Modelling Familiarity for Intelligent Personalized Social Mobilization

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Introduction

With the rise of the Internet and social media, social mobilization - large-scale mobilization manpower for scientific, social, and political (Michelucci and Dickinson 2016) activities through crowdsourcing - has become a widespread practice. Despite the success, social mobilization is not without its limitations. Local trapping of diffusion and the dependence on highly connected individuals to mobilize people in distance locations affect the effectiveness of social mobilization (Rutherford et al. 2013). Furthermore, as empirical studies on people's responses to various social mobilization approaches are lacking, it is a significant challenge for artificial intelligence (AI) researchers to design effective and efficient decision support mechanisms to help manage this emerging phenomenon (Yu et al. 2015; 2016).

In my thesis, I conduct large-scale empirical studies to help the AI research community establish baseline personal variabilities in different people's response patterns to social mobilization approaches. Based on the collected dataset, I will further propose computational algorithmic crowdsourcing (Yu et al. 2016a) mechanisms which leverage the empirical evidence to improve the effectiveness and efficiency of social mobilization, towards achieving superlinear productivity (Sornette et al. 2014). Throughout this process, I will also incorporate human factors (e.g., emotion (Lin et al. 2015), persuasion (Tao et al. 2011), incentives (Lin et al. 2015), and trust (Yu et al. 2014b)) into the computational models to benefit social mobilization efforts.

Empirical Study on Social Mobilization

The study of social mobilization depends heavily on instances which have successfully mobilized large-scale participation. Although empirical studies based on such successful instances may suffer from survival bias, data derived from such studies can still shed light on important aspects of social mobilization. One of the critical research questions is "how do people from different backgrounds respond to various social mobilization approaches?" Quantitative answers to this question can provide useful insights into the design of future incentive mechanisms for social mobilization.

In 2016, Pokemon Go (`http://www.pokemongo.com/`) swept through the world attracting millions of players. The game, incorporated with the main features of social mobilization including 1) gamification, 2) time-critical incentives, 3) inter-personal interactions, and 4) location-awareness, is an useful and timely example with the potential to support large-scale empirical studies. As the Singapore's multi-racial population consists of people of Chinese, Indian, Malay and Caucasian origins, a study will capture any behaviour variability as a result of ethnic identity. Thus, since August 2016, I have initiated an online survey studying to how people from different backgrounds respond to social mobilization approaches involving the aforementioned 4 features based on the Pokemon Go game.[1]

The survey consists of two major sections: 1) individual background, and 2) individual behaviour patterns in social mobilization. Under the first section, participants were asked about their demographic information, and to complete a 10-question Big Five personality test (Matthews, Deary, and Whiteman 2003) as well as a 20-question affective disposition test. Under the second section, behaviour patterns such as depth of participation (e.g., time, effort, and money spent), willingness to collaborate (e.g., to what extent a participant played the game alone or with others), motivation (e.g., reasons of participation), and degree of familiarity with Pokemons before the release of the game were collected. So far, over 300 people have participated in the survey. The data are currently being analyzed. The dataset is, to our knowledge, the first large-scale study on how different people respond to technology powered social mobilization.

Modelling Familiarity

In order for AI-powered crowdsourcing to interact successfully with human beings in the loop, it is important for the AI recommendations to take into account human factors. Some aspects of human factors (e.g., the need to balance work and leisure) have been incorporated into existing algorithmic crowdsourcing for more effective social mobilization (Yu et al. 2014a). In my thesis, I focus on *familiarity* which has been found to play a critical role in collaborative activities.

The effect of familiarity on the interactions typical to a human-in-the-loop technology system can be divided into

[1] `http://dx.doi.org/10.7303/syn7500215.1`

three stages (Toth 1996). The first stage is the "Cognitive stage" which revolves around the acquisition of basic knowledge for task execution. The second stage is the "Associative stage" in which people move to process-based performance of the action. The more familiar a person is with the task, the faster the speed of execution and the lower the amount of effort required. The third stage is the "Autonomous stage" in which the actions follow a smooth procedure and are executed quickly with minimal effort.

In (Pan et al. 2015), I have proposed a framework for modeling familiarity design in human-computer interactions based on this 3-stage model. It consists of three elements: 1) *Symbolic Familiarity*, 2) *Cultural Familiarity*, and 3) *Actionable Familiarity*. Preliminary studies have shown that higher perceived familiarity can lead to a better user performance in the system, a greater perceived usefulness of the system, and a higher likelihood of adoption by users.

Dynamic Teamwork

In order to improve the efficiency of social mobilization, algorithmic crowdsourcing approaches have been proposed which intelligently allocate tasks to participants based on their performance track records to make trade-offs between quality, timeliness and cost. Existing approaches assume that a task can be effectively completed by an individual (Yu et al. 2013; 2015). Even in crowdsourcing with complex workflows, the same assumption still holds (Tran-Thanh and et al. 2015). In my thesis, I propose a new algorithmic crowdsourcing approach - *CrowdAsm* - which relaxes this assumption and provides intelligent decision support in cases where collaboration by people with diverse skills is required to tackle complex tasks (Pan et al. 2016).

CrowdAsm enables dynamic team formation in social mobilization. It makes efficient quality-time-cost trade-offs in collaborative crowdsourcing systems by dynamically organizing people into teams while jointly considering the budgets, the availability of people with the required skills, and their track records in order to complete the target tasks efficiently. It maximizes the expected rate of success, minimizes the expected waiting time, and balances a given budget. I proposed a novel $\{$*mobilization - utility*$\}$ objective function based on the Lyapunov network optimization framework. This enables CrowdAsm to produce solutions in real-time through distributed computing. Through rigorous theoretical analysis, CrowdAsm has been shown to asymptotically optimal if workers do not deviate from the recommendations. I am building more realistic multi-agent simulations to study CrowdAsm under various scenarios.

Future Research

To date, I have completed three major building blocks in my thesis which are needed for proposing an intelligent personalized social mobilization approach for complex tasks. Nevertheless, much work remains to be done in order for such an approach to come to fruition. Specifically, I plan to further analyze the data collected from the survey study to establish a computational model for the baseline variability of human responses to social mobilization approaches, paying special attention to the role of familiarity. The derived model will then be used to produce a computational model of how familiarity interacts with important aspects of human productivity (e.g., motivation, willingness to collaborate, effort output). Such a model will be applied to realistic simulation systems to support further research in social mobilization. Currently, I am building a collaborative crowdsourcing mobile app which involves tasks requiring collaborative efforts (Yu et al. 2016b). I will incorporate future results and findings into this platform for real-world evaluations.

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