International Journal of Advanced Technology and Innovative Research
ISSN 2348–2370
Vol.09,Issue.03,
March-2017,
Pages:0457-0459
www.ijatir.org

An Efficient and Scalable Location-Aware Recommender System

B. SRILAKSHMI[1], K. SUNIL KUMAR[2]
[1]PG Scholar, Dept of CSE, DJR Institute of Engineering &Technology, Andhrapradesh, India,
Email: bh.srilakshmi@gmail.com.
[2]Associate Professor, Dept of CSE, DJR Institute of Engineering &Technology, Andhrapradesh, India,
Email: sunil_ketineni@yahoo.co.in.

Abstract: This paper proposes LARS, a location-aware recommender system that uses location-based ratings to produce recommendations.Traditional recommender systems do not consider spatial properties of users nor items; LARS, on the other hand, supports a taxonomy of three novel classes of location-based ratings, namely, spatial ratings for non-spatial items, non-spatial ratings for spatial items, and spatial ratings for spatial items. LARS exploits user rating locations through user partitioning, a technique that influences recommendations with ratings spatially close to querying users in a manner that maximizes system scalability while not sacrificing recommendation quality. LARS exploits item locations using travel penalty, a technique that favors recommendation candidates closer in travel distance to querying users in a way that avoids exhaustive access to all spatial items. LARS can apply these techniques separately, or together, depending on the type of location-based rating available. Experimental evidence using large-scale real-world data from both the foursquare location-based social network and the Movie Lens movie recommendation system reveals that LARS is efficient, scalable, and capable of producing recommendations twice as accurate compared to existing recommendation approaches.

Keywords: LARS, Collaborative Filtering (CF).

I. INTRODUCTION

In this paper, we propose LARS, a novel location aware recommender system built specifically to produce high-quality location-based recommendations in an efficient manner. LARS produces recommendations using a taxonomy of three types of location-based ratings within a single framework: (1) Spatial ratings for non-spatial items, represented as a four-tuple (user, ulocation, rating, item), where ulocation represents a user location, for example, a user located at home rating a book; (2) non-spatial ratings for spatial items, represented as a four-tuple (user, rating, item, ilocation), where ilocation represents an item location, for example, a user with unknown location rating a restaurant; (3) spatial ratings for spatial items, represented as a five-tuple (user, u location, rating, item, ilocation), for example, a user at his/her office rating a restaurant visited for lunch. Traditional rating triples can be classified as non-spatial ratings for non-spatial items and do not fit this taxonomy. RECOMMENDER systems make use of community opinions to help users identify useful items from a considerably large search space (e.g., Amazon inventory [1], Netflix movies1).

The technique used by many of these systems is collaborative filtering (CF) [2], which analyzes past community opinions to find correlations of similar users and items to suggest k personalized items (e.g., movies)to a querying user u. Community opinions are expressed through explicit ratings represented by the triple (user, rating, item) that represents a user providing a numeric rating for an item. Currently, myriad applications can produce location-based ratings that embed user and/or item locations. For example, location-based social networks (e.g., Foursquare2 and Facebook Places [3]) allow users to “check-in” at spatial destinations (e.g., restaurants) and rate their visit, thus are capable of associating both user and item locations with ratings. Such ratings motivate an interesting new paradigm of location-aware recommendations, whereby the recommender system exploits the spatial aspect of ratings when producing recommendations.Existing recommendation techniques [4] assume ratings are represented by the (user, rating, item) triple, thus are ill-equipped to produce location aware recommendations.

II. EXISTING SYSTEM

Recommender systems make use of community opinions to help users identify useful items from a considerably large search space. The technique used by many of these systems is collaborative filtering (CF), which analyzes past community opinions to find correlations of similar users and items to suggest k personalized items (e.g., movies) to a querying user u. Community opinions are expressed through explicit ratings represented by the triple (user, rating, item) that represents a user providing a numeric rating for an item. Myriad applications can produce location-based ratings that embed user and/or item locations. Existing recommendation techniques assume ratings are represented by the (user, rating, item) triple.

A. Disadvantages of Existing System

- The existing systems are ill-equipped to produce location aware recommendations.

- The existing system provides more expensive operations to maintain the user partitioning structure.
- The existing system does not provide spatial ratings.

III. PROPOSED SYSTEM

We have proposed LARS, a location-aware recommender system that uses location-based ratings to produce recommendations. LARS, supports a taxonomy of three novel classes of location-based ratings, namely, spatial ratings for non-spatial items, non-spatial ratings for spatial items, and spatial ratings for spatial items. LARS exploits user rating locations through user partitioning, a technique that influences recommendations with ratings spatially close to querying users in a manner that maximizes system scalability while not sacrificing recommendation quality. LARS exploits item locations using travel penalty, a technique that favors recommendation candidates closer in travel distance to querying users in a way that avoids exhaustive access to all spatial items. LARS can apply these techniques separately, or together, depending on the type of location-based rating available. Within LARS, we propose:

- A user partitioning technique that exploits user locations in a way that maximizes system scalability while not sacrificing recommendation locality
- A travel penalty technique that exploits item locations and avoids exhaustively processing all spatial recommendation candidates.

A. Advantages of Proposed System

- LARS, supports a taxonomy of three novel classes of location-based ratings, namely, spatial ratings for non-spatial items, non-spatial ratings for spatial items, and spatial ratings for spatial items.
- LARS achieves higher locality gain using a better user partitioning data structure and algorithm.
- LARS exhibits a more flexible tradeoff between locality and scalability.
- LARS provides a more efficient way to maintain the user partitioning structure.

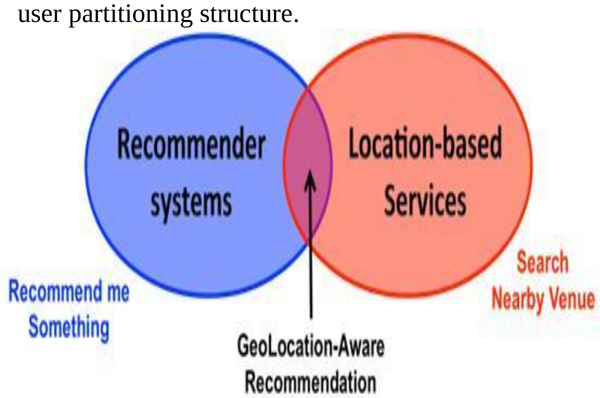

Fig1. System Architecture.

V. RELATED WORK

Location-based services. Current location-based services employ two main methods to provide interesting destinations to users. (1) KNN techniques [22] and variants (e.g., aggregate KNN [24]) simply retrieve the k objects nearest to a user and are completely removed from any notion of user personalization. (2) Preference methods such as skylines[25] (and spatial variants [26]) and location-based top-k methods [27] require users to express explicit preference constraints. Conversely, LARS is the first location based service to consider implicit preferences by using location-based ratings to help users discover new items. Recent research has proposed the problem of hyper-local place ranking [28]. Given a user location and query string (e.g., “French restaurant"), hyper-local ranking provides a list of top-k points of interest influenced by previously logged directional queries (e.g., map direction searches from point A to point B). While similar in spirit to LARS, hyper-local ranking is fundamentally different from our work as it does not personalize answers to the querying user, i.e., two users issuing the same search term from the same location will receive exactly the same ranked answer.

Traditional recommenders. Wide arrays of techniques are capable of producing recommendations using non spatial ratings for non-spatial items represented as the triple (user, rating, item) (see [4] for a comprehensive survey). We refer to these as “traditional" recommendation techniques. The closest these approaches come to considering location is by incorporating contextual attributes into statistical recommendation models (e.g., weather, traffic to a destination) [29]. However, no traditional approach has studied explicit location-based ratings as done in LARS. Some existing commercial applications make cursory use of location when proposing interesting items to users. For instance, Netflix displays a “local favorites” list containing popular movies for a user’s given city. However, these movies are not personalized to each user (e.g., using recommendation techniques); rather, this list is built using aggregate rental data for a particular city [30]. LARS, on the other hand, produces personalized recommendations influenced by location-based ratings and a query location. Location-aware recommenders. The City Voyager system [31] mines a user’s personal GPS trajectory data to determine her preferred shopping sites, and provides recommendation based on where the system predicts the user is likely to go in the future. LARS, conversely, does not attempt to predict future user movement, as it produces recommendations influenced by user and/or item locations embedded in community ratings.

VI. CONCLUTION

LARS, our proposed location-aware recommender system, tackles a problem untouched by traditional recommender systems by dealing with three types of location-based ratings: spatial ratings for non-spatial items, non-spatial ratings for spatial items, and spatial ratings for spatial items. LARS employs user partitioning and travel penalty techniques to support spatial ratings and spatial items, respectively. Both techniques can be applied separately or in concert to support the various types of location-based ratings. Experimental analysis using real and synthetic data sets show that LARS is efficient, scalable, and provides better quality recommendations than techniques used in traditional recommender systems.

VII. REFERENCE

[1] G. Linden, B. Smith, and J. York, “Amazon.com recommendations: Item-to-item collaborative filtering,” IEEE Internet Comput., vol. 7, no. 1, pp. 76–80, Jan./Feb. 2003.
[2] P. Resnick, N. Iacovou, M. Suchak, P. Bergstrom, and J. Riedl, “GroupLens: An open architecture for collaborative filtering of netnews,” in Proc. CSWC, Chapel Hill, NC, USA, 1994.
[3] The facebook blog. Facebook Places [Online]. Available: http://tinyurl.com/3aetfs3
[4] G. Adomavicius and A. Tuzhilin, “Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions,” IEEE Trans. Knowl. Data Eng., vol. 17, no. 6, pp. 734–749, Jun. 2005.
[5]MovieLens[Online].Available:http://www.movielens.org/
[6] Foursquare [Online]. Available: http://foursquare.com
[7] New York Times - A Peek into Netflix Queues [Online]. Available:http://www.nytimes.com/interactive/2010/01/10/nyregion/20100110-netflix-map.html
[8] J. J. Levandoski, M. Sarwat, A. Eldawy, and M. F. Mokbel, “LARS: A location-aware recommender system,” in Proc. ICDE, Washington, DC, USA, 2012.
[9] B. Sarwar, G. Karypis, J. Konstan, and J. Riedl, “Item-based collaborative filtering recommendation algorithms,” in Proc. Int. Conf. WWW, Hong Kong, China, 2001.
[10] J. S. Breese, D. Heckerman, and C. Kadie, “Empirical analysis of predictive algorithms for collaborative filtering,” in Proc. Conf. UAI, San Francisco, CA, USA, 1998.
[11] W. G. Aref and H. Samet, “Efficient processing of window queries in the pyramid data structure,” in Proc. ACM Symp.PODS, New York, NY, USA, 1990.
[12] R. A. Finkel and J. L. Bentley, “Quad trees: A data structure for retrieval on composite keys,” Acta Inf., vol. 4, no. 1, pp. 1–9, 1974.
[13] A. Guttman, “R-trees: A dynamic index structure for spatial searching,” in Proc. SIGMOD, New York, NY, USA, 1984.
[14] K. Mouratidis, S. Bakiras, and D. Papadias, “Continuous monitoring of spatial queries in wireless broadcast environments,” IEEE Trans. Mobile Comput., vol. 8, no. 10, pp. 1297–1311, Oct. 2009.
[15] K. Mouratidis and D. Papadias, “Continuous nearest neighbor queries over sliding windows,” IEEE Trans. Knowl. Data Eng., vol. 19, no. 6, pp. 789–803, Jun. 2007.
[16] M. F. Mokbel, X. Xiong, and W. G. Aref, “SINA: Scalable incremental processing of continuous queries in spatiotemporal databases,” in Proc. SIGMOD, Paris, France, 2004.
[17] J. L. Herlocker, J. A. Konstan, L. G. Terveen, and J. T. Riedl, “Evaluating collaborative filtering recommender systems,” ACM TOIS, vol. 22, no. 1, pp. 5–53, 2004.
[18] M. J. Carey and D. Kossmann, “On saying "Enough Already!" in SQL,” in Proc. SIGMOD, New York, NY, USA, 1997.
[19] S. Chaudhuri and L. Gravano, “Evaluating top-k selection queries,” in Proc. Int. Conf. VLDB, Edinburgh, U.K., 1999.
[20] R. Fagin, A. Lotem, and M. Naor, “Optimal aggregation algorithms for middleware,” in Proc. ACM Symp.PODS, New York, NY, USA, 2001.
[21] J. Bao, C.-Y.Chow, M. F. Mokbel, and W.-S.Ku, “Efficient evaluation of k-range nearest neighbor queries in road networks,” in Proc. Int. Conf. MDM, Kansas City, MO, USA, 2010.
[22] G. R. Hjaltason and H. Samet, “Distance browsing in spatial databases,” ACM TODS, vol. 24, no. 2, pp. 265–318, 1999.
[23] K. Mouratidis, M. L. Yiu, D. Papadias, and N. Mamoulis, “Continuous nearest neighbor monitoring in road networks,” in Proc. Int. Conf. VLDB, Seoul, Korea, 2006.
[24] D. Papadias, Y. Tao, K. Mouratidis, and C. K. Hui, “Aggregate nearest neighbor queries in spatial databases,” ACM TODS, vol. 30, no. 2, pp. 529–576, 2005.
[25] S. Börzsönyi, D. Kossmann, and K. Stocker, “The skyline operator,” in Proc. ICDE, Heidelberg, Germany, 2001.
[26] M. Sharifzadeh and C. Shahabi, “The spatial skyline queries,” in Proc. Int. Conf. VLDB, Seoul, Korea, 2006.
[27] N. Bruno, L. Gravano, and A. Marian, “Evaluating top-k queries over web-accessible databases,” in Proc. ICDE, San Jose, CA, USA, 2002.
[28] P. Venetis, H. Gonzalez, C. S. Jensen, and A. Y. Halevy, “Hyperlocal, directions-based ranking of places,” PVLDB, vol. 4, no. 5, pp. 290–301, 2011.
[29] M.-H. Park, J.-H.Hong, and S.-B. Cho, “Location-based recommendation system using Bayesian user’s preference model in mobile devices,” in Proc. Int. Conf. UIC, Hong Kong, China, 2007.
[30] Netflix News and Info - Local Favorites [Online]. Available: http://tinyurl.com/4qt8ujo
[31] Y. Takeuchi and M. Sugimoto, “An outdoor recommendation system based on user location history,” in Proc. Int. Conf. UIC, Berlin, Germany, 2006.

Author’s Profile:

B. Srilakshmi received her B.Tech degree in computer science and engineering in the year 2013 and pursuing M.Tech degree in computer science and engineering from DJR Institute of Engineering &Technology.

K. Sunil Kumar received his M.Tech degree and B.Tech degree in computer science and engineering. He is currently working as an Assoc Professor in DJR Institute of Engineering &Technology.