Topic-Based Recommendation with User-Product Subgroup Model

Aarepu Lakshman[1], Kandru Arun Kumar[2]

[1,2]Assistant Professor, Department of CSE
[1,2]Malla Reddy Engineering College (A), Hyderabad, Telangana, India.

Abstract

Recommendation systems is successfully used to provide items of interest to the user's traditional recommendation systems do not consider the location as a relevant factor when providing suggestions. A novel unsupervised method called heterogeneous graph based soft clustering is developed to derive an intent indicator for each object based on the constructed heterogeneous graph. With the proposed co-clustering method is enhance the quality of intent understanding by taking advantage of different types of data. Fuzzy sets appear to be a proper paradigm to handle the uncertainty and fuzziness of human decision-making activities and successfully model the normal sophistication of human behavior. The proposed factorization model for the observed rating reconstruction. Clustering model for the user item subgroup analysis, and regularization terms to connect the above two components into a unified formulation. We develop an efficient collaborative filtering method new product recommendation method called TCRec is also studied. We present the main applications of this systems in several recommendation scenarios, such as music, news, restaurants, etc. Finally, we discuss new avenues and open issues in the area.

Index Terms*: Location-aware recommendation systems, mobile computing, open issues, fuzzy linguistic, recommender systems. Heterogeneous Graph Clustering.*

1. Introduction

Collaborative Filtering (CF) is an effective and widely adopted recommendation model. Different from content-based recommender systems which rely on the profiles of users and items for predictions, CF methods make predictions by only utilizing the user-item interaction data such as transaction history or item satisfaction expressed in ratings [1]. Traditional intent learning methods uses only text information from queries or web pages [2]. Such methods are handling ambiguous queries properly. Later studies leverage web search log to facilitate user interest interpretation in learning search intents [3]. One general assumption is multiple web pages tend to share the same search intent clicked under similar queries. Unfortunately, this assumption has some intrinsic limitation due to the nature of web search. With the advent of e-commerce, the combination of recommendation system methods and LBS has been of significant interest for researchers. The inclusion of the location dimension in these types of systems access obtaining very effective recommendations is called Location Aware Recommendation Systems (LARS). We provide new location-aware recommendation systems for mobile computing [4]. Despite being effectively used in many domain areas high order fuzzy logic is not widely employed in recommendation systems. Fuzzy logic provides high value properties to recover items stored in a database and as a consequence to provide recommendations for users then fuzzy sets have the ability to manage concepts such as similarity, preference and uncertainty in a unified way and they also have the aptitude to perform rough reasoning. Fuzzy logic is helping to minimize the sparsely problem which is the main drawback current recommender systems suffer from [5].

2. Related Work

Collaborative filtering is an effective recommendation system preference of a user on an item is predicted based on the preferences of other users with similar interests. A big challenge in using collaborative filtering methods is data sparsely problem which often arises because each user typically only rates very few items and hence the rating matrix is extremely sparse [6]. To solve the MCF problem the knowledge to be adaptively transferred across different domains by automatically learning the correlation between domains [7]. Traditional document clustering methods is work well on queries due to their limited number of keywords. Search log is containing user interests is one kind of data widely used for query clustering [8], and is further combined with query content to achieve better performance Our work is similar to [9] in terms of the motivation of seeking a better interpretation for learned intents. We achieve the interpretation by leveraging semantic concepts in Wikipedia. Recommendations are based on the similarity between the searched item and other items the user liked in the past. As opposed to the case of item based collaborative filtering, this item similarity is computed by comparing the contents of the items [10]. Hybrid recommendation method combine both collaborative and content-based algorithms, to benefit from the advantages of each paradigm while trying to avoid their specific disadvantages [11].

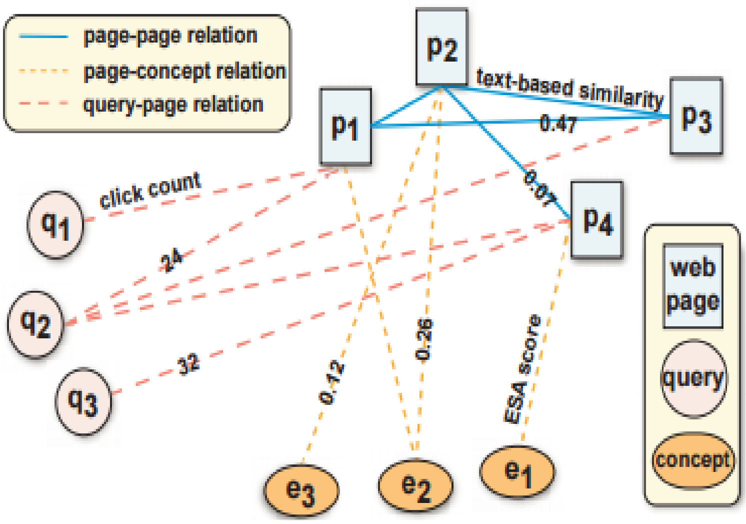

Figure 1. An illustration of the constructed heterogeneous graph

3. System Architecture

A bi-clustering model is subgroup analysis and two regularization terms to connect the two components into a unified formulation. Bi-clustering model is formulated to make full use of the duality many users and items to cluster them into subgroups [12]. The underlying method is the labels of a user and item for their subgroup identification should be the same and strongly associated a high rated user item pair should be grouped together.bi-clustering model which is also a two-sided clustering methods a specific domain is a user item subgroup. In the bi clustering formulation high rating score rated by a user to an item encourages the user and the item to be assigned to the same subgroups together [13].

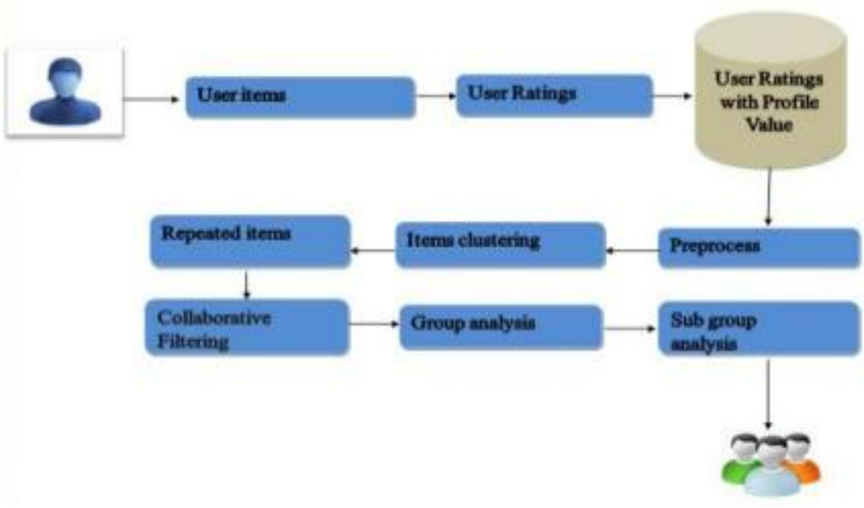

Figure 2. Bi-Clustering

4. Proposed Fuzzy Recommend System

Our novel CF algorithm is combining a model based collaborative filtering algorithm fuzzy logic one to alleviate the preferences vagueness of recommender systems model is variations in human decision making and subsequently enhance recommendation quality and effectiveness. We first use the fuzzy rating and weighted arithmetic averaging operator to aggregate all individual fuzzy decision matrices provided by the user [14]. Due to the subjective imprecise and vague of user preference data, the fuzzy linguistic approach is adopted to represent the user's preferences. In addition, Fuzzy Multicriteria Decision Making (FMCDM) method is chosen to rank items for a user based on the user-item ratings matrix in collaborative recommendation context [15].

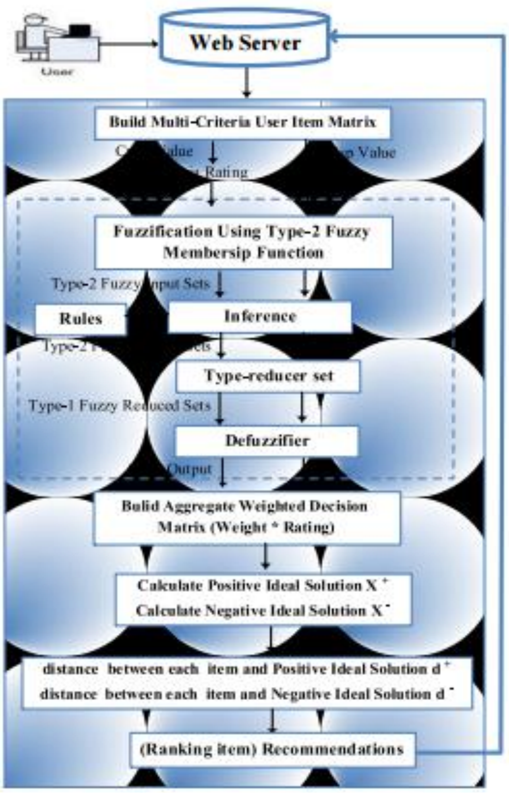

Figure 3. fuzzy Recommender System

5. The RecTree Algorithm

Rec Tree is the acronym for a new data structure and collaborative filtering algorithm called the RE Commendation Tree. The RecTree algorithm [16] partitions the data into cliques of approximately similar users by recursively splitting the dataset into child clusters. Splits are chosen such that the intra-partition similarity between users is maximized while the inter-partition similarity is minimized. RecTree less susceptible to this dilution effect yielding a higher overall accuracy. The chain of intermediate clusters leading from the initial dataset to the final partitioning is maintained in the RecTree data structure [17],

6. TCREC ALGORITHM

To achieve the ultimate target, TCRec [18] involves three components to exploit the consumer rating history record, the social-trust network and the product category information, respectively

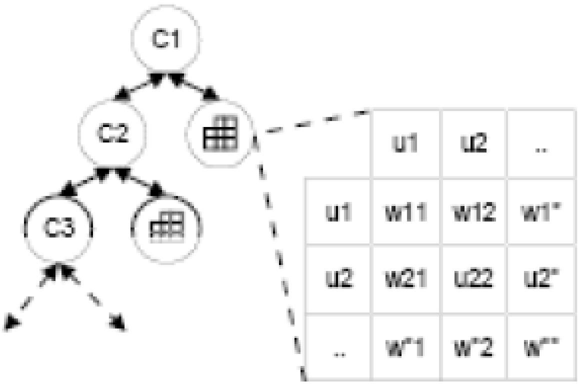

Figure 4. The Rec Tree Data Structure

A. Rating History Record

There are many products, and a customer may only rate a small portion of the whole item set practically.

B. Social-trust Network

We assume that customer interest to products is influenced by the other linked customers in social-trust network [19].

C. Product Category Information

The products in different categories should be discriminated by exploring the product-specific latent representations.

7. Domain-Independent Approaches For Lars

In the recent years, thanks to advances of mobile devices, ubiquitous computing, and wireless communication technologies, a significant number of works have been carried out in the field of LARS.

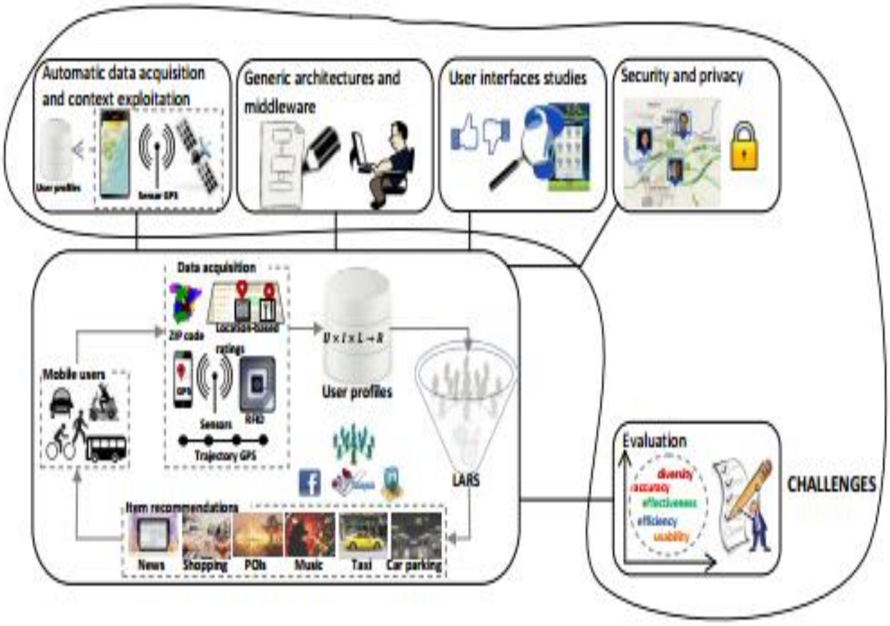

Figure 5. Overview of LARS

To obtain spatial ratings, the authors applied an approach of user partitioning based on the user locality the scalability to large numbers of users, and the influence of the users, to control the size of the neighborhood. Other approaches consider the impact of the locations not only as a pre-filtering step but directly on the application of collaborative filtering. Presented an improvement of collaborative filtering that combines the user's geographical information and the content of items in order to learn location-based user group preferences, considered by the authors as a rating distribution of a group of items. [20] Proposed location-based recommendation architecture for dynamic and ubiquitous environments. The authors combine in the proposed architecture, the ideas of location, personalization, and content-based recommendation [21].

A. Clustering on Graphs

Another group of related work is graph-based clustering which groups single or multiple types of objects with respect to their graph structure. Typical methods include spectral clustering on homogeneous graph and co-clustering on bipartite graph [22]. In particular, Guan exploit affinity and bipartite relationships between users, documents and social tags by graph embedding in recommendation. Recently, several studies exploit heterogeneous graphs which consist of heterogeneous types of objects [23]. Click-through relations between queries and web pages form a bipartite query-page sub graph. We assume that a query and a web page are more likely to share the same intent if the number of users who click the web page after issuing the query is larger. We propose to approximately compute concept intent features by first aggregating information from web page-concept sub graph into a concept-based web page affinity sub graph, and then deriving concept intent indicator based on learned web page intent indicator and web page-concept sub graph. The computational burden is largely reduced by getting rid of the parameter space of FE during the learning process.

8. Experiment Result

To evaluate the accuracy of the proposed method, we conduct a set of experiments and compare the proposed method with traditional fuzzy recommendation algorithm. Our experiments were implemented **Data Set and Setup** In order to evaluate the proposed approach, a set of user submitted ratings are collected from the music recommender system developed for this experiment. During the user relevance feedback collection, the user is asked to provide their ratings on the heard music item. **Metrics** A number of metrics are available to evaluate the recommender system performance. These include statistical accuracy metrics such as mean absolute error that determine the prediction accuracy of the algorithms, and recommendation accuracy metrics that determine how well the recommendation algorithm can predict items the user would rate highly. The performance of traditional fuzzy based recommendation algorithm is compared with our approach using the precision, recall, and F1-measure. The average precision recall and F1-measure of the users during Top-5 recommendations These values reveal a good performance of the proposed approach.

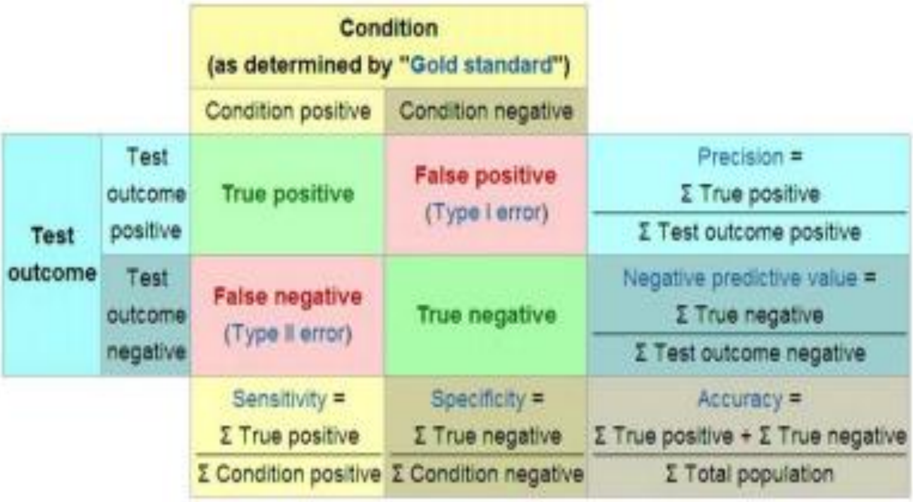

Figure 6. Performance evaluation matrices

9. Conclusion and Future Work

The user-item subgroup analysis in multiple product item dataset, simultaneously in which a user-item subgroup is deemed as a domain consisting of a subset of items with similar attributes and a subset of users who have interests in these items proposed. Location-aware recommendation approaches made an important progress thanks to significant efforts developed by the research community fuzzy multicriteria decision making approach has great potential in collaborative recommender systems and can be successfully used to build accurate and flexible recommender systems. Future work extending our method to automatically learn the importance of different types of relations and enabling our method to update the intent indicator in an online manner so that newly emerged search intents can be efficiently included.

References

[1] Y. Zhang, B. Cao, and D.-Y. Yeung, “Multi-domain collaborative filtering,” in Proc. 26th Conf. Annu. Conf. Uncertainty Artif. Intell., 2010, pp. 725–732.

[2] N. Craswell and M. Szummer. Random walks on the click graph. In SIGIR, 2007.

[3] I. S. Dhillon. Co-clustering documents and words using bipartite spectral graph partitioning. In SIGKDD, 2001

[4]. Y. A. Asikin and W. W¨orndl. Stories Around You: Location-based serendipitous recommendation of news articles. In 2nd International Workshop on News Recommendation and Analytics

[5] Zenebe, A., & Norcio, A. F. (2009). Representation, similarity measures and aggregation methods using fuzzy sets for content-based recommender systems. Fuzzy Sets and Systems, 160(1), 76-94

[6]. Zeng, Y. Yu, and Z. Chen, "Scalable collaborative filtering using cluster-based smoothing, "in Proc. Res. Develop. Inf. Retrieval, 2005,pp. 114–21.

[7]. Bellogin and J. Parapar, "Using graph partitioning techniques for neighbour selection in user-based collaborative filtering," in Proc. 6th ACM Conf. Recommender Syst., 2012, pp. 213–216

[8] J. C. K. Cheung and X. Li. Sequence clustering and labeling for unsupervised query intent discovery. In WSDM, 2012.

[9] N. Craswell and M. Szummer. Random walks on the click graph. In SIGIR, 2007.

[10] H. Costa, B. Furtado, D. Pires, L. Macedo, and A. Cardoso. Context and intention-awareness in POIs recommender systems. In 6th ACM Conference on Recommender Systems, 4th Workshop on Context-Aware Recommender Systems (RecSys), 2012.

[11] J. Das, S. Majumder, and P. Gupta. Voronoi based location aware collaborative filtering. In 3rd National Conference on Emerging Trends and Applications in Computer Science (NCETACS), pages 179–183. IEEE, 2012.

[12]. T. George and S. Merugu, "A scalable collaborative filtering framework based on co-clustering," in Proc. 5th IEEE Int. Conf. Data Mining, 2005, pp. 625–628.

[13]. B. Xu, J. Bu, C. Chen, and D. Cai, "An exploration of improving collaborat ive recommender systems via user-item subgroups," in Proc. 21st Int. Conf. World Wide Web, 2012, pp. 21–30

[14] Palanivel, K., & Sivakumar, R. (2010). Fuzzy multicriteria decision-making approach for collaborative recommender systems. International Journal of Computer Theory and Engineering, 2(1), 57-63.

[15] Lakiotaki, K., Matsatsinis, N. F., & Tsoukiàs, A., Multi-criteria user modeling in recommender, 2011.

[16] M. Fazel, H. Hindi, and S. Boyd. Log-det heuristic for matrix rank minimization with applications to hankel and Euclidean distance matrices. In Proceedings American Control Conference, pages 2156–2162, 2003.

[17] J. L. Herlocker, J. A. Konstan, A. Borchers, and J. Riedl, An Algorithmic Framework for Performing Collaborative Filtering, In *Proc. 1999 Conf. Research and Development in Information Retrieval*, pp. 230-237, Berkeley, CA, August 1999.

[18] Y. Jiang, J. Liu, X. Zhang, Z. Li, and H. Lu, "TCRec: Product recommendation via exploiting social-trust network and product category information," in Proc. 22nd Int. Conf. World Wide Web, 2013.

[19] S. Han, S. Chee, J. Han, and K. Wang, "RecTree: An efficient collaborative filtering method," in Proc. 3rd Int. Conf. Data Warehousing Knowl. Discovery, 2001.

[20] J. J. Levandoski, M. Sarwat, A. Eldawy, and M. F. Mokbel. LARS: A location-aware recommender system. In 28th International Conference on Data Engineering (ICDE), pages 450–461. IEEE, 2012.

[21] X. Li, Z. Mi, Z. Zhang, and J. Wu. A location-aware recommender system for tourism mobile commerce. In 2nd International Conference on Information Science and Engineering (ICISE), pages 1709–1711. IEEE, 2010.

[22] Y. Sun, Y. Yu, and J. Han. Ranking-based clustering of heterogeneous information networks with star network schema. In SIGKDD, 2009.

[23] X. Wang, D. Chakrabarti, and K. Punera. Mining broad latent query aspects from search sessions. In SIGKDD, 2009

