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Context-Aware Venue Suggestions Cloud Based System

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Abstract: 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. The purpose of the survey is to design a more absolute and ever-present location based recommendation algorithm which can infer user's preferences and think about time geography including similarity measurements automatically for the better user experience. The system learns user preferences by drawing out a person's social network profile. The physical constraints are surrounded by a user's location, and form of transportation that is automatically detected through the use of a decision tree followed by a discrete Hidden Markov Model.

I. INTRODUCTION

Large-scale information systems (IS) are area under discussion to enthusiastically changing state of affairs in the IS delivery phase. The existing situation can be elaborated by different perspective data that can be defined as any information required characterizing the circumstances of an entity where an entity is a person, place, or object which is considered to be significant to the communication among the user and the application together with the user and the applications themselves. The context data can be taken into account in IS delivery thereby increasing the usability and user satisfaction.

Composite and widespread IS may reduce the user pleasure and, if possible, users may choose substitution ways of carrying out their tasks. Like for instance, general public are avoiding use of public e-services and are favouring physical services. Recommender systems are extensively used in order to recover the practice of software and tools which provide suggestions by recommending the items which the users might likely be interested for. The recommender systems are gradually becoming more popular. A variety of such systems pay attention on civilizing and evaluating the collaborative-filtering technique. They use secret information about historical user activity, user profile information and other information to match users with recommended items.

Progressively, the recommender systems initiate to use more diverse data and data sources, for instance, social network data. In a number of cases the perspective information may be applicable to estimate the most suitable recommendations for users by making use of context-aware recommendation systems. Latest investigations are made on location-based and weather-dependent recommendation algorithms and methods. Discovering proper context data is yet a confront in recommender systems evaluation. The projected approach involves the use of different context data that can be retrieved from both internal and external data sources. The context dealing out includes not only reading the context data, but also context data analysis that helps to forecast the context data and user behaviour. textual analysis, e.g. in the area of research, citations can be suggested for the research by analyzing words in research papers. With the intention of improve the recommender algorithms, hybrid recommender systems are urbanized by combining different recommendation algorithms and methods into one information system. The approach considers that recommendations could be any kind of software entity and instances of recommendations involve suggestions to carry out a function, procedure, and workflow or to perform data processing operations.

Different type of context information be capable of be using an input to the recommendation module. The modelling phase is well thought-out as significant as the models can help to deal with complexity and are easy perceptible for stakeholders without any specific IT skills. Recommendation modelling includes specifying a set of business rules that help to describe the software entities context dependencies and decides which recommendations should be run in each background situation.

At the moment variability in IS delivery becomes progressively more important. When business processes changes, software sustaining the processes must be accustomed in view of fulfilling the goals of the organization. Spirited software ought to be capable to deal with the changeability including minimal efforts. Variation in business processes can be exaggerated by internal and/or external context. Adjusting software to changes in form of user recommendations by combining the recommendation module in existing software that permit to deal with inconsistency without an important effort as the recommendations can be easily altered in recommendation module exclusive of changing the underlying software.

The potential of using context-aware recommendations, and proposal for an approach for modelling context aware recommender systems had been described by various authors. The modelling approach is based on the Capability Driven Development (CDD) method used in development of adaptive systems. The potential of using context-aware recommender systems is analyzed by exploring a use case from the e-government domain.

II. SYSTEM OVERVIEW

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 MobiContext BORF approach. The following are some of the major components of the proposed framework.

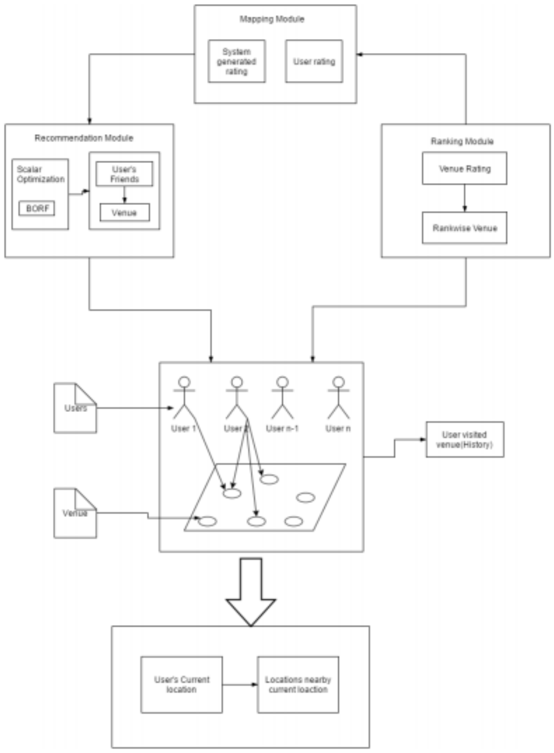

Figure 1

A. USER PROFILES

As reflected, the MobiContext framework maintains records of users' profiles for each geographical region. The arrows from users to venues at lower right of Fig. 1 indicate the number of check-ins performed by each user at various venues. A user's profile consists of the user's identification, venues visited by the user, and check-in time at a venue.

B. 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 relationships. 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 (s)he 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.

C. 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.

D. RECOMMENDATION MODULE

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.

E. ALGORITHM

ALGORITHM 1: GENERAL ALGORITHM

Input: Current User: c, region: R

Step 1: $Nc \leftarrow \emptyset; zagg \leftarrow \emptyset;$
Step 2: $Sr \leftarrow computsimset$ (c,E)
Step 3: for *each* $e \in Sr$ do
Step 4: S $\leftarrow \{v{:}V\ e|v \notin V\ c\}$
Step 5: $\varsigma ce \leftarrow (computsi(lc,$S))
Step 6: [e] $\leftarrow comput(sce\ ,\varsigma ce)$
Step 7: end for
Step 8: $Nc \leftarrow computRec($c, $zagg)$
Step 9: $Toprec \leftarrow sort\ (Nc)$

Output: $Toprec$= A set S' of top-N venues.

This algorithm is used for cloud based Mobicontext hybrid framework used scalar optimization technique. In this technique used this algorithm used for nearest venue finding.

The online recommendation module utilizes bi-objective optimization to generate an optimized list of venues. Suppose an current user A is interested in venue type T that must be located closest to the current location of the current user within a specific region R. In such a scenario, the current user requires the best preferred venues as well as the closest venues from the user's current location. To meet both the aforementioned objectives, utilize biobjective optimization in the proposed MobiContext recommendation framework.

ALGORITHM 2: RATING ALGORITHM

Input: Rating of user

Step 1: get user feeling
Step2: calculate average rating
Step3: Avg Rating = (User1 Rating) + (User2 Rating)/(Total Number Of Rating)

Output: Average rating of overall user

The algorithm is based on the Bayesian Average. This is a mathematical term, a calculation of an object's ranking based on the "credibility" of the ratings it receives. The calculation applies the number of votes and the ratings of the individual submissions, as well as the ratings of all other submissions and the overall number of votes cast. This ensures that the aggregate is always taken into account, which also makes it possible to represent quality.

Bayes' Formula: Avg Rating = (User1 Rating)+(User2 Rating)/(Total Number Of Rating)

III. LITERATURE REVIEW

A Context-aware Cloud-Based Venue Recommendation framework[1]It proposess a cloud-based framework Mobicontext that produces optimized recommendations by simultaneously considering the trade-offs among real-world physical factors, such as person's geographical location and location closeness. Context-aware Citatioon Recommendation [2] it describes the novel problem of context-aware citation recommendation, and built a context-aware citation recommendation prototype in CiteSeerX. Scalable Architecture for Context-Aware Activity-Detecting Mobile Recommendation Systems[3]It has demonstrated both that a client-server based mobile recommendation system is practical for large scale deployment and that a good density of users per server node can be obtained. A Survey on Context-aware Recommender Systems Based on Computational Intelligence Techniques[3]it describes a state-of-the-art in context-aware recommender systems based on the CI techniques, such as the fuzzy sets, ANNs, EC, SI, and the AISs.

IV. MATHAMATICAL MODEL

S is the main system it holds the four different modules. M1 first execute the admin phase which set the all pricing module.M2 introduces the user authentication module. M3 will work at the time user service accessing and meanwhile update the service pricing and timings.M4 finally display all analysis graphs as well user usage details.

S= {M1, M2,M3,M4}
M1={p1,p2……..pn}
M2= {U1, U2……Un}
U (i)={ p1,p2,p3….pn}

M3 update the pricing module user time usage at the time session ending.

M4 ={g1,g2……..gn} these the analysis graphs
Success condition
When M1!=null
Failure condition
M1==Null and U(i) cant able to access {p1,p2..pn}

V. CONCLUSIONS

Bi-Objective Recommendation Framework (BORF) represent the optimal solution in the form of venue based on active user preferences.

These factors include the availability of new types of contextual information in recommender systems, the development of new applications including recommendation technology, the reform of evaluation procedures for recommendation performance, the exploration of new crossovers amongst recommender systems and other areas, and the recognition of new fundamentals and concepts in recommender systems.

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