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Cloud-Based Venue Recommendation Framework in Mobi-Context

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ABSTRACT

Recommendation systems have seen significant evolution in the field of knowledge engineering. Existing recommendation systems based their models on collaborative filtering approaches that make them simple to implement. However, performance of most of the existing collaborative filtering-based recommendation system suffers due to the challenges, such as: (a) cold start, (b) data sparseness, and (c) scalability. Moreover, recommendation problem is often characterized by the presence of many conflicting objectives or decision variables, such as users' preferences and venue closeness. Here proposed Mobi Context, a hybrid cloud-based Bi-Objective Recommendation Framework (BORF) for mobile social networks. To address the issues pertaining to cold start and data sparseness, the BORF performs data pre-processing by using the Hub-Average (HA) inference model. Moreover, the Weighted Sum Approach (WSA) is implemented for scalar optimization and an evolutionary algorithm (NSGA-II) is applied for vector optimization to provide optimal suggestions to the users about a venue. Comprehensive experiments on a large-scale real dataset confirm the accuracy of the proposed recommendation framework.

Keywords: Cloud, System, Data, Mobi, NGSA, HA, WSA, BORF.

1. Introduction

Overview: The popularity of digital cameras and camera phones has contributed to evolving approval of sharing on Internet communities such as Flickr (flicker.com) and YouTube Using these online community sites, users tend to expose more and more about their experiences on the Web through rich media data such as photos and videos. The development of location-based social media such as Face-book and Gowalla is not only transforming the landscape of computing but also stimulating social changes of various computing but also stimulating social changes of various kinds, and this phenomenon has moved social media from cyberspace to real place The growing size of individual and community footprints on the Web and fast-evolving Internet communities provides evidence about the extent to which the information has pervaded in our lives. These multimedia data such as photos contain not only contain textual information such as tags, title, notes and description but are also tagged with temporal context. An enormous amount of users generated content in the form of social media that exhibit their travelling experiences, which provides, a great opportunity to build a recommendation system for travel assistance with the following features.

2. Existing System

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

2.1 Disadvantages for Existing System

- **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 as parsley 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 the traditional recommendation system suffered from scalability issues. The fast and dynamic expansion of number of user's causes recommended system to parse millions of check-ins records to find the set of similar users. Some of the recommendation system employs data mining and machine learning techniques to reduce the dataset size. However there is an inherent trade-off between reduced dataset size and recommendation quality.

3. Proposed System

Here 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.

3.1 Advance of Proposed System

Most of the existing recommendation systems utilize centralized architectures that are not scalable enough to process large volume of geographically distributed data. The centralized architecture for venue recommendations must simultaneously consider users' preferences, check-in history, and social context to generate optimal venue recommendations. Therefore, to address the scalability issue, we introduce the decentralized cloud-based Mobi Context. BORF approach.

4. System Architecture

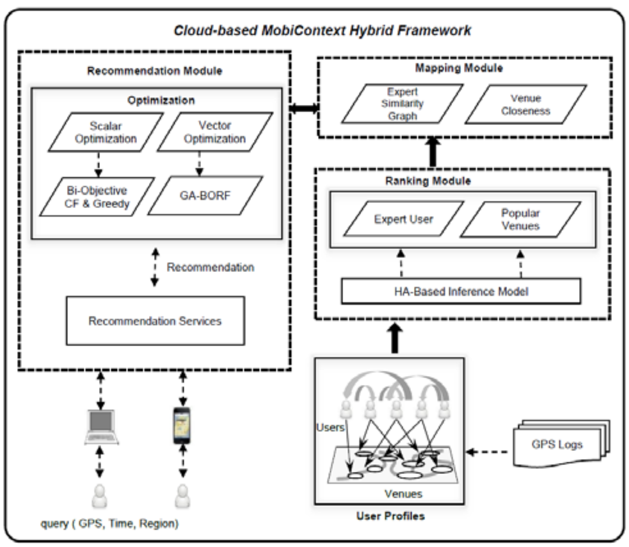

Figure 1: System Architecture

5. Module Descriptions

5.1 USER PROFILE: The Mobi Context framework 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.

5.2 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.

5.3. 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.

5.4. 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.

6 Future Enhancements

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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