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Destination suggester with positive destination critic

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ABSTRACT: In recent years, the boundaries between e-commerce and social networking have become increasingly blurred. Many e-commerce websites support the mechanism of social login where users can sign on the websites using their social network identities such as their Face book or Twitter accounts. Users can also post their newly purchased products on micro blogs with links to the e-commerce product web pages. In this paper we propose a novel solution for cross-site cold-start product recommendation, which aims to recommend products from e-commerce websites to users at social networking sites in "cold start" situations, a problem which has rarely been explored before. A major challenge is how to leverage knowledge extracted from social networking sites for cross-site cold-start product recommendation. We propose to use the linked users across social networking sites and e-commerce websites (users who have social networkingaccounts and have made purchases on e-commerce websites) as a bridge to map users' social networking features to another feature representation for product recommendation. In specific, we propose learning both users' and products' feature representations (called user embeddings and product embeddings, respectively) from data collected from e-commerce websites using recurrent neural networks and then apply a modified gradient boosting trees method to transform users' social networking features into user embeddings. We then develop a feature-based matrix factorization approach which can leverage the learnt user embeddings for cold-start product recommendation. Experimental results on a large dataset constructed from the largest Chinese micro blogging service SINA WEIBO and the largest Chinese B2C e-commerce website JINGDONG have shown the effectiveness of our proposed framework.

I. INTRODUCTION

The ongoing rapid expansion of the Internet and easy availability of numerous e-commerce and social networks services, such as Amazon, Foursquare, and Gowalla, have resulted in the sheer volume of data collected by the service providers on daily basis. The continuous accumulation of massive volumes of data has shifted the focus of research community from the basic information retrieval problem to the filtering of pertinent information thereby making it more relevant and personalized to user's query. Therefore, most research is now directed towards the designing of more intelligent and autonomous information retrieval systems, known as Recommendation Systems.

A. Research Motivation

Recommendation systems are increasingly emerging as an integral component of e-business applications For instance, the integrated recommendation system of Amazon provides customers with personalized recommendations for various items of interest. Recommendation systems utilize various knowledge discovery techniques on a user's historical data and current context to recommend products and services that best match the user's preferences. In recent years, emergence of numerous mobile social networking services, such as, Facebook and Google Latitude has significantly gained the attraction of a large number of subscribers A mobile social networking service allows a user to perform a "check-in" that is a small feedback about the place visited by the user Large number of check-ins on daily bases results in the accumulation of massive volumes of data. Based on the data stored by such services, several Venue-based Recommendation Systems (VRS) were developed Such systems are designed to perform recommendation of venues to users that most closely match with users' preferences. Despite having very promising features, the VRS suffer with numerous limitations and challenges. A major research challenge for such systems is to process data at the real-time and extract preferred venues from a massively huge and diverse dataset of users' historical check-ins Further

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complexity to the problem is added by also taking into the account the realtime contextual information, such as: (a) venue selection based on user's personal preferences and (b) venue closeness based on geographic information.

B. Research Problem

In scientific literature, several works, have applied Collaborative Filtering (CF) to the recommendation problem in VRS. The CF-based approaches in VRS tend to generate recommendations based on the similarity in actions and routines of users However, despite being less complicated, most CF-based recommendation techniques suffer from several limitations that make them less ideal choice in many real-life practical applications 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 checkins 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-tovenu 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.

C. Methods and Contributions

In this paper, we propose Coldstart, a hybrid cloud based Bi-Objective Recommendation Framework (BORF) that overcomes the limitations exhibited by traditional CF-based approaches. The Coldstart framework combines memory-based and model-based approach of CF in a hybrid architecture to generate optimal recommendations for the current user. The memory based CF model utilizes a user's historical data and user to- venue closeness to predict venues for the current user. To address data sparseness caused by zero similarities, we utilize a metric known as confidence measure. The confidence measure defines the conditional probability that two users will show interest in the same set of venues and is expressed as the ratio of the number of venues visited by both users together to the number of venues visited by any one of the two users The confidence measure is utilized to compute link weight between two users, if and only if the similarity between the users is zero. In this way, confidence measure helps replacing many zero similarity entries in user-to-user to matrix by alternate non-zero entries, thereby improving recommendation quality. The proposed framework also suggests a solution to cold start problem by utilizing model-based Hub-Average (HA) inference method. The HA method computes and assigns popularity ranking to venues and users at various geographical locations. With such ranking available, the new user can be recommended with venues that have highest ranking in a geographical region. To improve scalability performance, the cloud-based Coldstart framework follows Software as a Service (SaaS) approach by utilizing a modular service architecture. The primary advantage of this approach is that the proposed framework can scale on demand as additional virtual machines are created and deployed. We adopt a bi-objective optimization approach that considers the two primary objectives: (a) venue preference and (b) location closeness. Venue preference determines how much the venue meets the criteria of user's interests, whereas venue closeness indicates how closely a desired venue is located relative to a user's location. The Coldstart framework generates optimized recommendations by simultaneously considering the trade-offs between the aforementioned objectives. In summary, the contributions of our work are as follows.

- We propose a cloud-based framework consisting of bi objective optimization methods named as CF-BORF and greedy-BORF. The Genetic Algorithm based BORF (GA-BORF) utilizes Non-dominated Sorting Genetic Algorithm (NSGA-II) to optimize the venue recommendation problem.
- We introduce a pre-processing phase that performs data refinement using HA.
- We perform extensive experiments on our internal Open Nebula cloud setup running on 96 core Super micro Super Server SYS-7047GR-TRF systems. The experiments were conducted on real-world "Gowalla" dataset To the best of our knowledge this is the first work to incorporate the bi-objective optimization techniques into

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VRS. The rest of the paper is organized as follows. Section 2 presents the system overview. In Section 3, we discuss the proposed BORF framework. Section 4 presents the complexity analysis of the proposed framework and the performance evaluation with simulation results. The related work is reviewed in Section 5, and Section 6 concludes the paper.

II. IMPLEMENTATION

A. Module description

Number of Modules :**After careful analysis the system has been identified to have the following modules:**

- **User Profiles**
- **Ranking Module**
- **Mapping Module**
- **Recommendation Module**

User Profiles

The Coldstartframework maintains records of users' profiles for each geographical region. A user's profile consists of the user's identification, venues visited by the user, and check-in time at a venue.

Ranking Module

On top of users' profiles, the ranking module performs functionality during the pre-processing phase of data refinement. The pre-processing can be performed in the form of periodic batch jobs running at monthly or weekly basis as configured by system administrator. The ranking module applies model-based HA inference method on users' profiles to assign ranking to the set of users and venues based on mutual reinforcement relationship. The idea is to extract a set of popular venues and expert users. We call a venue as popular, if it is visited by many expert users and a user as expert if she has visited many popular venues. The users and venues that have very low scores are pruned from the dataset during offline pre-processing phase to reduce the online computation time.

Mapping Module

The mapping module computes similarity graphs among expert users for a given region during pre-processing phase. The purpose of similarity graph computation is to generate a network of like-minded people who share the similar preferences for various venues they visit in a geographical region. The mapping module also computes venue closeness based on geographical distance between the current user and popular venues.

Recommendation Module

The online recommendation module that runs a service to receive recommendation queries from users. A user's request consists of: (a) current context (such as, GPS location of user, time, and region), and (b) a bounded region surrounding the user from where the top *N* venues will be selected for the current user (*N* is number of venues).The recommendation service passes the user's query to optimization module that utilizes scalar and vector optimization techniques to generate an optimal set of venues. In our proposed framework, the scalar optimization technique utilizes the CF-based approach and greedy heuristics to generate user preferred recommendations. The vector optimization technique, namely GA-BORF, utilizes evolutionary algorithms, such as NSGA-II to produce optimized recommendations.

Below is the architecture diagram which consists of cloud server , admin , remote user , web database which are connected as shown below :

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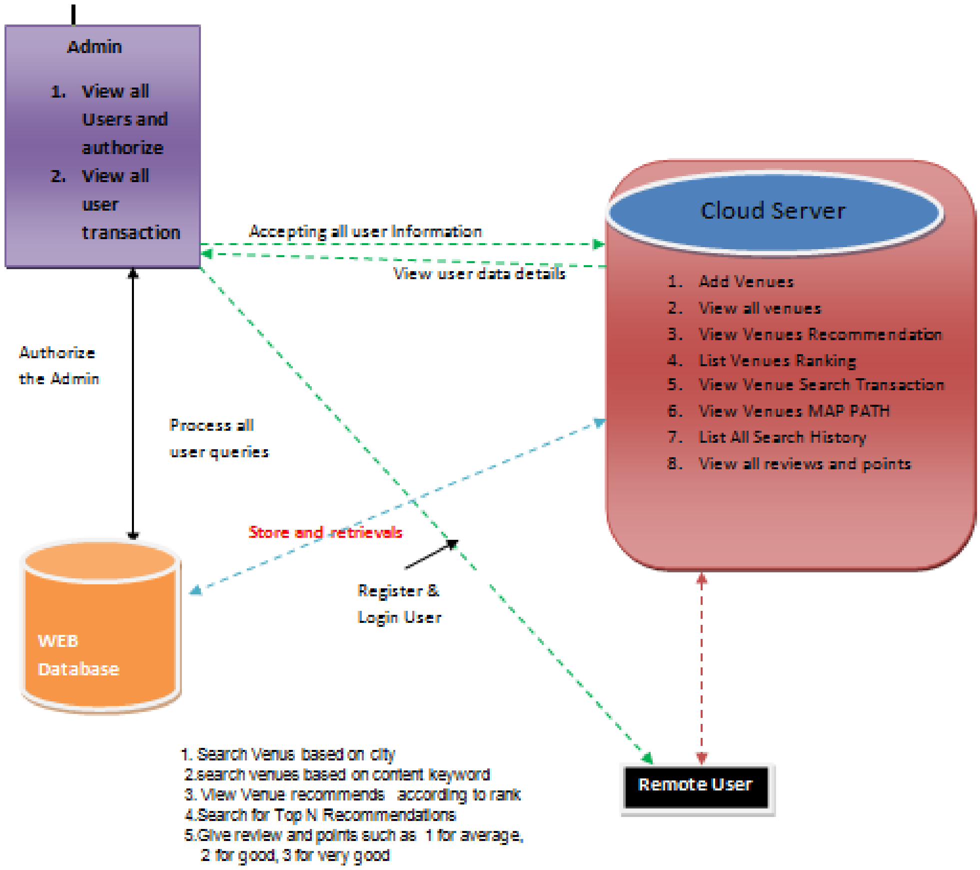

III. CONCLUSION

We proposed a cloud-based framework .ColdStart that produces optimized recommendations by simultaneously considering the trade-offs among real-world physical factors, such as person's geographical location and location closeness. The significance and novelty of the proposed framework is the adaptation of collaborative filtering and bi-objective optimization approaches, such as scalar and vector. In our proposed approach, data sparseness issue is addressed by integrating the user-touser similarity computation with confidence measure that quantifies the amount of similar interest indicated by the two users in the venues commonly visited by both ofthem. Moreover, a solution to cold start issue is discussed by introducing the HA inference model that assigns ranking to the users and has a precompiled set of popular unvisited venues that can be recommended to the new user. In the future, we would like to extend our work by incorporating more contextual information in the form of objective functions, such as the check-in time, users' profiles, and interests, in our proposed framework. Moreover, we intend to integrate other approaches, such as machine learning, text mining, and artificial neural networks to refine our existing framework.

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