate location sensitive recommendation.

1) Based on the proposed M-Fast-Floyd algorithm and MFriendTNS algorithm, calculate the M-FriendTNS similarity matrix and corresponding prediction ratings.

2) Using the location information especially the distance within a city or a specific zone, e.g., a common city's radius is around 50,000 m, t-BG i.e., user location matrix is to be generated

3) And then should calculate the similarity matrix and corresponding prediction ratings.

VII. CONCLUSION

The recommendations are suggested using the spatial social union approach. Time based selective records are taken from the database and much importance is given to old products in the market. Hence the time-interval based recommendations are studied. Updating of the products launched in some locations and their recommendations by the web site are included. Age group-wise similarity is also taken into consideration for generating recommendations. This enhancement in SSU approach can result with the effective generation of the recommendations in social networks.

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