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Social pervasive systems: the harmonization between social networking and pervasive systems

Soumaia Al Ayyat
soumaia@aucegypt.edu

Social Pervasive Systems: The Harmonization Between Social Networking and Pervasive Systems

Soumaia Ahmed Al Ayyat
Department of Computer Science
The American University in Cairo
Cairo, Egypt
Email: soumaia@aucegypt.edu

Abstract—**The recent advancement in mobile device sensor technology, coupled with the wealth of structured accessible data of social networks, form a very data-wealthy ecosystem. Such an ecosystem is rich in bi-directional context that can flow between the mobile and social worlds enabling the creation of an elitist breed of pervasive services and applications. We label the breed resulting from the merger as Social Pervasive Systems (SPS).**

Social Pervasive Systems Vision, Challenges and Proposed Solutions: We have reviewed literature of the domains of social networks and mobile pervasive systems to study prior research attempts to merge both domains. We started by presenting our observations in a timeline, as shown in figures 1 and 2, that illustrates the progress of the merger attempts. From our observations, we detected two phases along the merger process between the two domains. The first phase, illustrated in figure 1, started in the late 90s till 2006 which was characterized by few attempts that benefit from the context information attained from the pervasive systems and the social systems. The second phase of merger, illustrated in figure 2, started in 2007 and witnessed more mature merger attempts. The emergence of this second phase is attributed to the exponential improvement in mobile sensor technology and network infrastructure. From this study, we were able to identify a set of application families that can be a prospect byproduct of the merger. We also identified a set of challenges that deter the formation of such systems and proposed solutions for them. We then empirically focused on a sub-domain of Social Pervasive Systems; one that deals with data forwarding algorithms used in mobile systems. We focused on the challenges facing such algorithms and the drawbacks in performance in terms of efficiency, effectiveness and fairness as presented in figure 3. This vision has been published as a conference paper [1].

From there, we proposed and experimented with solutions to improve the performance of opportunistic forwarding algorithms that are much needed in environments lacking network infrastructure or those vulnerable to frequent disruptions. To achieve improvement, we used bi-directional context from the mobile and social worlds pertaining to user mobility, social interest, power awareness, and contact durations. Three major contributions were proposed. Two of them demonstrate an improvement over popular opportunistic forwarding algorithms, namely the interest and power insensitive algorithms PeopleRank [2] and SocialCast [3]. The third one proposes proper social metrics for social recommender systems in academic social networks.

Interest-Aware Social-based Forwarding: The first contribution demonstrates how eliciting interest-awareness knowledge facilitates context-dissemination to interested nodes; thus reducing the cost of massive uninteresting information dissemination that overwhelms nodes without gained benefit. It is necessary to bring in an incentive to motivate nodes in the forwarding process participation, especially in environments lacking communication infrastructure where reliance on the available mobile nodes is highly substantial. However, the owners of these mobile devices cherish their limited resources. Consequently, it is essential for these forwarding approaches to introduce incentives to gain forwarder nodes willingness

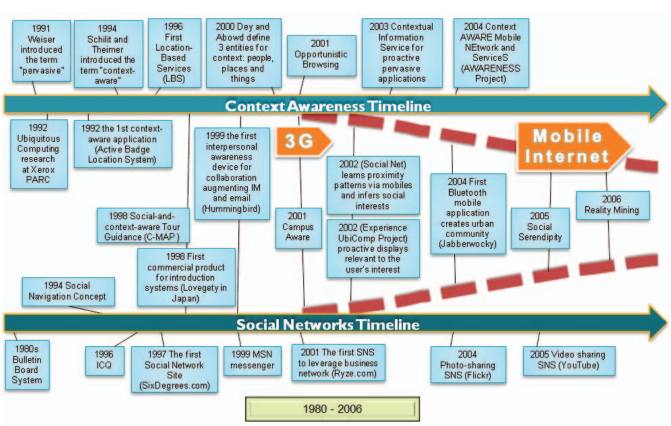

Fig. 1: The Evolution of both Social Networks and Context-aware Systems from the 1980s to 2006

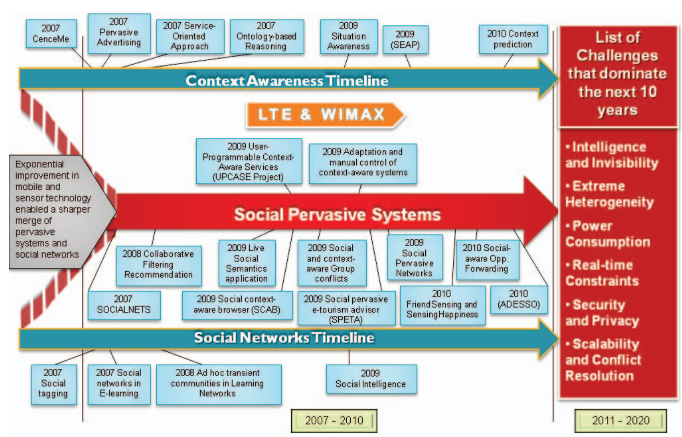

Fig. 2: The Merger between Social Networks and Context-aware Systems since 2007

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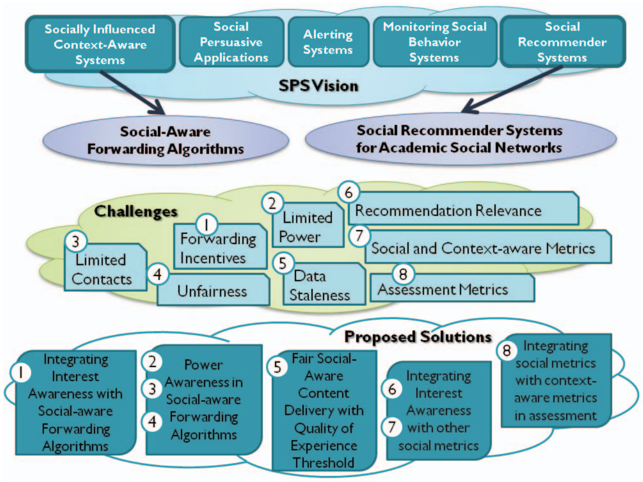

Fig. 3: Social Pervasive Systems Challenges and Proposed Solutions

to participate in the forward process. The user's interest in the content can be an effective incentive to forwarder nodes as they will mutually benefit by receiving this same content, which is of partial interest to them. This proposed solution has already been empirically evaluated via simulation-based experimentation and presented in a conference [4]. The proposed algorithm IPeR is an Interest-Aware version of the PeopleRank algorithm that rewards/penalizes the node's social rank based on its interest. IPeR achieves an extra 70% precision and extra 107% accuracy over PeopleRank by significant reduction in the contacted ratio of uninterested forwarders while contacting comparable ratio of interested forwarders and destination nodes. This is complemented by a significant reduction in forwarded messages per unit delivery ratio as summarized by the 8-metric space in figure 4. In this figure, we can notice the comparable performance of IPeR to two other popular social aware forwarding algorithms namely ProfileCast [5] and SocialCast [3] which rely on the concept that users of similar interest have similar mobility patterns. Accordingly, ProfileCast algorithm relies on behavioral profiles in forwarder node selection. On the other hand, SocialCast relies on the higher probability of the forwarder candidate's colocation with the destination nodes as well as its change degree of connectivity to select the best forwarder nodes. In the current stage of this research work, we are empirically evaluating the improvement in performance of the SocialCast after integrating interest-awareness through rewarding potentially interested nodes' utility function and penalizing the uninterested ones. Generally speaking, integrating interest-awareness in social-based forwarding approaches maintains a balance between utilizing interest and social context information which improves the performance of these forwarding algorithms in case of any discrepancy in interest information availability.

Power-Aware Social-based Forwarding: The second contribution tackles four main challenges. First, lacking power-awareness in the forwarder selection process of the social forwarding approaches. That is, despite maintaining interest-awareness, these forwarding algorithms may not be aware of the nodes' resource capability to sustain the forward process accomplishment. Second, unbalanced resource utilization of the participating forwarder nodes in the system; where power-fairness-oblivious forwarding algorithms overutilize some forwarder nodes while others are lightly utilized. Third, overlooking the assessment of the sufficiency of contact duration between the encountered nodes for complete message transfer causes waste of non-trivial resources. Finally, lack in maintaining a balance between the trade-off goals of preserving power and fairness versus minimizing the delay in delivery may cause targeted users' loss of interest in the delivered content. Solutions to three of those challenges have been empirically evaluated via simulation experiments and published in a conference paper [6]. The proposed PIPeR algorithm integrates power awareness into the interest-aware forwarding algorithm IPeR by reward/penalty based on remaining power, expected contact duration and depletion rate. Through simulations, we present and evaluate four modes of PIPeR in comparison to the power-oblivious interest-aware IPeR and the social-oblivious power-aware SCAR [7]. The four proposed modes of PIPeR mainly vary in their selection of a fixed predefined battery level threshold or an adaptive threshold that is dynamically updated along the forward process. These PIPeR modes also vary based on whether they include an extra ranking component that explicitly favors power-capable nodes held by potentially interested users. As depicted from the 7-metric Space in figure 5 PIPeR modes are fairer and preserve at least 22% of the

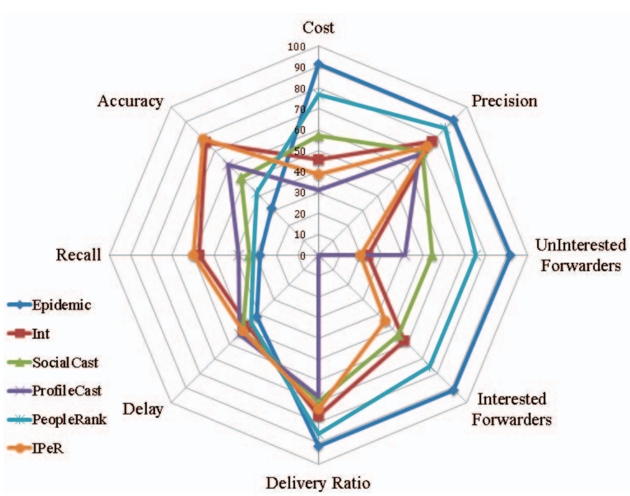

Fig. 4: The 8-Metric Analysis of IPeR

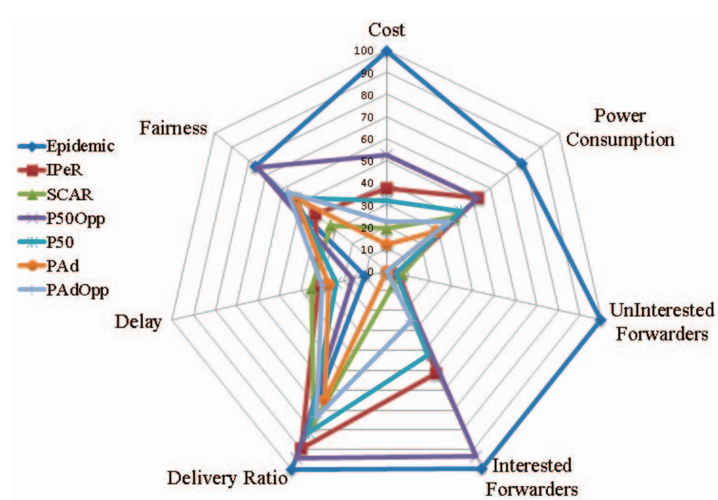

Fig. 5: The 7-Metric Analysis of PIPeR

power IPeR consumes with less delay, while relying more on interested forwarders and with comparable cost to maintain a similar delivery ratio. More interestingly, the power-aware SCAR algorithm is the least fair with the highest delay and low ratio of contacted interested nodes as it consumes moderate power to reach comparable delivery ratio to that of the adaptive PIPeR versions. From our analysis to the four PIPeR modes, we conclude that the opportunistic fixed threshold PIPeR version (P50Opp) maintains the highest level of fairness by focusing on the highest ratio of contacted interested users with power capable nodes. Thus, in comparison to IPeR and SCAR, this PIPeR version achieves a higher delivery ratio and higher effectiveness with comparable power consumption and less delay. On the other hand, the adaptive PIPeR versions minimize cost and overall consumed power with some delay.

Social Recommender Systems in Academic Social Networks: We also present a third possible contribution that argues the merit of the collective integration of social and mobile context in recommender systems. It is a proposal of a simulation-based social recommender system and exploring how recommendations can be better formed in academic environments to support an enhanced learning process. This solution tackles the following problems: First, the improper selection of social metrics that lead to ineffective recommendation process. Second, there is a need to combine more relevant social and context-aware metrics to improve the recommendation quality. Initial attempts from other research works show how the improvement in the efficiency of the recommendation process is mainly dependent on the selected social metrics [8]. Third, we hypothesize that the combination of social and context-aware metrics in the assessment process will lead to better quality of user experience (QoE). We intend to demonstrate our hypotheses in two case studies. The first one is a social recommender system for research collaboration recommendations among academic researchers. This recommender system will rely on a collection of social and context-aware metrics to rank researchers as per the researcher seeking recommendation. There is a preliminary set of metrics for ranking researchers which is subject to empirical experimentations to reach the optimum ranking index. The initial set of metrics include the common interest in terms of the field of research, common co-authors both researchers worked with previously, the rank of these co-authors, common keywords in both researchers' published papers, the researcher's rank as per the number of citations to their own work, the rank of the researcher's published papers as per the publishing conferences/journal's rank, and a modified version of the so-called collaboration supportiveness index [9] of each researcher. We intend to compare the effectiveness of our approach to another recent research work's performance [9]. The second case study is a social recommender system for academic helpers within academic institutes where students face difficulties in their studies and seek consultancy and help from more experienced colleagues. We propose relying on the contextual histogram of each user in inferring their mobility patterns and interests. In addition, the recommender system computes a set of social and context-aware metrics to rank the students. Among those metrics, we propose the common free timeslots, friends, attended classes and common academic major. For both case studies, we need to devise an assessment metric for the quality of users' experience with respect to the recommendations they received.

Throughout our research, we conduct simulations by our own built Visual C# simulator. These simulations utilize datasets that include both realistic [10] [11] and synthesized mobility traces [12], social profiles [13], social relationships [14] [15], power consumption models [16] [17], as well as data that is generated by our simulator. We also devised evaluation metrics for performance comparison that measure the algorithms' effectiveness, efficiency, power consumption and fairness.

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