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USN: Multi-Objective User-centric Social Networks with Decision Making

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ΤΜΗΜΑ ΠΛΗΡΟΦΟΡΙΚΗΣ

ΠΑΝΕΠΙΣΤΗΜΙΟ ΚΥΠΡΟΥ

DEPARTMENT OF COMPUTER SCIENCE

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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., working memory, data comprehensibility). 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 as well as a preliminary evaluation of our framework. We show that USN enhances usability and satisfaction of the user while in parallel provides optimal system-choices for the performance of the network.

1 Introduction

The evolution of smartphone devices (e.g., Android, iPhone) along with the ascend of social networks (e.g., Facebook, Twitter) has enabled the invention of myriads of applications that continuously interact and share social data (i.e., images, videos, documents). This is more evident in the case of mobile smartphone users, where new data is generated arbitrary at runtime within the context of a social event (e.g., taking pictures of sights, participation at social events). This data is typically accessed using a portal provided by the social network provider, which often includes utilities for searching and retrieving social data based on keywords that desribe their content. Additionally, since this data are socially related with real events, they are often augmented by time and location properties that enables mobile users to search/query data based on spatio-temporal parameters. The results of the query process are often ranked based on their social relevance to the query user. Social factors (e.g., common friends, popularity, similar interests) are fed into the ranking process in order to present to the user what is perceived to be the "most relevant" content for his/her query. Even though these social factors can efficiently determine the *what* social content is more relevant, they do not take into consideration the *how* this social content is presented to the query user.

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 based on predetermined categorization). For example, searching for images of the Parthenon in Athens will always return a list of relevant images in a predefined manner (i.e., thumbnail, description). However, this global scheme is not always optimized based on specific user intrinsic characteristics (e.g., cognitive learning ability) that could significantly enhance its understanding and satisfaction. Hence, a number of researchers studied adaptivity and personalization [10; 3; 11; 5; 6] to address the comprehension and orientation difficulties presented in such systems; to alleviate navigational difficulties and satisfy the heterogeneous needs of the users.

Content adaptation techniques require the existense of a user profile which is constructed based on a number of user-centric parameters. A subset of these parameters quantify the users intellectuality, mental capabilities, socio-psychological factors, emotional states and attention grabbing strategies. These are further augmented by the traditional user characteristics (i.e., name, age, education, etc.) in order to constitute a more comprehensive user profile that typically classifies users to various cognitive typologies (e.g., imager/verbalizer[1]). The process of content adaptation takes into account the parameters included in the user profile and returns the best adaptive environment that meets the inidividual preferences and demands of each user. The majority of social network portals do not take into consideration this process thus decreasing the usability of the results and the performance of the network. An example that demonstrates this argument is a verbalizer requesting recent newsfeeds on his/her friends. The results may include undesirable content (i.e., images) that can significantly hamper the user's comprehension capability and additionally require more resources (i.e., energy, time) in order to be transmitted. One way to cope with the former is to introduce a content adaptation layer on each user's mobile device that dynamically adapts the presentation of the data in order

[1] users that belong in the imager class can process image content more efficiently than text whereas users that belong in the verbalizer class the oposite.

to meet the individual requirements of the user.

Enabling dynamic adaptation of the environment while in parallel aiming to optimize the runtime performance requirements of the network is not a trivial task. This process becomes even more complicated if we additionally take into account the recourse limitations of smartphone devices (e.g., battery, screen size) and the security/privacy[2] requirements of the user. Because so many different aspects 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 to facilitate decision making.

In particular, in this paper we present User-centric Social Networks (USN), a novel framework that increases usability by incorporating user-centric performance metrics into the optimization process. Additionally, we present the architecture of this framework and show how user profiles can further assist the content adaptation process at the network as well as the device level. To the best of our knowledge, no previous work has combined the disciplines of content adaptation and personilization with multi-objective optimization in order to increase the usability and performance of the network.

Our main contributions are summarized as follows:

- We present an inter-disciplinary model that incorporates usability performance metrics into the optimization process along with the traditional network performance characteristics.
- We propose a novel framework, named USN, that enables content adaptation at both the device and network level, increasing in this way the usability metrics for each individual user.
- We present a preliminary evaluation of the proposed framework using datasets with user profiles and mobility patterns derived from the GeoLife project [13].

The remainder of the paper is organized as follows: Section 2 discusses the related work. In Section 3 and Section 4 we present the model and a formal definition of the proposed problem. The architecture of the proposed framework is introduced in Section 5, providing details for each component. The experimental methodology, setup and results are shown in Section 6. Finally, Section 7 concludes the paper.

2 Background and Related Work

In this section we provide related research work on user modeling and multi-objective optimization, both of which lie at the foundation of our framework.

User Profiling: Effective personalization of content involves two important challenges: i) accurately identifying users comprehensive profiles, and ii) mapping any content

[2]In this paper, we do not consider security/privacy requirements but we plan to address them in a future work.

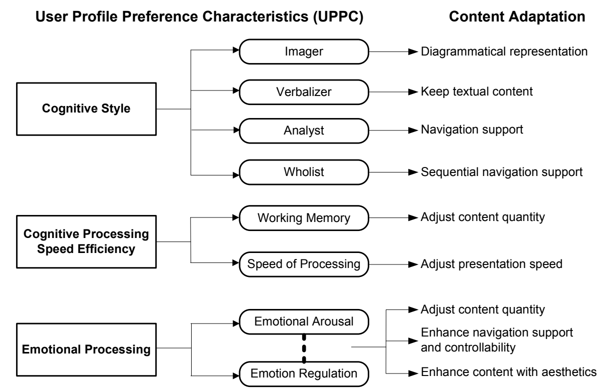

Figure 1: Cognitive Styles Classification

and processes in such a way that enables efficient and effective navigation and presentation during the adaptation process. User Perceptual Preference Characteristics (UPPC) [5; 6], serve as the primal personalization filtering element that emphasizes on critical factors, apart from the "traditional" (predetermined characteristics), that 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. These characteristics (see Figure 1), which have been primarily discussed in our previous work [5; 6], have a major impact on visual attention, cognitive and emotional processing that takes place throughout the whole process of accepting an object of perception (stimulus), until the comprehensive response to it. Figure 1 also shows the possible content transformations/enhancements during the adaptation process based on the influence of the human factors and the theory of individual differences. The information processing parameters that we have used and evaluated in the case of an eLearning and eServices [6] environment comprise a comprehensive user model that includes the following three dimensions: i) Riding's and Cheema's Cognitive Style Analysis [10], ii) Cognitive Processing Speed Efficiency, and iii) Emotional Processing (EP). The first dimension is unitary, whereas Cognitive Processing Efficiency is comprised of (a) Working Memory Span [2], (b) speed and control of information processing, and (c) visual attention.The emotional aspect of the model additionally focuses on different aspects of anxiety [3; 11] and self-regulation.

In our context-based mobile social network setting, where the dynamicity, performance, recall, energy etc., constraints are directly related to user-centric adaptation, we have currently opted for the Cognitive Style and Working Memory Span personalization paremeters that we consider of high significance in such environment.

Multi-Objective Optimization (MOO): is a new area in smartphone networks and relatively new area in mobile/wireless networks, in general. Therefore, it is difficult to apply an existing linear/single objective method to effectively tackle a Multi-objective Optimization Problem (MOP), giving a set of non-dominated solutions. On the other hand,

Table 1: Table of Symbols

Symbol	Description
$\mathcal{S}$	Social Network Portal
$\mathcal{U}$	Users of $\mathcal{S}$ ($\{u_1, u_2, ..., u_N\}$)
$\mathcal{P}$	User Profiles of $\mathcal{S}$ ($\{p_1, p_2, ..., p_N\}$)
p_i^{wm}	Working Memory value stored in u_i'profile
p_i^{cs}	Cognitive Style value stored in u_i'profile
u_0	Query User
$\mathcal{Q}$	Query for social data
$\mathcal{G}$	Social Network Graph
$\mathcal{R}_Q$	Social data results for query Q

Multi-Objective Evolutionary Algorithms (MOEAs) used in this work, have been shown effective in obtaining a set of non-dominated solutions in a single run. In the literature, several MOPs were proposed in the context of Wireless Sensor Networks and Mobile Networks [7], tackled in most cases by Pareto-dominance based MOEAs, such as the state-of-the-art Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) [4] etc. The particular class of decompositional MOEAs (MOEA/D) [12] utilized in this work, have been shown to be efficient and effective with combinatorial real life MOPs [9; 8] by incorporating scalar knowledge and techniques. MOEA/D has been applied to the Deployment and Power Assignment Problem (DPAP) of Sensor Networks [9] as well as the Mobile Agent-based Routing problem [8].

3 System Model

In this section we formalize our system model and the basic terminology upon which we describe our framework. The main symbols and their respective definitions are summarized in Table 1. Let $\mathcal{S}$ denote a social network portal that maintains a set of users $\mathcal{U} = \{u_1, u_2, ..., u_N\}$ along with their respective profiles $\mathcal{P} = \{p_1, p_2, ..., p_N\}$. The profile p_i of a user u_i contains its UPPC attributes, including its cognitive style p_i^{cs}, and its working memory p_i^{wm}. We augment each user u_i with a set of social data (e.g., text, images, documents). At an arbitrary moment, a user u_i disseminates a query $\mathcal{Q}$ to the network requesting social data from other users. Users in close proximity to u_i may be queried using short range wireless connectivity (e.g., Bluetooth). This process can be repeated recursively in order to reach users that are located more than 1-hop away from u_i. Finally, other users can be queried through the social network portal $\mathcal{S}$ which creates a network with users that are currently online and in social or location proximity to the query user. In this paper, we adopt the notion of a *social network graph*, $\mathcal{G}$ ($\mathcal{G} \subseteq \mathcal{U}, \mathcal{G} \neq \emptyset$), for all the users that receive Q from u_i (i.e., in close proximity, or through the network portal) . Finally, the results of the query Q, denoted as $\mathcal{R}_Q$, are returned to the query user u_i.

4 Problem Formulation

In order to formulate our problem as a Multi-objective Optimization Problem (MOP) with Decision Making (DM), we need to explicitly define the MOP objectives as well as the objectives for posteriori DM. These objectives are classified into two categories: i) system-oriented objectives and ii) user-oriented objectives, respectively. In this work, we consider S1:Energy Consumption, S2:Time Overhead and S3:Recall as representative objectives of the system category:

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

$$Energy(\mathcal{G}) = MIN(\sum_{u_i \in \mathcal{G}} e(u_i, \mathcal{Q})). \quad (1)$$

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 and 3G).

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

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

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.

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

$$Recall(\mathcal{G}, \mathcal{Q}) = MAX(\frac{Relevant(\mathcal{G}, \mathcal{Q}) \cap Retrieved(\mathcal{G}, \mathcal{Q})}{Relevant(\mathcal{G}, \mathcal{Q})}) \quad (3)$$

When a user u_i posts a query $\mathcal{Q}$ to its social network $\mathcal{G}$, our framework utilizes the aforementioned system objectives in order to obtain the PF. In order to facilitate DM 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, based on the user profile p_i of u_i:

Objective U1: *Maximize Comprehension Ability*

$$CA(\mathcal{X}, p_i) = MAX cs(r(\mathcal{X}), p_i). \quad (4)$$

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*.

Objective U2: *Minimize Cognitive Overload:*

$$CO(\mathcal{X}, p_i) = MIN(wm(r(\mathcal{X}), p_i)). \quad (5)$$

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*.

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).

$$FitnessError = |CA(\mathcal{X}, p_i) - p_i^{cs}| + |CO(\mathcal{X}, p_i) - p_i^{wm}|. \quad (6)$$

5 System Architecture

In this section we provide the initial design of the USN framework's architecture including the description of its major components. Figure 2 illustrates the components of the USN architecture and their interactions.

In the USN framework, each device stores its data (e.g., images, documents) in the *User Content Database*. This data

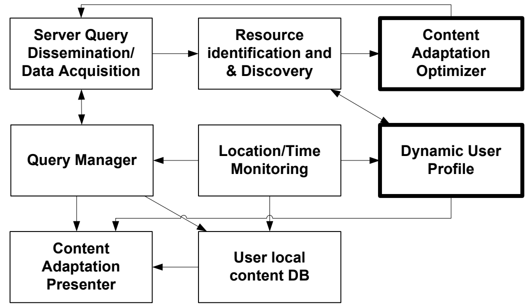

Figure 2: USN Framework Architecture

can be augmented with location and time attributes to enable spatio-temporal queries. This is accomplished by the *Location/Time Monitoring* component, which continuously tracks the location of the user and the time that the device is used. The current location can be retrieved either by using absolute means (e.g., GPS) or relative means (e.g., WiFi RSSI).

When a user decides to search for social data, then the device interface generates a query using the *Query Manager* API. The Query Manager acts both as a client (i.e, disseminates queries to the social network and returns the results to the user) and as a server by recursively forwarding queries to users not in proximity to the query user, similar to citeinfosys11. When a query is received, then the *Resource Identification and Discovery* component identifies candidate users that can participate in a query based on their user profile which is maintened by the *Dynamic User Profile* component. Candidate users can be in close social proximity (i.e., the query is received by the portal) or in actual proximity (i.e., the query is received by another smartphone device, which then forwards the query to near-by users).

As soon as candidate users are selected then their user profiles are forwarded to the *Content Adaptation Optimizer* which generates solutions (i.e., a set of users that will participate in the query and the connectivity among them) based on the system and user-oriented objectives. The most efficient solution is returned to the *Query Manager* which then communicates with all users and generates a result set. The resultset is then dispatched to the query user's smartphone. In order to display the results more efficiently to the query user, USN utilizes the *Content Adaptation Presenter*, which adapts/transforms any social content retrieved based on the profile of the user (see Figure 1).

The two sections below we provide insight on the two major components of the USN framework; the *Dynamic User Profile* and the *Content Adaptation Optimizer*.

Dynamic User Profile

The Dynamic User Profile comprises of all the information related to the user (traditional characteristics, cognitive characteristics, and characteristics that change over time (i.e., users current location, navigation experience, etc.). It consists of two phases:

1. *User Profile Construction*: The user profile construction process takes place on a workstation with adequate resources (e.g., large screen size) because the online real-time psychometric tests each user has to undertake require realtime performance. Users provide their traditional characteristics (i.e., name, age, education, etc.) and perform a number of interactive tests using attention and cognitive processing efficiency grabbing psychometric tools [5; 6] in order to quantify the cognitive characteristics of the user.

2. *User Profile Maintenance*: The user profile maintenance process is responsible for maintaining up-to-date profiles with regards to the dynamic characteristics of the user (i.e., time and location, navigation experience, device/channel characteristics, etc.). This is achieved by continuosly profiling the user's navigation experience on the personalized content (e.g., with the use of click streams or explicit feedback of the user).

Content Adaptation Optimizer (CAO)

The MOEA/D approach is utilized for generating the Pareto-optimal set of solutions (i.e., Pareto-Front), since it has been shown primising in dealing with real life MOPs as discussed in Section 2. In order to accomplish this, the MOP is firstly decomposed into m subproblems by adopting any technique for aggregating functions [12] (e.g., the Tchebycheff approach used here). The i^{th} subproblem is in the form

$$maximize \quad g^i(\mathcal{G}|w^i_j, z^*) = max\{w^i_j|f_j(\mathcal{G}) - z^*_j|\} \tag{7}$$

where f_j, $(j = S1, S2, S3)$, are the system-oriented objectives of our MOP formulated earlier in Section 4, $z^* = (z^*_1, z^*_2, z^*_3)$ is the reference point, i.e. the maximum objective value $z^*_j = max\{f_j(\mathcal{G}) \in \Omega\}$ of each objective f_j and Ω is the decision space. For each Pareto-optimal solution $\mathcal{G}^*$ there exists a weight vector w such that $\mathcal{G}^*$ is the optimal solution of (7) and each solution is a Pareto-optimal solution of the MOP in Section 4.

In MOEA/D, the Internal Population (IP), which is the set with the best solutions found for each subproblem i during the search, is randomly initialized. At each generation (i.e., iteration) a new solution O is generated using the genetic operators [12] (tournament selection, 2x crossover, random mutation). Next (during update), the IP, the neighborhood of i (i.e., the solutions of the T closest subproblems of i in terms of their weight coefficients $\{w_1,..., w_m\}$) and the external population (i.e., the PF which stores all the non-dominated solutions found so far during the search) are updated with O. The search stops after a predefined number of generations. More details on MOEA/D are presented in [12].

Secondly, CAO calculates the fitness error of each solution $\mathcal{X} \in PF$ based on Equation 6. Finally in the third step, CAO ranks the solutions and opts for the k most efficient ones w.r.t the user preferences. The intuition behind utilizing a ranking mechanism instead of opting for a single solution $\mathcal{X}$ w.r.t the fitness error is that in some cases, a solution $\mathcal{X}$ with the lowest fitness error may be less preferable than a solution $\mathcal{Y}$ w.r.t its system-oriented objective values (e.g., $\mathcal{Y}$ requires less energy than $\mathcal{X}$).

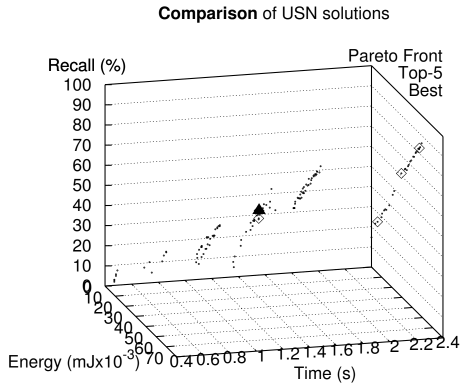

Figure 3: Optimal and Top-k solutions compared to the Pareto-Front (PF) solutions provided by the USN framework.

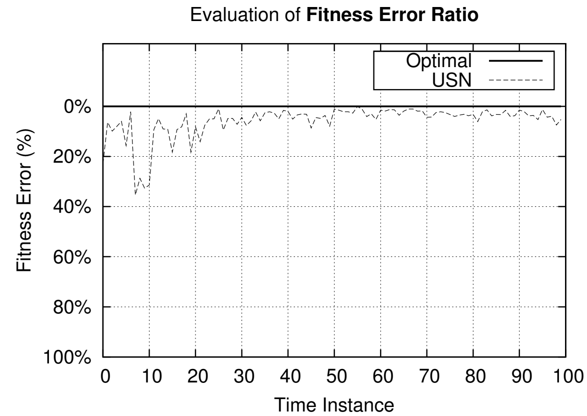

Figure 4: Comparison of the fitness error of the best solution provided by the USN framework with the actual/exact values of the query user's cognitive style.

6 Experimental Evaluation

In this section we present our experimental methodology and the results of our evaluation.

6.1 Experimental Methodology

Datasets and Queries: For our problem setting, we have used the following three datasets:

i) *UPPC*: This is a real dataset, obtained by the AdaptiveWeb project[3] which includes data of psychometric experiments on a number of students of the University of Cyprus and University of Athens. It contains profiles of 327 students; 40% male, and 60% female, with ages varying from 19 to 23. Each profile contains information regarding the students cognitive characteristics including its Cognitive Style (objective U1) and Working Memory Span (objective U2).

ii) *SocialData*: In order to augment each user profile with social data content similar to Facebook, we have generated a dataset that includes social data (i.e., images,text) for the users of the UPPC dataset. Each social data object includes a description, which is later used for keyword-based querying.

iii) *GeoLife* [13]: In order to introduce mobility in our experiments, we have utilized a real dataset by Microsoft Research Asia, which includes 1,100 trajectories of a human moving in the city of Beijing over a life span of two years (2007-2009). The average length of each trajectory is $190,110 \pm 126,590$ points, while the maximum trajectory length is 699,600 points. In order to link datasets (i) and (iii) we have randomly selected 327 users of the GeoLife dataset and mapped them with users of the UPPC dataset.

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 (e.g., dancing).

Experimental Setup: Our simulation experiments were performed on a Lenovo Thinkpad T61p PC with an Intel Core 2 Duo CPU running at 2.4GHz and 4.0 GB of RAM. In order to collect realistic results for a long period of time, we collect statistics for 100 timestamps in each experiment. To increase the fidelity of our measurements we have repeated each experiment 5 times and present the average performance for each type of plot.

[3]The AdaptiveWeb Project, http://adaptiveweb.cs.ucy.ac.cy/

6.2 Experimental Results

Experimental Series 1: Comparison of USN solutions
In the first experimental series we study the Pareto-Front (PF) solutions provided by the USN framework. More specifically, we compare the best solution and the top-k solutions w.r.t the fitness error. In Figure 3, 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. Additionally, the execution time required for generating the solutions is $\approx$32562$\pm$3409ms which is not applicable for systems requiring realtime performance. However, parallel processing can greatly reduce the processing speed by evaluating each solution in each generation independently. Since network operators employ typically 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.

Experimental Series 2: Evaluating the fitness error of the USN framework
In the second experimental series, we evaluate the fitness error of the USN framework by using 100 consecutive times-

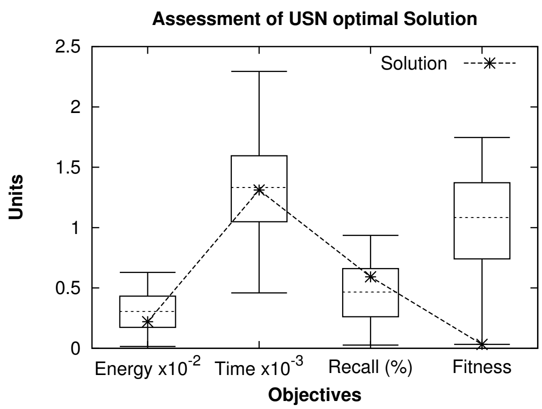

Figure 5: Assessment of USN optimal solution w.r.t. fitness error in comparison with the system oriented metrics.

tamps from the GeoLife dataset. At each timestamp τ, we show the ratio of the best solution generated by the USN framework compared to the actual/exact values of cognitive style p_0^{cs} and working memory p_0^{wm} stored in the profile p_0 of the query user u_0.

Figure4 illustrates the results of our experiment. We observe that in most timestamps, the fitness error of the USN framework is very close to the (5±6%) optimal case. This means that the distribution of data provided to the query user closely matches the cognitive style attributes stored in its profile. However, in τ=5-10 we observe that the fitness error ratio drops to 24±12%. This is because the number of users rapidly decreases $\approx 21 \pm 6\%$ during these timestamps. This had a significant effect on the overall number of images and text of the network thus decreasing the near-optimal combinations and therefore solutions in the objective space. Overall, the USN framework minimizes the fitness error, which translates to a high satisfaction level with respect to the query user's profile demands.

Experimental Series 3: Leveraging System Performance Metrics

In the final experimental series we assess the optimal solution provided by the USN framework in comparison with the system oriented objectives. Once more, we utilize 100 consecutive timestamps from the GeoLife dataset and record the values for all system performance metrics and fitness error. In order to demonstrate the distribution of values for each objective we have chosen the boxplot graph. We plot each objective as a seperate boxplot and compare the best solution using a dotted line.

Figure 5 show the results of our analysis. We observe that in order to maintain a minimal fitness error (i.e., satisfy the user objectives) the best solution uses low energy (1^{st} Quartile), average time (1^{st} Quartile) and high recall (3^{rd} Quartile). In conclusion, the best solution provided by the USN framework minimizes the fitness error while in parallel leveraging the performance of the system.

7 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 of our framework, which demonstrates that USN enhances usability and satisfaction while in parallel optimizing the performance of the network w.r.t energy, time and recall.

In the future, we plan to implement our framework on real smartphone devices and perform a more comprehensive evaluation utilizing a number of different settings (e.g., real datasets, different query sets, network failures). Additionally, we plan to study the effect of security/privacy requirements and investigate collaboration aspects amongst users.

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