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Results for Web Graph Mining Base Recommender System for Query, Image and Social Network using Query Suggestion Algorithm and Heat Diffusion Method

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Abstract: *In Previous paper, We have already discussed a general framework on Web graphs mining based recommender system for Query, Image and Social Network using Query Suggestion Algorithm and Heat Diffusion Method. In this paper we are discussing final results on the same. 1) we first propose an general implementation of web graph mining base recommender system for Query, Image and social network suggestion 2) secondly we discuss results of Query and Image recommender system 3) And at the end we discuss the implementation and results of our recommendation system for social networks, which is an extension to our web graph mining base recommender system; Hao Ma, Irwin King et al in their paper "Mining Web Graphs for Recommendations" have proposed a system for query suggestion and image recommendation using heat diffusion by taking reference of that we are adding a social recommendation. Aim of this paper is to discuss the implementation and results for the proposed system.*

Keywords: *Recommendation, diffusion, query suggestion, image recommendation, social recommendation, Trust value*

I. Introduction

Organize and use information effectively and efficiently is a very difficult task now a days. Mining useful information on web from different sources is also difficult. To satisfy the need of information of web user, recommender system has been well studied in academic and in industries. There are various recommender systems available on web. For example Movielens, Which recommends movies to user based on the already collected and well organized data which was taken through a feedback from the previous users who rate the movies on that web site. Another beautiful example can be a online shopping web site i.e. Amezon.com. Generally, recommender systems are based on Collaborative Filtering [1], which is a technique that automatically predicts or infer the interest of an active user by collecting rating information from other similar users or items. Another technique that can be used in social network recommendation is trust value relationship between the users on network. Based upon this concept we have implemented social network recommendation. In this paper we will see the implementation and results of previous review paper which had proposed architecture and the visual models(UML diagrams) of the web graph mining base recommender system which works for the query, image-tags and social network using query suggestion and heat diffusion method.

II. Problem definition

Typically, recommender systems are based on Collaborative Filtering, and collaborative filtering algorithms require a user-item rating matrix which contains user-specific rating preferences to infer users' characteristics. However, in most of the cases, rating data are always unavailable since information on the Web is less structured and more diverse. Problem in this system is we have to use different approaches for different recommendations.

III. Proposed solution

To provide a solution to this we are implementing generaliseWeb graph mining based recommender system using query suggestion algorithm and heat diffusion method along with recommendation for social network using trust relationship among users as a contribution work. Following section IV provides proposed solution.

IV. General Implementation for Web Graph mining based recommender system

Query Suggestion is a technique widely employed by commercial search engines to provide related queries to users' information need. In this section, we demonstrate how our method can benefit the query suggestion, and how to mine latent semantically similar queries based on the users' information need. We construct our query suggestion graph based on the clickthrough data of the AOL search engine shown in Fig.1.

Clickthrough data record the activities of Web users, which reflect their interests and the latent semantic relationships between users and queries as well as queries and clicked Web documents. Each line of clickthrough data contains the following information: a query (q) issued by the user, a URL (l) on which the user clicked, the rank (r) of that URL, and the number of clicked on URL. From a statistical point of view, the query word set corresponding to a number of Web pages contains human knowledge on how the pages are related to their issued queries. Thus, in this paper, we utilize the relationships of queries and Web pages for the construction of the bipartite graph containing two types of vertices. The information regarding user ID, rank and calendar time is ignored.

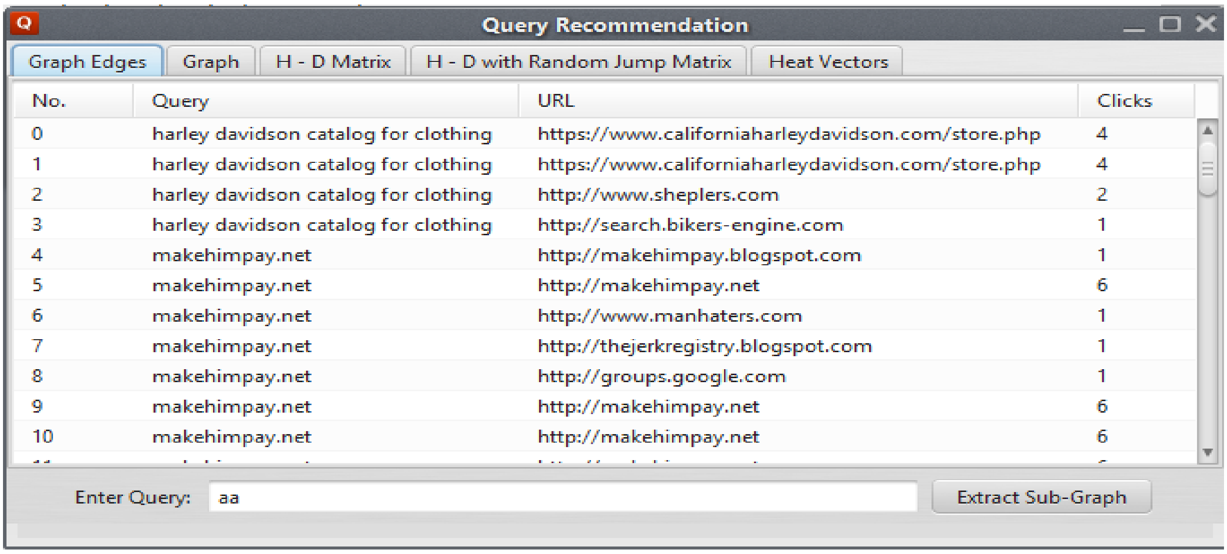


Fig.1 Clickthrough Data

The weight on a directed query-URL edge is normalized by the number of times that the query is issued, while the weight on a directed URL-query edge is normalized by the number of times that the URL is clicked. Graph construction has been depicted in following Fig.2.

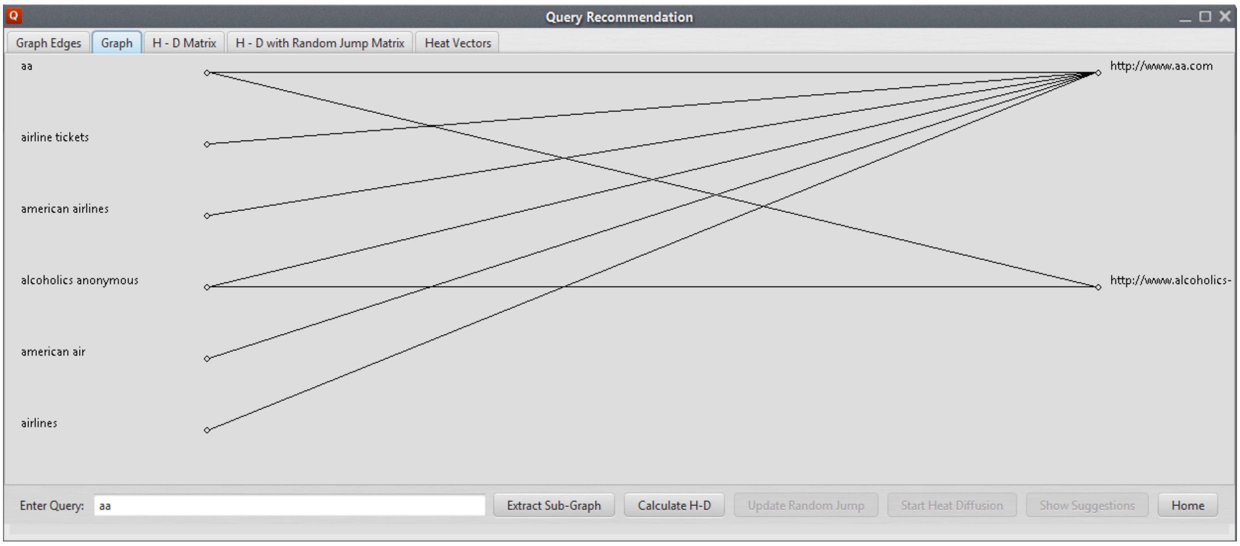
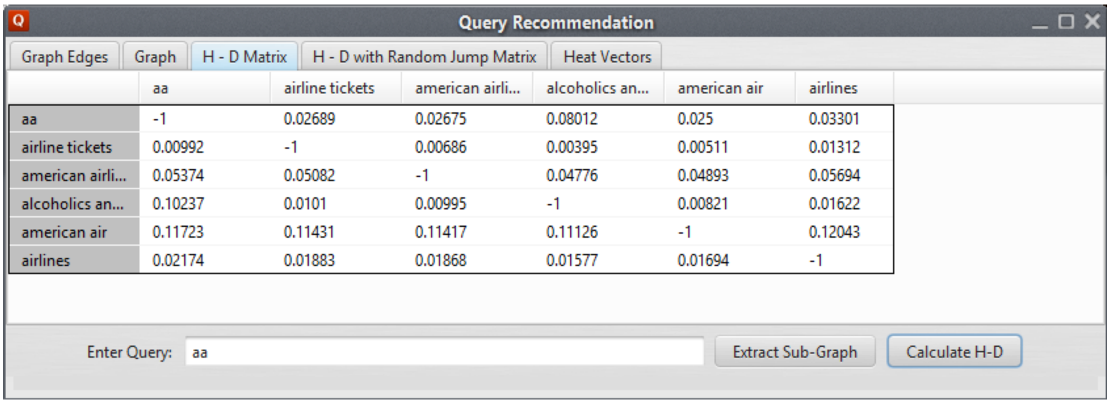


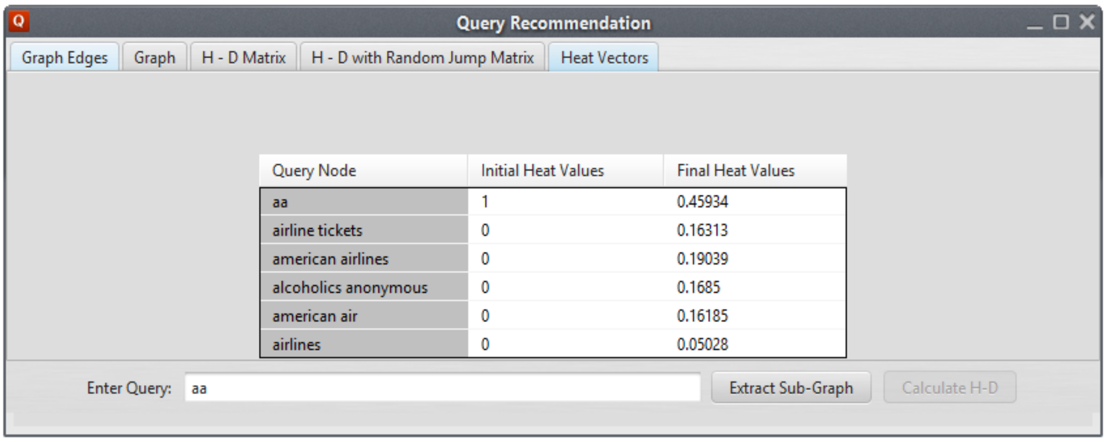
Fig.2 Undirected Sub-Graph

In this paper, we use heat diffusion to model the similarity information propagation on Web graphs. In Physics, the heat diffusion is always performed on a geometric manifold with initial conditions. However, it is very difficult to represent the Web as a regular geometry with a known dimension. This motivates us to investigate the heat flow on a graph. The graph is considered as an approximation to the underlying manifold, and so the heat flow on the graph is considered as an approximation to the heat flow on the manifold. The closest node to the heat source, gains more heat than other nodes. This also indicates that if a node has more paths connected to the heat source, it will potentially obtain more heat. This is a perfect property for recommending relevant nodes on a graph. Heat diffusion is shown in following Fig.3 and Fig.4



	aa	airline tickets	american airli...	alcoholics an...	american air	airlines
aa	-1	0.02689	0.02675	0.08012	0.025	0.03301
airline tickets	0.00992	-1	0.00686	0.00395	0.00511	0.01312
american airli...	0.05374	0.05082	-1	0.04776	0.04893	0.05694
alcoholics an...	0.10237	0.0101	0.00995	-1	0.00821	0.01622
american air	0.11723	0.11431	0.11417	0.11126	-1	0.12043
airlines	0.02174	0.01883	0.01868	0.01577	0.01694	-1

Fig.3 Heat Diffusion(H-D) Matrix

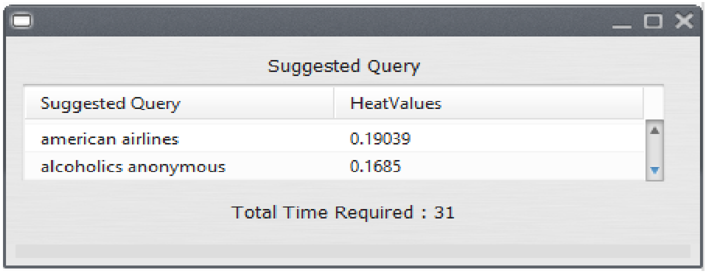


Query Node	Initial Heat Values	Final Heat Values
aa	1	0.45934
airline tickets	0	0.16313
american airlines	0	0.19039
alcoholics anonymous	0	0.1685
american air	0	0.16185
airlines	0	0.05028

Fig.4 Heat-Diffusion

V. Result Of Query And Image Recommendation System

Above generalize recommender system works well also for Image recommender system. Following Fig.5 and Fig.6 shows results for Query and Image recommendation. Following figures shows total time required to recommend suggestion. From the results, we observe that our recommendation algorithm not only suggests queries which are literally similar to the test queries, but also provides latent semantically relevant recommendations.



Suggested Query	HeatValues
american airlines	0.19039
alcoholics anonymous	0.1685

Fig.5 Result of Query Recommender System

Basically, the graph construction for image recommendation is similar to the one introduced in query recommendation. The only difference is that here the nodes in bipartite graph are tags. By using the similar algorithm which is introduced in query recommendation, we can also provide image recommendations. The recommendation results are shown in Fig. 6

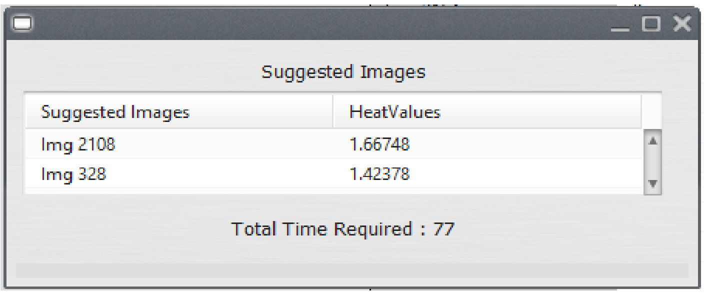


Fig.6 Result of Image Recommender System

VI. Result Of Social Recommendation System

Social recommendation, which produces recommendations by incorporating users' social network information, is becoming to be an indispensable feature for the next generation of Web applications. The social recommendation problem includes two different data sources, which are social network and user item relation matrices. An example is shown in Fig.7. We can see that in the social network graph, there are trust scores between different users, while in the user-item relation matrix, binary relations connect users and items.

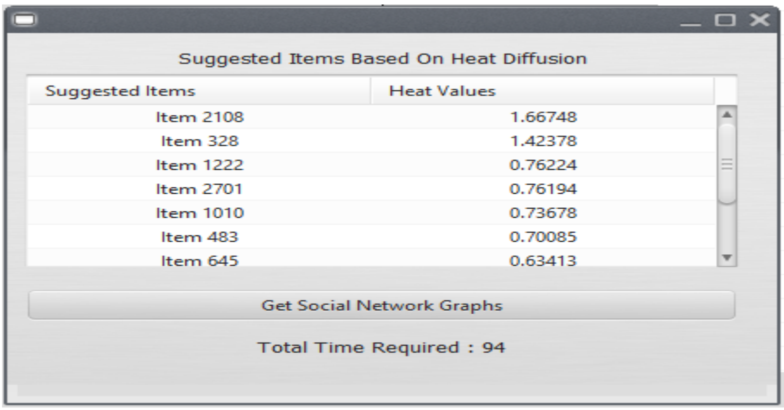


Fig.7 Results based on User-Item Relationship

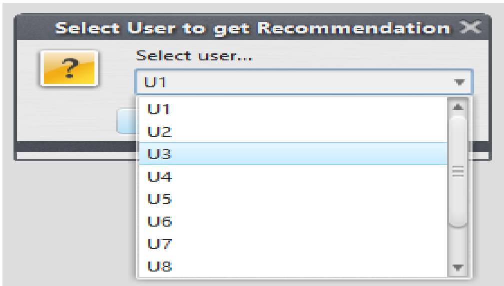


Fig.8 Selecting User to give recommendation

Fig.9 shows graph generated for social recommendation based upon trust-value, each user in a social network has a trust upon other user with variable trust-value. Trust-value differs because user U1 may have more trust upon user U3 than user U2. Following graph in Fig.9 shows combined relation of user-user and user-item. All the edges has a weight which is nothing but a trust value. In Fig.9 user U3 in blue dot is expected to get recommendation by it's most trusted user.

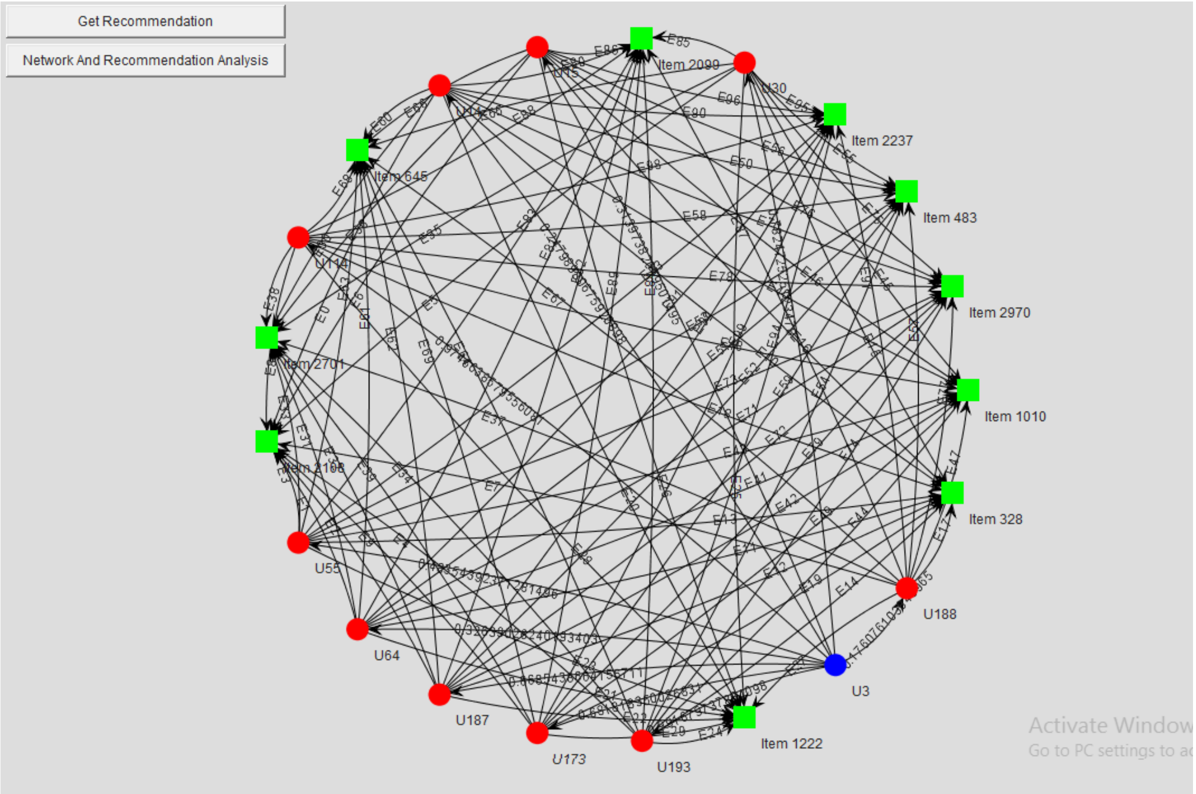


Fig.9 Graph for Social Recommendation

Finally, Fig.10 shows a social recommendation analysis in which user-item and user-user relation is displayed along with recommended Item 645 by most trusted user U193.

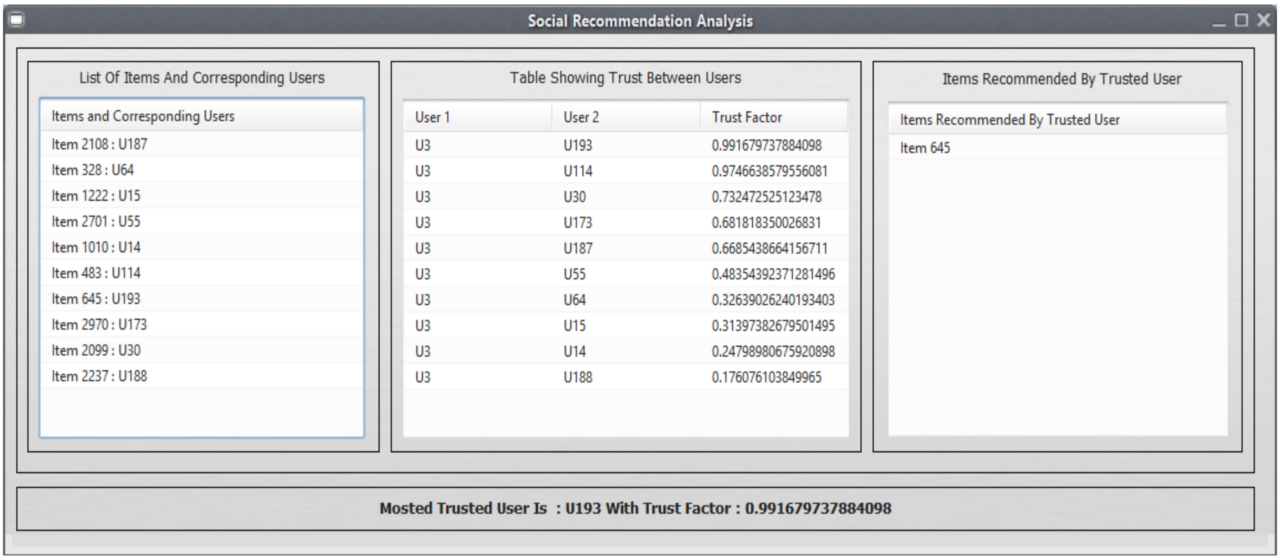


Fig.10 Social Recommendation Analysis with Final Result

VII. Conclusion

In this paper we first saw a general implementation of web graph mining base recommender system for Query, Image and social network suggestion. Secondly, we discuss results of Query and Image recommender system. And at the end we discuss the implementation and results of our recommendation system for social networks, which is an extension to our web graph mining base recommender system;

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