Swarm and Evolutionary Computation 17 (2014) 25–36

Contents lists available at ScienceDirect

Swarm and Evolutionary Computation

journal homepage: www.elsevier.com/locate/swevo

Regular Paper

Context aware filtering using social behavior of frogs

Shikha Mehta [a,*], Hema Banati [b]

[a] Jaypee Institute of Information Technology, Department of Computer Science Engineering, Noida, India
[b] Dyal Singh College, Department of Computer Science, University of Delhi, Delhi, India

ARTICLE INFO

Article history:
Received 12 December 2012
Received in revised form
10 January 2014
Accepted 21 February 2014
Available online 3 March 2014

Keywords:
Shuffled frog leaping algorithm
Context aware social filtering
Contextual three dimension social filtering
Demographic context
Context aware recommendations
Collaborative filtering

ABSTRACT

The problem of information overload surfaced with the emergent popularity of dynamic web applications. To tackle this issue, various context awareness approaches have been developed to filter the information. Conventional context aware social filtering techniques predominantly focus on time and location as context of the users. However, another relevant context that of user's demographic information is often left out. The paper presents demographic context based filtering using social behavior of frogs. The approach employs shuffled frog leaping algorithm (SFLA) to perform the context modeling and handle the sparsity and scalability issues in social filtering. The work proposes two distinct methodologies to model the demographic context – SFLA based Contextual two dimensional (SC2D) and SFLA based Contextual three dimensional (SC3D) approach. SC2D approach primarily develops a model based on social behavior and subsequently incorporates the personal demographic (occupation, gender, etc.) context to compute the most relevant items. In the SC3D approach, personal demographic context is amalgamated with social behavior to develop the model and thereafter a contextual model is used to generate most relevant items. Experimental studies revealed that SC2D approach is able to reduce the error up to 15% and 8% as compared to MAC2D and GAC2D, respectively, and SC3D approach improves the accuracy upto 31% with respect to MAC3D and upto 26% as compared to GAC3D. Analysis of variance (ANOVA) test results for all approaches corroborate that the differences between the means of SC2D, MAC2D and GAC2D and SC3D, MAC3D and GAC3D are highly significant. These results improve confidence in SFLA as a better optimization algorithm for context aware filtering.

1. Introduction

The increased interactivity over World Wide Web in the recent past has led to an explosive growth of information which far exceeds the ability of human beings to process them. To alleviate this information overload problem, intelligent applications are being devised to automatically identify the needs of web users and offer products, information and services to potentially interested users. These intelligent dynamic web applications are popularly known as recommender systems. Nowadays, recommender systems are the most widely explored web applications e.g., Amazon for books, Netflix for movies, etc. The prevalent techniques used to develop the recommender systems include collaborative filtering (Goldberg et al. [19]) and content based filtering (Balabanovic and Shoham [7]). Content based filtering approach filters out the irrelevant content based on the past preferences made by the user itself. It involves analysis of the content information associated with the user (e.g., user's interests, past purchase history, etc.) and items (product details) to match the user's interests with the items. Mehta et al. [32] presented GA-CBR (Genetic Algorithm-Case Base Reasoning) based approach to solve the cold-start problem prevailing in content based filtering systems. Cold-start problem arises when preferences of the new users are not available and it is hard to identify the community of the new user. Social context filtering technique primarily identifies the community of the active users by comparing the profile of active users with the community of other users and then filters the relevant content based on the community preferences. This technique does not require any content information about the items and is based on the hypothesis that similar users tend to like similar items. Herlocker et al. [22] studied the various social filtering algorithms and analyzed the various components of social filtering approach. Adomavicius and Tuzhilin [3] pointed that conventional social context filtering (Lynda et al. [31]) technique considers only two types of entities, users and items, to identify the most relevant items for the target users. This approach does not take into account any additional contextual information, such as time, location, weather, demographic background, or the company of other people, etc. to compute the relevance. In the real world, interests and preferences of the users are never static, they change according to the variations in the demographic profile of

* Corresponding author.
E-mail addresses: mehtshikha@gmail.com (S. Mehta), banatihema@hotmail.com (H. Banati).

http://dx.doi.org/10.1016/j.swevo.2014.02.003
2210-6502

the users, e.g., age, gender and type of occupation they are involved in. During school life, people are more energetic and full of enthusiasm, thus may be more interested in adventurous or thrilling movies for example, which may change to comedy movies as they become professional. Interests also vary according to the gender of the user. Nevertheless, most existing social context filtering algorithms assume that the users' and the items' characteristics are stagnant and ignore the demographic dimension of the user. While such assumptions are acceptable for relatively short time period of time, for long periods, interests of the users change as they pass through various lifecycle stages such as childhood, teen, adult and old age. Thus, demographic context of the user is an important factor to cope with the evolutionary nature of the user's personal interest. This paper presents two distinctive approaches to integrate the demographic context of the users in social filtering technique based on recommender system. The work primarily improves the performance of conventional social context filtering technique using nature-inspired algorithm namely, shuffled frog leaping algorithm (SFLA) [17]. Subsequently, demographic context of the user is incorporated to further improve the performance. Rest of the paper is organized as follows: Section 2 provides an insight of context modeling in prevalent social filtering systems. The SFLA based social filtering approach is discussed in Section 3 followed by context modeling approaches to contextual social filtering using SFLA in Section 4. Section 5 presents experiments and discussion of results. Conclusion and Future work are presented in Section 6.

2. Context modeling in social filtering systems

The notion of context has been widely studied in multiple research disciplines such as computer science applications, cognitive science, linguistics, philosophy, psychology, and organizational sciences. Schilit et al. [37] introduced the concept of context-aware computing and described it as "context-aware software adapts according to the location of use, the collection of nearby people, hosts, and accessible devices, as well as changes to such things over time. A system with these capabilities can examine the computing environment and react to changes in the environment". Dey [15] emphasized that the ability to enhance the behavior of any application by informing it of the context of its use remains a challenge in the field of ubiquitous computing. Dey et al. [16] defined context as any information that can be used to characterize the situation of entities (i.e. whether a person, place or object) that are considered relevant to the interaction between a user and an application, including the user and the application themselves. Context is typically the location, identity and state of people, groups and computational and physical objects. Allan et al. [4] observed contextual web search as an important long term challenge and defined contextual retrieval as "Combine search technologies and knowledge about query and user context into a single framework in order to provide the most 'appropriate' answer for a user's information needs." Adomavicius and Tuzhilin [2] defined the context-aware systems, as the applications that deal with modeling and predicting user's tastes and preferences by including the user's contextual information into the process of computing relevant items as explicit additional categories of data. Classically, in social context filtering systems, the process of computing relevant items for the target user begins with the specification of the user's feedback in the form of initial set of ratings that are either provided explicitly by the users or are implicitly inferred by the system. Subsequently, the system tries to estimate the rating function R for (user, item) pairs that have not yet been rated by the users.

$$\textit{Traditional Rating Function}(R): \ \textit{User} \times \textit{Item} \rightarrow \textit{Rating} \tag{1}$$

Rating is an ordered set of numbers (e.g., non-negative integers or real numbers) within a certain range, and User and Item are the domains of users and items respectively. Once the function R is estimated for the whole $User \times Item$ space, search system can retrieve the highest-rated item (or N highest-rated items) for each user. Such systems are called as two-dimensional (2D) as they consider only User and Item dimensions to identify the most relevant items for the users. On the other hand in the Context aware applications, additional dimension of context is incorporated to compute the rating function 'R' as follows:

$$\textit{Contextual Rating Function}(R): \ \textit{User} \times \textit{Item} \times \textit{Context} \rightarrow \textit{Rating} \tag{2}$$

where Context specifies the contextual information associated with the application. Thus, contextual approach estimates the relevancy of items using multiple dimensions (3D) – $User \times Item \times Context$ instead of two dimensions as used in conventional systems. Adomavicius and Tuzhilin [1] presented three algorithmic paradigms to incorporate the contextual information into the filtering process. These include Contextual pre-filtering (CPreF), Contextual post-filtering (CPoF) and Contextual modeling (CM). In all the three approaches, the process starts with "Data" on users, items, ratings and contextual information ("Context") and results in generating context-specific items for the user. In CPref, contextual information is used to filter out irrelevant ratings before they are used to compute the ratings of relevant items using standard (2D) methods whereas in CPoF contextual information is used after the classical (2D) filtering technique is applied to the standard ratings data. In context modeling, contextual information is embedded within the algorithm used for filtering out irrelevant information/items. This study was limited to present the various methods for incorporating 'context' in recommender systems where performance evaluation was not performed. In the recent years, various studies have been performed to show the effect of incorporating 'context' in information filtering systems as shown in Table 1. Herlocker and Konstan [23] studied context in the form of knowledge of user's current task and presented a task based recommender system. Kenta et al. [28] emphasized that users' action patterns change according to their current contexts and presented a context-aware approach that considered both users'

Table 1
"Context" dimensions studied in the literature.

Sr. no.	Reference	Context studied	Scalability problem handled	Sparsity problem handled
1	Herlocker and Konstan [23]	Task	×	×
2	Kenta et al. [28]	Task+Temporal	×	×
3	Pedro et al. [36]	Temporal	×	×
4	Wang et al. [40]	Mood	×	×
5	Nathan et al. [34]	Temporal(Week)	×	×
6	Gantner et al. [18]	Temporal	×	×
8	Lee et al. [30]	Date, temperature and weather	×	×
9	Panniello et al. [35]	Time of the year and intent of purchase	×	×