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Generative location sensitive recommendations

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ABSTRACT - Social recommendation is popular and successful among various urban sustainable applications like products recommendation, online sharing and shopping services. Users make use of these applications 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 investigate 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. This project 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. This project evaluates and compares the proposed approach with the existing rating prediction and item recommendation algorithms. The 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. The project has been developed using ASP.NET as front end and SQL Server 2000 as back end. C# is used the coding language.

1. INTRODUCTION

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. The majority of earlier work in Rating Prediction and Recommendation of products (e.g. Collaborative Filtering) mainly takes into account ratings of users on products. However, in SRNs users can also built their explicit social network by adding each other as friends. In this paper, they are propose Social-Union, a method which combines similarity matrices derived from heterogeneous (unipartite and bipartite) explicit or implicit SRNs. Moreover, we propose an effective weighting strategy of SRNs influence based on their structured density. We also generalize our model for combining multiple social networks. The perform an extensive experimental comparison of the proposed method against existing rating prediction and product recommendation algorithms, using synthetic and two real data sets.

Social networking sites, like Epinions and Flixter, have attracted huge attention after the widespread adoption of Web 2.0 technology. In such systems, people often belong to multiple explicit or implicit social networks because of different interpersonal interactions. For example, in Epinions and Flixter, people add each other as friends constructing a large uni partite friendship network. However, besides the explicit friendship relations between the users, there are also other implicit relations. For example, users can co-comment on products and they can co-rate products. A similar situation stands for authors who co-authored a research paper, but also have co-cited the same papers or attended the same conferences. Social-Union takes into account the local and global characteristics of the graphs such as graph density, user's profile density, nodes structure etc. Moreover, we present a well-defined framework for combining heterogeneous social networks, i.e. unit partite and bipartite networks. It is obvious that not all social networks contribute equally or contain valuable information. In addition, even though a social network is informative, particular features may be irrelevant and noisy for a specific user. For these reasons, we propose an effective automatic weighting strategy of the social networks influence based on their structured density. In particular, we take into account the local (i.e. user's profile density) and global (i.e. network's density) characteristics of multimodal social graphs. Based on these characteristics, for each target user we analogously calibrate the influence of each social network. For example, a user could have very few friends in the friendship network, but many interactions in co-commenting or co-rating products (i.e. user-items rating network). In such a case, the weighting strategy of our model promotes the information given by the user-item rating network. Finally, generalize proposed model for combining multiple social networks. In particular, our model can incorporate many unit partite (e.g. user-user) or bipartite(e.g.user-item) social networks.

In this proposed system introduced a generalized framework that exploits multi-modal social networks to provide item recommendations in SRNs. The performences extensive experimental result is comparison of our method Social-Union, against the real data for existing well-known item recommendation algorithms, using a synthetic and two real data sets (pinions and Flixter).In the future, except item recommendations, we indent to apply our framework also for friend recommendations (i.e. Link Prediction), where the majority of earlier work infers new future interactions between users by mainly focusing on structural properties of a single type of network. Finally, except uni-partite and bipartite graphs and will extend this framework by incorporating also other higher-order implicit social networks such as tri-partite graphs (e.g. social tagging systems with users, items and tags).

2. RELATED WORK

2.1 Collaborative Recommendation

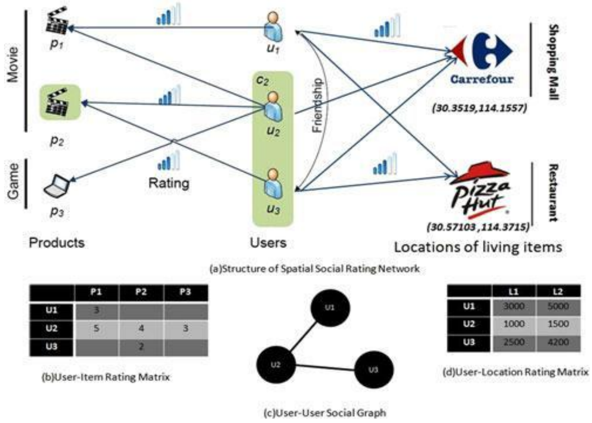
Generally, the collaborative recommendation systems are classified into two types: a content-based system and col-laborative filtering. A content-based system usually selects items based on the correlation between the content of the items and the users' preferences .Collaborative filtering systems are divided into two categories: mem-ory-based and model-based. In the memory- based sys-tems, the similarity between all users is calculated based on their ratings of items using some heuristic measures such as the cosine similarity and the Pearson correlation score. Then, a missing rating is predicted by aggregating the ratings of the k nearest neighbors of the user who need the recommendations. The model-based filtering sys-tems assume that the users build up clusters based on their similar behavior in rating of items. Normally, a model needs to be learned based on the patterns recog-nized in the rating behaviors of users using clustering, Bayesian networks and other data mining techniques. The shortcoming of the model-based filtering system is that the poor knowledge of social networks and high training cost. Also, none of these collaborative filtering methods have been used to support database queries for spatial objects. Symeonidis et al. proposed a general-ized framework that exploits multi-modal social networks to provide item recommendations in social rating net-works. They proposed Social union, a method that com-bines similarity matrices derived from heterogeneous explicit or implicit social rating networks. The Social union has no any spatial properties which cannot cope with the recommendation in location-based social net-works. Recently, a number of hybrid methods have been investigated. Yang et al. presented a novel approach to improving recommendation accuracy by introducing the concept of inferred category-specifical circles of friends. The idea is to determine the best subset of a user’s friends, i.e., an category-specifical inferred circle, for mak-

The remainder of this paper is structured as follows. Section 2 presents the related work on collaborative rec-ommendation and location-based ad-hoc social networks. The problem statement and solution framework are given in Section 3. Section 4 presents the approach of similarity measurements and rating prediction based on user-item bipartite graph, user-user social graph and user-location bipartite graph, respectively. Then, the spatial social union is proposed based on the combination of similarity matri-ces induced from user-item bipartite graph, user-user

Proposed a novel probabilistic factor analysis frame-work, which naturally fuses the users tastes and their trusted friends’ favors together in recommender system. However, the possible diffusions of trusts between vari-ous users are not considered. Matrix Factorization has become the dominant technique for recommendation sys-tem for its ability to handle latent factors and also to accommodate additional information like biases, temporal dynamics and confidence level. In par-ticular, Rendle took the poor choice of good values for the regularization parameters into account and pro-posed a learning algorithm LibFM for matrix factorization model parameters. Their learning regularization parame-ters are as easy as learning model parameters and thus

2.2 Recommendation in Location-Based Ad-hoc Social Networks

A location-based ad-hoc social network does not only mean adding a location to a general social network so that people in the social structure can share location-embed-ded information by their mobile devices, but also consists of the new social structure made up of individuals con-nected by the interdependency derived from their loca-tions in the physical world as well as their location-tagged media content, such as photos, video, and texts. The emergence of location-based social networking serv-ices offered by providers such as Rummble, GyPSii, and Whrrl is revolutionizing social networking, 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. Ludford et al. studied how people shared the location knowledge through different location types using two small scale controlled experiments. Ye et al. investigated the location recommendation services for large-scale location-based social networks, by exploiting the social and geographical characteristics of users and locations/places. However, they only solved the location recommendation issue based on collaborative ratings of places made by social friends, but not items recommenda-tion. In many situations social relationships are ad-hoc (i.e., set up by (mobile) users located in a limited geo-graphical area during a certain period in time). For example, an appearance of a mobile user in a specified location during a specified period in time is often associ-ated with a certain social event. However, with the dynamical structure and increased complexity of location-based ad-hoc social network data, a more generic model containing multiple node types (multi-modal), multiple edge types (multi-relational) and multiple descriptive fea-tures (multi-featured) associated with each should be pro-posed. Scellato et al. described and evaluated a link prediction model based on place properties of a loca-tion-based social networks via studying a large real-world service, Gowalla. Wang et al. proposed Tracommen-der, a context-aware recommender system, which uses background tracking information from smart phones to generate location-based recommendations. Kurashima et al. proposed a new topic model, called Geo Topic Model, that can jointly estimate both the user's interests and activity area hosting the user's home, office and other personal places that analyzes the location log data of mul-tiple users to recommend locations to be visited. Sarwat et al. considered the spatial features of the recom-mended items and proposed LARS*, a location-aware rec-ommender system that uses location-based ratings to produce recommendations. In this paper, we mainly study the items recommendation in a limited geographical area within a given period, namely location-sensitive recom-mendation in ad-hoc social networks.



3. EXISTING SYSTEM

- In existing system, the study presents **(Projection of input data).** It derives the user-item bipartite graph and user-location bipartite graph, respectively. Besides, the user-user social graph (G) from the social networks is derived.
- **(Similarity measurement).** Based on these derived graphs, similarity matrices between users can be constructed as simR (Rating), simA (User) and simD (Location).
- **(Similarity aggregation).** 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.

- **(Rating prediction and recommendation).** At last, It adopts the finalized similarity matrix to predict the missing ratings and provide the recommendations in terms of similarity.

DRAWBACKS

- All the records from the database are taken for matrix calculation and so importance is given to old products in the market also.
- Time interval based recommendations are not studied.
- New products launched in some locations and their recommendations by the web site itself are not included.

4. PROPOSED SYSTEM

In addition with all the existing system mechanism, the proposed study also presents age group based similarity measurement. Here Similarity measurement based on users' ages is also taken into study as simA (Age) along with simR (Rating), simA (User) and simD (Location). And so, Rating prediction and recommendation adopts the finalized similarity matrix with including simA to predict the missing ratings and provide the recommendations. In addition, time intervals are taken for matrix calculation.

ADVANTAGES

The proposed system has following advantages.

- Only time based selective records are taken from the database and so importance is not given to old products in the market.
- Time interval based recommendations are studied.
- New products launched in some locations and their recommendations by the application itself are included.
- Age group wise similarity is also taken into consideration.

SSU-AWARE LOCATION-SENSITIVE RECOMMENDATION ALGORITHM (NO TIME INTERVAL)

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 Cil, a given targeted location l, and type of recommendation Z. The output is the rating prediction and recommendation for the new user as well as a group of users. Lines 4 to 6 adopt the classical cosine similarity calculation and the proposed M-FriendTNS algorithm (b). Line 7 is the procedure of adapting where the parameters can be tuned manually or automatically. Line 9 applies the SSU model to solve the predicted rating scores. Lines 10 to 15 make the prediction based on the hypothesis that the new user who really wants some recommendations, e.g. he or she does not know the related quality of all the items. Lines 17 to 19 are to recommend the items property Cil into account.

a) SSU-AWARE LOCATION-SENSITIVE RECOMMENDATIONALGORITHM

Input:
user-item rating matrix R
user-user relationship matrix A
user-location metric matrix D
the number of users N
a group of users $\widetilde{U} = \{u'_1, u'_2, \ldots, u'_n\}$
property between item i and location l C_{il}
a given targeted location l'
type of recommendation ID Z
Output:
rating prediction vector P for new user and a group of users
switch(Z)
begin
case 1: /*recommendation for a single user*/
$sim_R \leftarrow$ apply cosine similarity in R
$sim_A \leftarrow$ apply M-FriendTNS in A
$sim_D \leftarrow$ apply cosine similarity in D
$sim_{SSU} = \alpha * sim_A + \beta * sim_R + \gamma * sim_D$
$sim \leftarrow$ extract column 2 to the end of sim_{SSU}
$P \leftarrow R * transposeofsim/(\sum sim)$
if $user$ has given some ratings **then**
  calculate the prediction except the given ratings
else then
  calculate the prediction for the brand new $user$
end if
make the recommendation for the new $user$
break
case 2: /*recommendation for a group of users*/
output = $\widetilde{I}(u'_1, l') \cap \widetilde{I}(u'_2, l') \cap \cdots \cap \widetilde{I}(u'_N, l')$
$\widetilde{I}(u'_i, l') = argmax^n_{i \in I} P(i|u'_i, l')C_{il}$
end

b) M-FRIENDTNS: MODIFIED-FRIENDTNS ALGORITHM

Input:
user-user relationship matrix A
the number of users N
Output:
sim_A
A = loadFile(path)
$sim_A \leftarrow N \times N$ zeros matrix
user degree: d $\leftarrow$ summation of matrix A's column
for $i = 1$ to N
  for $j = 1$ to N
    if $A[i,j] == 1$
      $sim_A[i, j] = 1/(d[i] + d[j] - 1)$
    end if
  end for
end for
$idx \leftarrow$ zeros matrix with the size of $[N*N, 2]$
$cnt \leftarrow 0$
for $i = 1$ to N
  for $j = 1$ to N
    if $A[i,j] == 0$ **then**
      cnt++
      $idx[cnt][1] = i$
      $idx[cnt][2] = j$
    end if
  end for
end for
D = ModifiedFastFloyd(sim_A)
for $i = 1$ to cnt
  $sim_A[idx[i][1], idx[i][2]] = D[idx[i][1], idx[i][2]]$
end for
for $i = 1$ to N
  for $j = 1$ to N
    $sim_A[i][j] = sim_A[j][i]$
  end for
end for

5. CONCLUSION

This project investigates the rating prediction and generates location-sensitive recommendations in ad-hoc social networks. It 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. Further, the SSU-aware location-sensitive recommendation algorithm is devised. It evaluates and compares the proposed approach to the existing rating prediction and item recommendation algorithms.

It shows that the 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, it plans to develop similar techniques in other urban sustainable applications, e.g. E-health field, to confirm that the approach is universally applicable in various domains.

It is believed that almost all the system objectives that have been planned at the commencements of the software development have been net with and the implementation process of the project is completed. A trial run of the system has been made and is giving good results the procedures for processing is simple and regular order. The process of preparing plans been missed out which might be considered for further modification of the application.

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