TOWARDS USER-CENTRIC SOCIAL NETWORKS

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Abstract: Social network portals, such as Facebook and Twitter, often discover and deliver relevant social data to a user's query, considering only system-oriented conflicting objectives (e.g., time, energy, recall) and frequently ignoring the satisfaction of the individual "needs" of the query user w.r.t. its perceptual preference characteristics (e.g., data comprehensibility, working memory). In this paper, we introduce *User-centric Social Network (USN)*, a novel framework that deals with the conflicting system-oriented objectives of the social network in the context of Multi-Objective Optimization and utilizes user-oriented objectives in the query dissemination/acquisition process to facilitate decision making. We present the initial design of the USN framework and its major components. Our preliminary evaluation with real datasets shows that USN enhances the usability and satisfaction of the user while in parallel provides optimal system-choices for network performance.

1 INTRODUCTION

The evolution of smartphone devices along with the ascend of social networks has enabled the invention of myriad of applications that allow users to continuously interact and share social data. This data is typically accessed using a portal provided by the social network provider, which enables querying the social data based on keywords that describe their content.

It is a fact that the environment of most social network portals is not user-centric (i.e., social content is presented using a global representation scheme applicable to all users). However, this global representation scheme is not always optimized based on specific user intrinsic characteristics (e.g., working memory span). In order to address the comprehension and orientation difficulties presented in such systems and satisfy the heterogeneous needs of the users, a number of researchers studied adaptivity and personalization (Brusilovsky, 2001; Lankhorst et al., 2002; Germanakos et al., 2008).

The process of content adaptation takes into account the parameters included in the user profile (e.g., working memory span, cognitive style) and returns the best adaptive environment that meets the individual preferences and demands of each user. However, enabling dynamic adaptation of the environment while in parallel aiming to optimize the runtime performance requirements of the network is not a trivial task as it requires tackling with a number of conflicting parameters (e.g., energy, time, usability). Because so many different parameters are involved, the respective problem is a proper object for *Multi-objective Optimization (MOO)*. In MOO, there is no single solution that optimizes all objectives simultaneously but instead a set of non-dominated solutions commonly known as the Pareto Front (PF). Our framework opts for a subset of these solutions that increase the usability of the social network taking into account the individual preferences of each user, facilitating in this way decision making.

In particular, in this paper we present User-centric Social Network (USN), a novel framework that combines system-oriented with user-oriented objectives in order to increase both the network performance as well as the query user's satisfaction. To the best of our knowledge, no previous work has combined the disciplines of multi-objective optimization and decision making with content adaptation and personalization in order to increase both network performance as well as usability.

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2 BACKGROUND AND RELATED WORK

We now provide related research work on multi-objective optimization and cognitive user profiles that lie at the foundation of the USN framework.

Multi-Objective Optimization (MOO) & Decision Making. It has been shown that *Multi-Objective Evolutionary Algorithms (MOEAs)* are more effective in tackling Multi-objective Optimization Problems (MOPs), as opposed to existing linear/single objective methods. In the literature, several MOPs were proposed within the context of Wireless Sensor Networks and Mobile Networks, tackled in most cases by Pareto-dominance based MOEAs, such as the state-of-the-art Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) (Deb et al., 2002). The particular class of decompositional MOEAs (MOEA/D) (Zhang and Li, 2007) utilized in this work, have been shown to be efficient and effective with combinatorial real life MOPs (Konstantinidis et al., 2010b; Konstantinidis et al., 2010a) by incorporating scalar knowledge and techniques. In general, a MOP solution obtained by MOEA refers to a feasible set of pareto-optimal solutions without committing any information about what represents a suitable compromise solution. This is due to the fact that all solutions are equally important. Therefore, in most cases a decision making phase (Chaudhuri and Deb, 2010) is required after the optimization phase to address this problem (i.e., select the most suitable compromise solution from the pareto-optimal set). A decision maker (Chaudhuri and Deb, 2010) is usually a human expert about the problem and is utilized for deciding which is the most appropriate solution. In our setting, the decision making is accomplished using the user-oriented objectives derived from the query user's cognitive profile.

Cognitive User Profiles. Effective personalization of content involves two important challenges: i) accurately identifying users comprehensive profiles, and ii) adapting any content and processes in such a way that enables efficient and effective navigation and presentation to the user. User Perceptual Preference Characteristics (UPPC) (Germanakos et al., 2008), serve as the primal personalization filtering element, which apart from the "traditional" (predetermined characteristics), emphasizes on a different set of characteristics, which influence the visual, mental and emotional processes that mediate or manipulate new information that is received and built upon prior knowledge, respectively different for each user or user group. It has been shown in environments such as

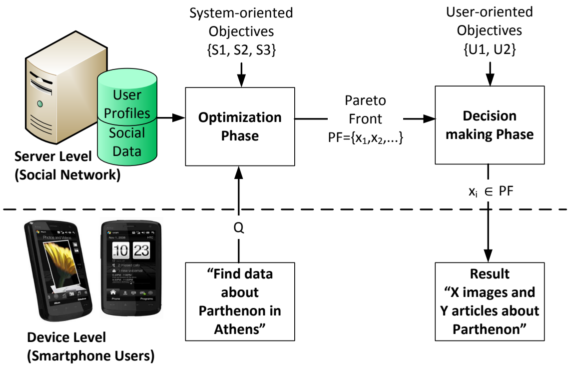

Figure 1: USN framework architecture.

eLearning and eServices (Germanakos et al., 2008) that these characteristics have a major impact on visual attention, cognitive and emotional processing.

In our context-based mobile social network setting, we have opted for two representative cognitive factors (i.e., user-oriented objectives), the Cognitive Style and Working Memory Span that are considered of high significance in such environments (Germanakos et al., 2008; Graf and Kinshuk, 2009). Mainly, our approach has been driven by the difference in cognitive information processing capabilities of the user.

3 USN FRAMEWORK

In this section, we provide the architecture of the USN framework including descriptions of its major components. Figure 1 illustrates the components of the USN framework and their interactions.

In the USN framework, each smartphone device stores its data (e.g., images, documents) in the device's local storage. When a user u_0 decides to search for social data, the device's interface generates a query Q and disseminates it to the social network. The social network portal recursively forwards Q to users not in close location or social proximity to u_0, similar to (Andreou et al., 2011). As soon as candidate users are selected (i.e., users that can participate in Q) they are forwarded to the *Optimizer* that generates solutions (i.e., sets of users, their social data and the connectivity among them), which are then evaluated using the system-oriented objectives until the set of non-dominated solutions (PF) is generated. The PF is then fed to the *Decision Maker*, which takes as input the query user's profile and extracts the user-oriented objectives. Each solution in PF is then ranked using the fitness error (calculated by the user-oriented objectives and the values in the query user's profile). The data of the most efficient solution are returned to the query user's smartphone. We now provide more detailed information on the major components of the USN framework.

3.1 User Profiles

The User Profile comprises of all the information related to the user such as traditional characteristics (e.g., age) and cognitive characteristics (e.g., working memory span). Additionally, each user profile is dynamically updated by continuously profiling the volatile characteristics of the user (e.g., time and location, navigation experience).

3.2 Optimizer

The USN optimizer utilizes the MOEA/D approach for generating the Pareto-optimal set of solutions (i.e., Pareto-Front). In order to accomplish this, the MOP is firstly decomposed into *m* subproblems (Zhang and Li, 2007). The i^{th} subproblem is in the form

$$maximize \quad g^i(\mathcal{G}|w^i_j, z^*) = max\{w^i_j|f_j(\mathcal{G}) - z^*_j|\} \quad (1)$$

where $\mathcal{G}$ denotes the Social Network Graph and f_j ($j = S1, S2, S3$) are the system-oriented objectives of our MOP, which are described below:

S1: *Minimize the total* Energy *consumption of* $\mathcal{G}$

$$Energy(\mathcal{G}) = MIN(\sum_{u_i \in \mathcal{G}} e(u_i, \mathcal{Q})). \quad (2)$$

where, $e(u_i, Q)$ denotes the energy consumption for transmitting all data objects of u_i that satisfy the filters of Q over the respective edge (WiFi, Bluetooth, 3G).

S2: *Minimize the* Time *overhead of* $\mathcal{G}$

$$Time(\mathcal{G}) = MIN(\sum_{u_i \in \mathcal{G}} t(u_i, Q)). \quad (3)$$

where, $t(u_i, Q)$ denotes the time overhead for transmitting all data objects of u_i that satisfy the filters of Q over the respective edge.

S3: *Maximize the* Recall *rate of* $\mathcal{G}$

$$Recall(\mathcal{G}, \mathcal{Q}) = MAX(\frac{Relev.(\mathcal{G}, \mathcal{Q}) \cap Retriev.(\mathcal{G}, \mathcal{Q})}{Relev.(\mathcal{G}, \mathcal{Q})}) \quad (4)$$

Our framework utilizes the aforementioned system objectives in order to obtain the pareto-front PF. In the final step, the generated PF solutions are fed into the Decision Maker for ranking.

3.3 Decision Maker

In order to facilitate decision making and opt for the most user-efficient solutions, the Pareto-optimal solutions $\mathcal{X} \in PF$ obtained are then evaluated using U1:Comprehension Ability and U2:Cognitive Overload user-oriented objectives. Note that the values for U1 and U2 are extracted from the profile p_i of user u_i:

U1: *Maximize Comprehension Ability*

$$CA(\mathcal{X}, p_i) = MAX\, cs(r(\mathcal{X}), p_i). \quad (5)$$

where, $cs(r, p_i)$ denotes the evaluation of the comprehension ability of user u_i over the results $r(\mathcal{X})$ based on its *cognitive style*.

U2: *Minimize Cognitive Overload:*

$$CO(\mathcal{X}, p_i) = MIN(wm(r(\mathcal{X}), p_i)). \quad (6)$$

where, $wm(r, p_i)$ denotes the evaluation of the cognitive overload of user u_i over the results $r(\mathcal{X})$ based on its *working memory*.

Decision Making/Support Fitness Error
In order to rank each PF solution, we define the *fitness error* as the *distance* of a solution $\mathcal{X}$ from the optimal solution (i.e., the difference between the obtained user-oriented objective values and the actual/exact values provided from the user profile).

$$FitnessError = |CA(\mathcal{X}, p_i) - p^{cs}_i| + |CO(\mathcal{X}, p_i) - p^{wm}_i|. \quad (7)$$

In the final step, USN ranks the solutions based on the fitness error and returns either the first one (i.e., automated decision making) or the *k*-most important ones (i.e., decision support). As soon as the final set of solution(s) is produced, the Decision Maker returns the results to the query processing mechanism, which in turn forwards the results to the query user.

4 EXPERIMENTAL EVALUATION

We have performed a preliminary evaluation of the USN framework using real datasets. We obtained user profiles from the AdaptiveWeb project (http:// adaptiveweb.cs.ucy.ac.cy/), which includes user profiles of 327 students of the University of Cyprus and University of Athens; 40% male, and 60% female, with ages varying from 19 to 23. Each profile contains information regarding the student's cognitive characteristics including his/hers Cognitive Style (objective U1) and Working Memory Span (objective U2). These profiles were derived after running a number of psychometric experiments provided by the AdaptiveWeb Project. Additionally, each user profile from the UPPC dataset

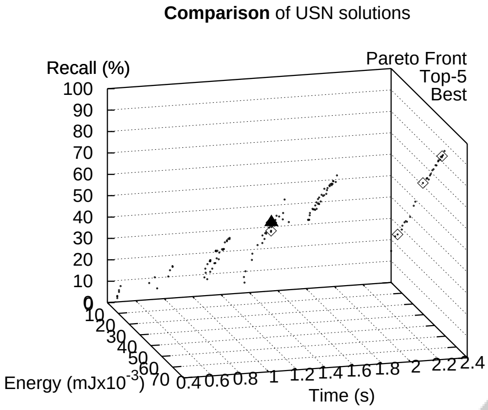

Figure 2: Optimal and Top-*k* solutions compared to the Pareto-Front (PF) solutions provided by USN.

was augmented with the user's social data content of Facebook. Finally, in order to introduce mobility in our experiments, we have utilized a publicly available real dataset by Microsoft Research Asia *GeoLife*, which includes 1,100 trajectories of a human moving in the city of Beijing over a life span of two years (2007-2009). At each timestamp, we select a user u_i as the query user and execute the following query (in SQL-syntax:
$\mathcal{Q}$= `` ``SELECT * FROM Users WHERE keyword LIKE filter'' ``, where *filter* is a keyword.

We study the Pareto-Front (PF) solutions provided by the USN framework. More specifically, we compare the fitness error provided by the best solution and the top-*k* solutions. In Figure 2, we demonstrate the results for a single timestamp (τ=19) for all solutions in the system-oriented objective space with the Energy,Time and Recall metrics. The PF solutions are represented by solid circles. The Top-*k* (*k*=5) solutions and the best solution are represented by diamonds and a solid triangle, respectively.

We observe that the Top-*k* solutions, w.r.t. the fitness error provided by the USN framework, almost spread across the whole system-oriented objective space. This is important as it enables the network decision maker to efficiently tune the system according to specific network requirements (e.g., low energy is more important than low time and high recall objectives) providing at the same time near-optimal user-oriented fitness. The execution time required for generating the solutions was $\approx$32562$\pm$3409ms, which is not applicable for systems requiring realtime performance. However, cloud-computing or parallel processing can alleviate this problem by evaluating each solution in each generation independently. Since network operators typically employ server farms that feature thousands of processing cores running in parallel, the execution time can be reduced by several orders of magnitude thus offering realtime performance.

5 CONCLUSIONS

In this paper, we introduced *User-centric Social Network (USN)*, a novel framework that incorporates user-oriented objectives in the search process. We presented the initial design of the USN framework as well as a preliminary evaluation, which demonstrates that USN enhances usability and satisfaction while in parallel optimizing the performance of the network w.r.t. energy, time and recall.

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