IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 5, Issue 4, April 2016

A Survey on Cloud-Based Remote Venue Recommendation System

Ms. K. C. Sonawane[1], Mrs. S. S. Ponde[2]

DIEMS, Aurangabad[1, 2]

Abstract: Now a days, recommendation systems have seen significant evolution in the field of knowledge engineering. The models of most of the existing recommendation systems based on collaborative filtering approaches that make them simple to implement. The challenges that affect the performance of most of the existing collaborative filtering-based recommendation system are (a) cold start, (b) data sparseness, and (c) scalability. In this paper, introduced Cloud-based Bi-Objective Recommendation Framework for mobile social networks. Multi-objective optimization techniques are used to generate personalized recommendations. Hub-Average (HA) inference model is used to address the issues pertaining to cold start. The Weighted Sum Approach (WSA) is implemented for CF-BORF and greedy-BORF Algorithm is applied for vector optimization to provide optimal suggestions to the users about a venue.

Keywords: Context-Aware Web Services, Multi-objective Optimization, Collaborative Filtering.

1. INTRODUCTION

In recent years, recommendation systems have seen crucial evolution in the field of knowledge engineering. Most of the recommendation systems based their models on collaborative filtering approaches that make them simple to implement. However, performance of most of the collaborative filtering- based recommendation system suffers due to the challenges, like (a) cold start, (b) data sparseness, and (c) scalability. Moreover, recommendation systems problem is often characterized by the presence of many contradictory objectives or decision variables, like users' preferences and venue closeness.

In this paper, introduced Cloud-based Bi-Objective Recommendation Framework (BORF) for mobile social networks. The Context put to use multi-objective optimization techniques to generate personalized recommendations. To address the issues pertaining to cold start as well as data sparseness, the BORF performs data pre-processing by using the Hub-Average (HA) inference model [1]. Furthermore, the Weighted Sum Approach (WSA) is implemented for CF-BORF and greedy-BORF Algorithm is applied for vector optimization to provide optimum suggestions to the users about a venue. The results of comprehensive experiments on a large -scale real dataset confirm the exactness of the proposed recommendation framework.

A good example of e-commerce applications is Amazon.com, Flipkart.com, where customers receive personalized recommendations on a variety of products. In the past years, several social networking applications, like as Foursquare, Gowalla, and Google Latitude were developed for mobile appliances. These applications allow users to perform a "check-in" at venues that they visit to share experiences in the form of a feedback or tip. Moreover, these services collect and hold huge volumes of users' geospatial check-in data. Based on the data extracted by the mobile social networking applications, several location-based recommendation systems were developed in the recent years which recommend venues to users closely related to their preferences. A major research challenge for these systems is to generate real-time venue recommendations for a given individual from a large I scale diverse dataset of users' historical check-ins. To generate an optimal recommendation for an individual, the system must simultaneously consider the following factors: **(a)** personal preferences, **(b)** past check-ins, **(c)** current context, like time and location, and **(d)** collaborative social opinions (other individuals' preferences).

The proliferation of wireless and cellular networks over the last years has led to a remarkable rise in the number of users who are using a variety of latest mobile Internet-enabled appliances such as iPhones, iPads, and Android-based phones to consume online services. Mobile users are growingly requiring services tailored to their context as they are on the move. So, enterprise services should be context-aware to deal with the changing environment. Context is any information that can be used to distinguished the situation of an entity. An entity is a person, place, or object that is considered suitable to the interaction between a user and an application, including the user and applications themselves.

Therefore, the amount of information that can be categorized as context information is abundantly wide. Location, time, temperature, humidity, pressure, and mobile user activity are the most extensively used context indicators by applications. Specialized favour, that we call context services, capture, store, analyze and collection data to provide high-level context information to consumer application services as needed [6]. Context services and consumers are often physically share. Besides, it is likely that these context sources give the same context information but with different QoC. The QoC concept is explained. Context-awareness raises challenges like aggregation of context data in a structured format, discovery, and selection of appropriate context services for context delivery to context consumers.

DOI 10.17148/IJARCCE.2016.5446

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 5, Issue 4, April 2016

1.1 Cloud services

Cloud computing enables a service-provisioning model for computing services that relies on the Internet. This model typically involves the provisioning of dynamically scalable and virtualized services. Applications or services offered by means of cloud computing are called cloud services. Typical examples of cloud services include office applications (word processing, spreadsheets, and presentations) that are traditionally found among desktop applications [11]. Nearly, all large software corporations, such as Google, Microsoft, Amazon, IBM, and Oracle, are providing various kinds of cloud services. Besides, many small businesses have launched their own Web-based services, mainly to take advantage of the collaborative nature of cloud services. The user of a cloud service has access to the service through a Web interface or via an API. Once started, the cloud service application acts as if it is a normal desktop application. The difference is that working documents are on the cloud servers.

1.2 Cloud services models are:

1.1.1 Infrastructure-as-a-Service (IaaS):
With IaaS, organizations rent computing resources and storage space and access them through a private network or across the Internet.

1.1.2 Platform-as-a-Service (PaaS):
With PaaS, organizations can develop their business applications in a cloud environment by using software tools supported by their cloud provider. Maintenance and management of the cloud infrastructure including severs and operating system is the responsibility of the cloud provider.

1.1.3 Software-as-a-Service (SaaS):
With SaaS, the cloud service application runs on the cloud provider servers and users access the service through a Web interface or via an API.

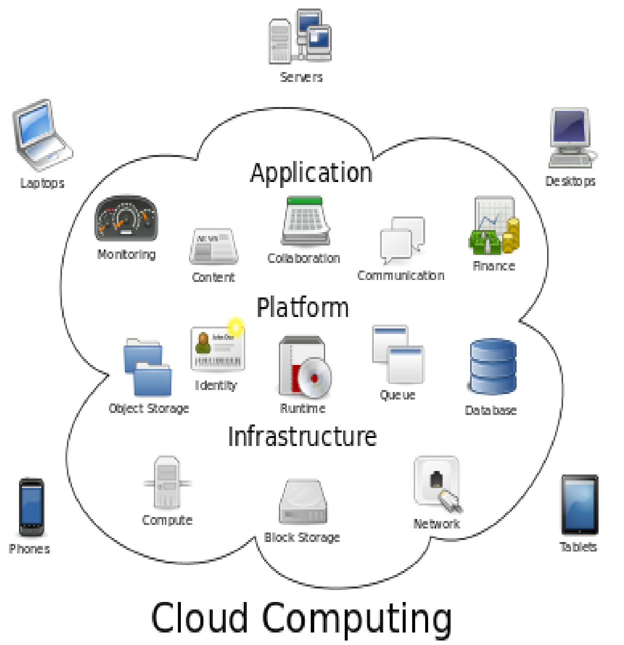

Figure 1: Cloud Computing

2. RELATED WORK

Jie Bao et al., suggest recent advances in position localization techniques have fundamentally enhanced social networking services, allowing users to share their locations and location-related content, such as geo-tagged photos and notes. We refer to these social networks as location-based social networks (LBSNs). Location data both bridges the gap between the physical and digital worlds and enables a deeper understanding of user preferences and behaviour. This addition of vast geospatial datasets has stimulated research into novel recommender systems that seek to facilitate users' travels and social interactions. In this paper, we offer a systematic review of this research, summarizing the contributions of individual efforts and exploring their relations. We discuss the new properties and challenges that location brings to recommendation systems for LBSNs. We present a comprehensive survey of recommender systems for LBSNs, analyzing 1) the data source used 2) the methodology employed to generate a recommendation, and 3) the objective of the recommendation. We propose three taxonomies that partition the recommender systems according to the properties listed above. First, we categorize the recommender systems by the objective of the recommendation, which can include locations, users, activities, or social media. Second, we categorize the recommender systems by the methodologies employed, including content-based, link analysis-based, and collaborative filtering-based methodologies. Third, we categorize the systems by the data sources used, including user profiles, user online histories, and user location histories.

Ling Chena et al., suggest the proliferation of digital cameras and the growing practice of online photo sharing using social media sites such as Flickr have resulted in huge volumes of geotagged photos available on the Web. Based on users' travelling preferences elicited from their travel experiences exposed on social media sites by sharing geotagged photos, we propose a new method for recommending tourist locations that are relevant to users (i.e., personalization) in the given context (i.e., context awareness). We obtain user-specific travel preferences from his/her travel history in one city and use these to recommend tourist locations in another city. Our technique is illustrated on a sample of publicly available Flickr dataset containing photos taken in various cities of China. Results show that our context-aware personalized method is able to predict tourists' preferences in a new or unknown city more precisely and generate better recommendations compared to other state-of-the-art landmark recommendation methods.

Justin J. Levandoski et al., suggest 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 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.

Zheng Wen et al., suggest recommendation system is a specific type of information filtering technique that attempts to present information items (such as movies, music, web sites, news) that are likely of interest to the user. It is of great importance for the success of e-commerce and IT industry nowadays, and gradually gains popularity in various applications (e.g. Netix project, Google news, Amazon). Intuitively, a recommendation system builds up a user's profile based on his/her past records, and compares it with some reference characteristics, and seeks to predict the `rating' that a user would give to an item he/she had not yet evaluated. In most cases, the recommendation system corresponds to a large-scale data mining problem. Based on the choice of reference characteristics, a recommendation system could be based on content-based approach or collaborative filtering (CF) approach or both. As their names indicate, content-based approach is based on the matching" of user profile and some specific characteristics of an item (e.g. the occurrence of specific words in a document) while collaborative filtering approach is a process of filtering information or pattern based on the collaboration of users, or the similarity between items. In this project, we build a recommendation system based on multiple collaborative filtering (CF) approaches and their mixture, using part of Netix project data as an example.

The following are the most common factors that affect the performance of many existing CF-based recommendation systems:

- Cold start

The cold start problem occurs when a recommendation system has to suggest venues to the user that is newer to the system. Insufficient check-ins for the new user results in zero similarity value that degrades the performance of the recommendation system. The only way for the system to provide recommendation in such scenario is to wait for sufficient check-ins by the user at different venues.

- Data sparseness

Many existing recommendation systems suffer from data sparseness problem that occurs when users have visited only a limited number of venues. This results into a sparsely filled user-to-venue check-in matrix. The sparseness of such matrix creates difficulty in finding sufficient reliable similar users to generate good quality recommendation.

- Scalability

Majority of traditional recommendation systems suffer from scalability issues. The fast and dynamic expansion of number of users causes recommender system to parse millions of check-in records to find the set of similar users. Some of the recommendation systems employ data mining and machine learning techniques to reduce the dataset size. However, there is an inherent tradeoff between reduced dataset size and recommendation quality. The immediate effect of the above-mentioned issues is the degradation in performance of most of the CF-based recommendation systems. Therefore, it is not adequate to rely solely on simplistic but memory-intensive CF approach to generate recommendations.

3. COMPARISONS OF VARIOUS ALGORITHMS WITH PARAMETERS

Table 1: Comparisons between various Algorithms

Algorithms	**Parameters**		
	Time complexity	**Space complexity**	**Frequency**
1. CF-BORF	Best	Better	Good
2. Greedy-BORF	Medium	Better	Average
3. NSGA-II	Average	Average	Average

Above Table 1 illustrated Comparisons between different algorithms with its parameters like Time Complexity, Space Complexity and Frequency. There are Three Recommendation Algorithms like CF-BORF, Greedy-BORF and NSGA-II are shown in above figure with its parameter. CF-BORF algorithm having Best Time complexity, Better Space complexity and Good Frequency. Second is Greedy-BORF algorithm having Medium Time complexity, Better Space complexity and Average Frequency. Third algorithm is NSGA-II having Average Time complexity, Space complexity and Frequency.

4. APPLICATIONS

Hotel recommendation

To alleviate the problems faced by KBS developers due to the complex nature of some methodologies and also the lack of standards for the knowledge modeling, we have proposed steps to develop a knowledge model for a system recommending Mauritian hotels. We have used UML for modeling the domain due to its common features between Object Oriented modeling and ontology modeling. We are presently working on the prototype of the application that will be used to validate the knowledge model.

Item recommendation

Recommender systems are a powerful new technology for extracting additional value for a business from its user data-bases. These systems help users and items they want to buy from a business. Recommender systems benefit

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 5, Issue 4, April 2016

users by enabling them to and items they like. Conversely, they help the business by generating more sales. Recommender systems are rapidly becoming a crucial tool in E-commerce on the Web. Recommender systems are being stressed by the huge volume of user data in existing corporate databases, and will be stressed even more by the increasing volume of user data available on the Web.

Venue recommendation

Venue recommendation system, we collected behavioral, social, and spatial data from Gowalla and Foursquare (via., Twitter) for a range of the world's metropolises, and evaluated how a variety of learning algorithms from simple, non-personalized popular venue recommendation to predictions based on matrix factorization methods were able to rank and classify the new venues for each user. We found that the collaborative filtering approaches that have been successful in online recommendation scenarios have not achieved a similar status with mobility data: instead, we found that our proposed random walk based model was able to consistently achieve the best performance, by learning from both social ties and venue-visit data simultaneously.

Web – Page recommendation

Web-page recommendation plays an important role in intelligent Web systems. Useful knowledge discovery from Web usage data and satisfactory knowledge representation for effective Web-page recommendations are crucial and challenging. This paper proposes a novel method to efficiently provide better Web-page recommendation through semantic-enhancement by integrating the domain and Web usage knowledge of a website. Two new models are proposed to represent the domain knowledge.

5. CONCLUSION

This paper introduced a cloud-based framework that produces optimized recommendations by simultaneously considering the factors, like person's geographical location and location closeness. The significance of the proposed framework is the adaptation of collaborative filtering (CF) and bi-objective optimization approaches, like scalar and vector. In this approach, data sparseness issue is determined by integrating the user-to user similarity computation with confidence measure that calculates the amount of similar interest indicated by the two users. Moreover, The solution to cold start issue is discussed by introducing the Hub-Average inference model that assigns ranking to the users and has a precompiled number of popular not visited venues that can be recommended to the new user.

6. FUTURE SCOPE

In the future, we would like to extend this survey by incorporating more contextual information in the form of objective functions. Moreover, we intend to integrate other approaches, like machine learning, text mining, and artificial neural networks to refine our existing framework. The results of comprehensive experiments on a large-scale real dataset confirm the accuracy of the proposed recommendation framework.

REFERENCES

[1] A. Majid, L. Chen, G. Chen, H. Turab, I. Hussain, and J. Woodward, "A Context-aware Personalized Travel Recommendation System based on Geo-tagged Social Media Data Mining," International Journal of Geographical Information Science, pp. 662-684, 2013.
[2] P. G. Campos, F. Díez, I. Cantador, "Time-aware Recommender Systems: A Comprehensive Survey and Analysis of Existing Evaluation Protocols," User Modeling and User-Adapted Interaction, vol. 24, no.1-2, pp. 67-119, 2014.
[3] C. Chow, J. Bao, and M. Mokbel, "Towards Location-Based Social Networking Services," In Proceedings of the 2nd ACM SIGSPATIAL International Workshop on Location Based Social Networks, ACM, pp. 31-38, 2010.
[4] M. Ye, P. Yin, and W. Lee, "Location recommendation for location-based social networks," In Proceedings of the 18th SIGSPATIAL International Conference on Advances in Geographic Information Systems, ACM, pp. 458-461, 2010.
[5] A. Noulas, S. Scellato, N. Lathia, and C. Mascolo, "A Random Walk around the City: New Venue Recommendation in Location-Based Social Networks," In Proceedings of International Conference on Social Computing (SocialCom), pp.144-153, 2012.
[6] Paired t test.Wiley Encyclopedia of Clinical Trials, 2008.
[7] J. Abimbola, "A Non-linear Weights Selection in Weighted Sum for Convex Multi-objective Optimization," Mathematics and Information, vol. 27, no. 3, 2012.
[8] H. Nasiri, M. Maghfoori, "Multiobjective Weighted Sum Approach Model reduction by Routh-Pade approximation using Harmony Search," Turkish Journal of Electrical Engineering and Computer Science, vol. 21, no.2,pp. 2283-2293, 2013.
[9] M. Ribeiro, A. Lacerda, A. Veloso and N. Ziviani, "Pareto-Efficient Hybridization for Multi-objective Recommender Systems," In Proceeding of 6th ACM Conference on Recommender Systems, pp. 19-26, 2012.
[10] K. Deb, A. Pratap, S. Agarwal and T. Meyarivan, "A Fast and Elitist Multi-objective Genetic Algorithm: NSGA-II," IEEE Transaction on Evolutionary Computations, vol. 6, no. 2, pp. 182-197, 2002.
[11] Y. Wang, S. Wang, N. Stash, L. Aroyo and G. Schreiber, "Enhancing Content-Based Recommendation with the Task Model of Classification," In Proceedings of the Knowledge and Management, pp. 431-440, 2010.
[12] J. Bobadilla, F. Ortega, A. Hernando, A. Gutiérrez, "Recommender Systems Survey," Knowledge-Based Systems,vol.46, pp. 109-132, 2013.
[13] J. Bao, Y. Zheng, M.F. Mokbel, "Location-based and Preference Aware Recommendation using Sparse Geo-Social Networking Data," In Proceeding of 20th International Conference on Advances in Geographic Information Systems, ACM New York, pp.199-208, 2012.
[14] B. Hidasi and D. Tikk, "Initializing Matrix Factorization Methods on Implicit Feedback Database," Journal of Universal Computer Science, vol. 19, no. 12, pp. 1835-1853, 2013.

 DOI 10.17148/IJARCCE.2016.5446