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Location Sensitive Recommendations in Ad-hoc Social Network Environments Generated using Learning-to-Rank Algorithm

Mohit Satarkar[1], Keith Ger[2], Suraj Gawas[3], Yash Mehta[4], Prof. Parth Sagar[5]

Student, Computer Department, RMDSSOE, Pune, India [1,2,3,4]

Professor, Computer Department, RMDSSOE, Pune, India [5]

Abstract: Social recommendation has been popular and successful in various urban sustainable applications such as online sharing, products recommendation and shopping services. These applications allow users to form several implicit social networks through their daily social interactions. The users in such social networks can rate some interesting items and give comments. The majority of the existing studies have investigated the rating prediction and recommendation of items based on user-item bipartite graph and user-user social graph, so called social recommendation. However, the spatial factor was not considered in their recommendation mechanisms. With the rapid development of the service of location-based social networks, the spatial information gradually affects the quality and correlation of rating and recommendation of items. The selection of the best service from the ones available is a conundrum to predict as different users will follow different selection techniques. Selection of the web service is directly related to the quality of service (QoS) provided. This paper proposes a learning-to-rank algorithm to comprehend the decision strategy of users in choosing the specific web service. This paper proposes spatial social union (SSU), an approach of similarity measurement between two users that integrates the interconnection among users, items and locations. The SSU-aware location sensitive recommendation algorithm is then devised. We evaluate and compare the proposed approach with the existing rating prediction and item recommendation algorithms subject to a real-life data set. Experimental results show that the proposed SSU-aware recommendation algorithm is more effective in recommending items with the better consideration of user's preference and location.

Keywords: Spatial Social Union (SSU), Quality of Service (QoS), Learning-To-Rank, Decision Strategy.

I. INTRODUCTION

Use of technology to carry out different daily tasks of people, some mundane while some crucial, has made the workload of the people a bit lighter. Rise of the internet has also given a rise to number of web services providing the different services we require. Users mostly choose a web service according to the different criteria of the details of the service provided. A user almost always has similar requirements when choosing a service. Understanding these recurring requirements of the user will make the job of choosing a service extremely efficient and simple.

Each service has specific QoS criteria according to which they are rated. Using a learning to rank algorithm, we can find out the order in which different QoS qualities are preferred. Instead of letting a user check all the different services and find out the service which matches the criteria, it is better to provide suggestions according to it beforehand. A number of models like the Multi-Criteria Decision Making (MCDM), Constraint Programming (CP) and Mixed Integer Programming (MIP), Skyline have been used in this context. One recommended way is to find the cumulative weight of the different criteria of the service, while others include comparison of specific QoS. But each one has its own advantages and disadvantages.

This paper proposes the preparation of a personalized ranking model according to the data saved from the previous searches and type of searches of the users and optimizing it accordingly. Users may follow different selection strategies at different searches, so optimization also includes the best service selection in the specific scenario. Study of service selection pattern and implementing it thereby would seem to be the best method in achieving this. It focuses on implementing location based recommendations by predicting rating of products on an ad-hoc social network, with the help of a proposed spatial social union (SSU) approach, which makes use of combination of similar matrices derived from user-user social graph, user-item bipartite graph and user-location graph. The most important part of SSU which differentiates this approach from social recommendation is that, it not only takes into consideration the relation between the user and items but user-user-social relationships, user-item relationships as well as user-location relationships. There are three major contributions of the paper:

A) Considering that user's decision strategy plays an important role in the service selection process and

ignoring it will affect the selection accuracy, we propose a QoS-based service selection approach in which both QoS criteria and decision strategies are taken into account.
B) Since users may follow multiple decision strategies depending on the context and in an implicit way, we propose to apply the machine learning technique to find the best matching strategies and the best ranking model combining them;
C) The proposed approach is flexible and extensible so that we can plug-in different QoS based selection models, decision strategies, as well as machine learning algorithms.

II. EXISTING METHODOLOGIES

Earlier, there has been number of related work, like online social networks (SRNs), which allowed the users to not only create implicit but explicit networks on which they interacted by commenting on same products or correlating products. Suggestions for better sorting of services led to development of current existing technologies which are discussed ahead. Earlier, the service would have been chosen from a few recommendations from the description of the service itself, which might be looking at it objectively. Therefore the need of learning-to-rank algorithms was felt when multiple services were available for use. Learning-to rank algorithms were starting to develop from as early as 1989. OPRF was developed by Norbert Fuhr in a similar vein as to learning-to-rank algorithms. The difference was that it was mostly a pattern recognition algorithm, with an approach to find out the optimum retrieval functions. This was a very primitive idea for a different type of problem, but the approach used is what the learning-to-rank algorithm will use. Thus we can trace the roots of this to the work of Herr Fuhr's point-wise algorithm.

A) RANKING SVM
The 'Ranking SVM'[3][4] is the first time a similar idea was developed. The SVM (Support Vector Mechanism) at first was better Google in its searching approach. It relied on a click-through mechanism i.e. kept a log of the clicks a user makes on his/her system and uses it to influence suggestions according to the specific pattern of the relevant user.

The Ranking SVM algorithm is a learning retrieval function that employs pair-wise ranking methods to adaptively sort results based on how 'relevant' they are for a specific query. The Ranking SVM function uses a mapping function to describe the match between a search query and the features of each of the possible results.
This mapping function projects each data pair (such as a search query and clicked web-page, for example) onto a feature space. These features are combined with the corresponding click-through data (which can act as a proxy for how relevant a page is for a specific query) and can then be used as the training data for the Ranking SVM algorithm.

Generally, Ranking SVM includes three steps in the training period:

1. It maps the similarities between queries and the clicked pages onto a certain feature space.
2. It calculates the distances between any two of the vectors obtained in step 1.
3. It forms an optimization problem which is similar to a standard SVM classification and solves this problem with the regular SVM solver.

B) RANKNET
While the algorithm 'RankNet[5]' was developed in 2005 as a pair-wise alternative. Investigating using gradient descent methods for learning ranking functions, it proposed a simple probabilistic cost function, and introduced RankNet, an implementation of these ideas using a An Ideal Approach For Detection and Prevention of Phishing Attacks neural network to model the underlying ranking function. However evaluation speed and simplicity was a critical constraint for such systems, so its principles were used to develop better solutions. A lot of the learning-to-rank algorithm framework is used to carry out the objectives in different fields like information retrieval, including document retrieval, sentiment analysis and online advertising. Training the data here is an important step, as this data is what you base your algorithm on. While different algorithms provide with new outlooks into this method, recent algorithms are results of assimilation of the positive qualities of each algorithm. But to know how the contemporary algorithms execute, it is vital to learn the earlier work developed resulting into this.

C) RANKBOOST
The RankBoost[8] algorithm was developed in 2003, which was the pioneer of pairwise algorithms. Yoav Freund, Raj Iyer, Robert. E. Schapire and Yoram Singer operated in rounds like almost all boosting algorithms. Providing higher weight to pair of iterations suggests higher importance to the weak learner.

Algorithm **RankBoost**
Given: initial distribution D over $X \times X$.
Initialize: $D_1 = D$.
For: $t = 1,\ldots..,T$
- Train weak learner using distribution D_1
- Get weak ranking h_1: $X \rightarrow R$
- Choose $\alpha \in R$
- Update: $D_{i+1(X_0,X_1)} = \frac{D_{t(X_0,X_1)} \exp(\alpha_t(h_t(X_0) - h_1(X_1)))}{Z_t}$

whereZ_1 is a normalisation factor chosen so that(D_{1+1} will be a distribution)
Output the final ranking: $H(x) = \sum_{t=1}^{T} \alpha_t \; h_t(x)$

D) CLOUDRANK
A contemporary algorithm for ranking used is the CloudRank[6] algorithm used for ranking of the Cloud computing services. Z.Zheng, Y.Zhang, M.R.Iyu

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developed this algorithm keeping in mind that badly functioning parts of the system included large amount of distributed components, As Cloud Computing is an important area of research and development today, this algorithm will provide the base for the services to be used in future applications surely.

E) ADARANK
The algorithm related the most to our work, i.e. AdaRank,[7] was performing a lot better than the previous algorithms such as the SVM. This is because AdaRank was a list-wise algorithm which considered interdependence between documents which algorithms which were pointwise and pairwise did not consider. The effectiveness it showed was tremendously helpful in advancement of this topic.

F) SINDBAD
Sindbad[9] have inherent spatial features and allows its users to receive notifications from the friends in their social and spatial graph. Sindbad supports three new services beyond traditional social networking services, namely, location-aware news feed, location aware recommender, and location-aware ranking. These new services not only consider social relevance for its users, but they also consider spatial relevance. Since location-aware social networking systems have to deal with large number of users, large number of messages, and user mobility, efficiency and scalability are important issues.

G) LOCATION BASED SOCIAL NETWORKS
A methodology is developed naming LBSN's[10] , which keeps a track of the user's past spatial behaviour and also its social interactions with other users, which helps in providing a resourceful background which helps in creating a more compatible and accurate recommendation model. This model makes use of four factors:
1. Past social behaviour.
2. Location
3. Social relationships amongst users.
4. Similarity in the users' behaviour.

H) SRN
The SRN[11] model proposed by P. Symeonidis, E.Tiakas, and Y. Manolopoulos, considered the user's rating on a particular product, but did not took into consideration the other spatial features such as location-based ad-hoc network. Like the above mentioned examples they all considered few spatial features for describing a relationship, either it be a user-user social relationship or user-item bipartite relationship. But, they didn't take user location relationship into an account; the relationship between these three aspects can be very helpful in giving resourceful information to an user about a product which they are seeking for.

I) FRIEND OF A FRIEND
Friend of a friend (FOAF)[12], is a trust based approach, in which a user can recommend how much he/she trusts an unknown user based on trust value path; Affiliation recommendation where the task is to predict or recommend new friendships or affiliations amongst users or a group based on the state of their friendship. Moreover this approach proposed by V.Vasuki, Z.lu focused only on path counts and not on the information which can be used for link formation.

J) LOCATION - AWARE RECOMMENDATION SYSTEM
LARS: Location Aware Recommendation System[13], which makes use of location-based ratings by users in that particular location for recommendations. This approach makes use of three novel classes: spatial ratings for non-spatial items, non spatial ratings for non-spatial items and spatial ratings for spatial items. LARS coups the user rating locations through user partitioning, which is a technique used to influence recommendations with ratings in a location spatially close to the user , in way that maximizes the system scalability.

K) GEO – TOPIC MODEL
Geo-Topic model[14], was proposed by Kurushima et al, which combinely estimate both user's activity area and interests by keeping a log of user's house, office and other personal places and compares it with other users in the same area to predict and suggest new places to be visited

III. PROJECT SPECIFICATION

This paper focuses on generating rating prediction in an ad-hoc social network. Spatial Social Union (SSU) is an approach which is a combination of three types of identical matrices namely: user-user social graph, user-item bipartite graph and user- location bipartite graph. A SSU approach helps giving detailed information to predict ratings and give a recommendation of a product to user according to the location of the user.

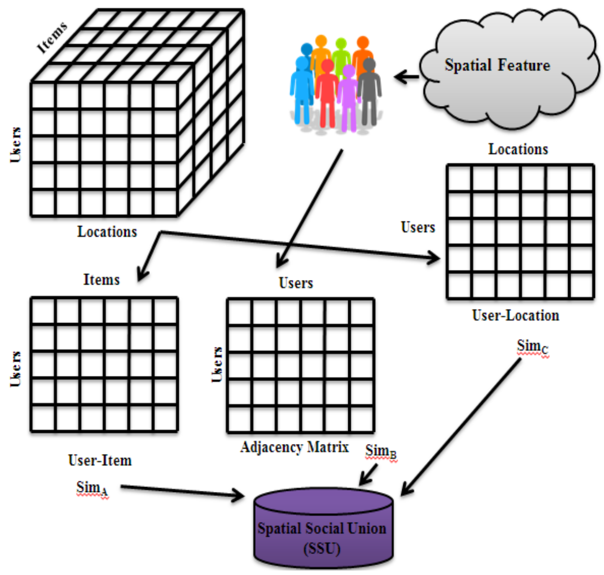

Fig. 1Framework for Social Spatial Union

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As specified above, we would now elaborate the different modules of SSU individually;

1. User - User Relationship:

$$\mathbf{Sim(u,v)}=\begin{cases} \mathbf{0,\ if\ (u,v) \notin E} \\ \mathbf{1,\ if\ u = v} \\ \mathbf{\max \prod_{i=0}^{k} \frac{1}{d(u_i)+d(u_{i-1})-1},\ otherwise} \end{cases}$$

2. User – Item Relationship:

$$\mathbf{Sim(u,v)}=\frac{\sum_{\forall i\in I}(r_{u,i}*r_{v,i})}{\sqrt{\sum_{\forall i\in I}(r_{u,i})^2}\sqrt{\sum_{\forall i\in I}(r_{v,i})^2}} \mathbf{where\ r_{x,i}= R(x,i)}$$

$$\mathbf{p_{u,i}}=\frac{\sum_{v\in U}(sim(u,v)*r_{v,i})}{\sqrt{\sum_{v\in U}(sim(u,v))}}$$

3. User – Location Relationship:

$$\mathbf{Sim(u,v)}=\frac{\sum_{\forall l\in L}(d_{u,l}*d_{v,l})}{\sqrt{\sum_{\forall l\in L}(d_{u,l})^2}\sqrt{\sum_{\forall l\in L}(d_{v,l})^2}} \mathbf{where\ d_{x,l} = D(x,l)}$$

$$\mathbf{p_{u,i}}=\frac{\sum_{v\in U}(sim(u,v)*r_{v,i})}{\sqrt{\sum_{v\in U}(sim(u,v))}}$$

Using SSU approach not only gives a precise rating and recommendation but also maximizes the system's stability while not degrading the quality of service. Furthermore, SSU aware location-sensitive recommendation and ration prediction algorithm can be devised. In which, the proposed approach is evaluated and compared to the already existing product rating prediction and product recommendation services in real life.

Learning-to-rank algorithm approaches can be divided into three types:
1. List-wise
2. Point-wise
3. Pair-wise

Point-wise and pairwise approaches do not consider the interdependence between documents, while list-wise does. Hence list-wise algorithm AdaRank is proposed for use here.

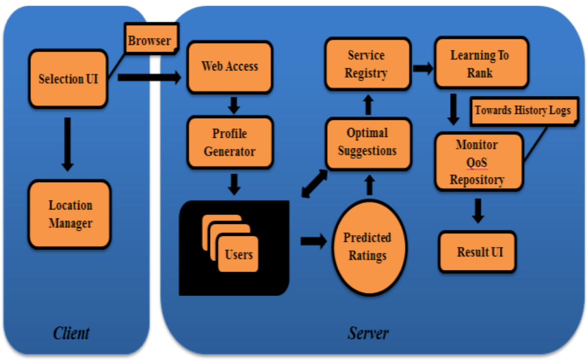

Fig. 2 System Architecture

IV. CONCLUSION AND FUTURE WORK

With the growing use of social networking in today's era, the social recommendation in an ad-hoc social network is also on a vast widespread. The SSU approach when experimented provided with the results that were convincing in predicting the rating of a product and recommending a product to the user in a location-sensitive ad-hoc social network. There are many other devised approaches as well for providing similar results to a user, but very few on the basis of location-sensitive approach. By proper planning and development of this approach along with Learning to Rank Algorithm, it could boost the use of social networking in almost all the domains in the real-life. This paper presents spatial social union, an approach that combines three types of similarity matrices derived from user-item bipartite graph, user-user social graph as well as user-location bipartite graph combined with learning to rank algorithm which refines the recommendation provided on the basis of user's past and present preferences. Further, the SSU aware location-sensitive recommendation algorithm is devised. The paper evaluates and compare the proposed approach to the existing rating prediction and item recommendation algorithms with a real-life data set. Experimental results show that our SSU algorithm is more effective in predicting rating of items and recommending items in location-based ad-hoc social networks. As the dramatic growth of online social network sites continues, the social recommendation in location-based ad-hoc social networks is widely used everywhere. From a social sustainable perspective, we plan to develop similar techniques in other urban sustainable applications, e.g. A restaurant finder application, online shopping application or an online music or video streaming application.

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