Smart Phone based Systems for Social Psychological Research: Challenges and Design Guidelines

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ABSTRACT

Social psychology research deals with understanding many aspects of human behavior, and this helps not only to gain insights into this complex phenomenon but also to provide useful feedback to the participants. Social psychological research is mainly conducted through self-reports and surveys, however, this methodology is laborious and requires considerable offline analysis. Moreover, self-reports are also found to be biased towards pleasant experiences. Mobile phones represent a perfect platform for conducting social psychological research as they are ubiquitous, unobtrusive, and sensor-rich devices. However, limited battery and computing power, and expensive data plans make it difficult to support various demanding sensing and computation requirements of the social psychological research. In this paper, we describe the specific challenges in building systems based on off-the-shelf mobile phones for conducting social experiments, and provide design guidelines based on our recent works for implementing such systems.

Categories and Subject Descriptors

C.2.1 [**Network Architecture and Design**]: Wireless Communication; H.1.2 [**User/Machine Systems**]: Human Information Processing; H.3.4 [**Systems and Software**]: Distributed Systems; J.4 [**Social and Behavioral Sciences**]: Psychology, Sociology

General Terms

Algorithms, Design, Experimentation.

Keywords

Mobile Phone Sensing, Social Psychology, System Design.

1. INTRODUCTION

Social psychology deals with the study of human behavior and the influence of various factors on it. Studying human behavior translates to studying fine-grained phenomenon like emotions, mood swings, interactions and the effect of various external factors like co-located people, location, and physical activity on them. A significant part of the research in social psychology is conducted through self-reports, and social scientists analyzing them offline. Even the most advanced of these procedures like automated experience sampling [3], and audio recordings [4], require considerable offline analysis. Moreover, these mechanisms are found to be biased [5] to some extent as users generally share pleasant experiences. Furthermore, real-time feedback and intervention mechanisms are hard to provide through these methods.

Mobile phones represent a perfect platform for conducting social psychological studies as they are ubiquitous, unobtrusive, and sensor-rich devices. They are carried by billions of people, and users are not generally conscious of their presence. They are equipped with many sensors like accelerometer, Bluetooth, camera, GPS, microphone, and proximity-detection. Moreover, conducting large-scale studies is feasible with the advent of *application stores* [1, 2], and this paves way for collecting data at an unprecedented scale. However, there are many challenges in building such systems: limited battery life and processing power, inaccurate sensors, expensive data plans, and privacy concerns. In this paper, we outline the challenges in building smart phone based systems for capturing behavior of the users and based on our previous works [6, 7, 8], we provide a set of high level design guidelines on how to address these challenges and build efficient social sensing systems.

2. CHALLENGES

In this section, we present the main challenges in building mobile systems for conducting social psychological research.

Limited resources: Mobile phones have limited battery capacity, memory, and processing power. Even though memory and processing power capabilities of phones are increasing (for example, modern smart mobile phones like Samsung Galaxy S2 are equipped with 1GB RAM and 1200MHz dual-core processor), battery technology has not seen similar level of growth. Therefore, sensor sampling to capture user behavior should not be performed at an aggressive rate as it might drain the battery faster, at the same time, conservative sampling might lead to loss of valuable behavioral data.

Expensive data plans: Even though some mobile phones have high processing power, using these local resources to perform intensive computations (like speech or face recognition) consumes a lot of energy. Therefore, an efficient alternative is to consider performing these computations remotely in the cloud, however, due to expensive data plans this is not always a cost-effective option.

Inaccurate sensors: The sensors in mobile phones are not designed for capturing human behavior. For example, the

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microphone sensor maybe of lower quality on some phones and may not be perfectly suitable for speech recognition, and same problem exists for camera sensor for face recognition. Therefore, accurate algorithms should be designed to derive inferences based on raw data from not so accurate sensors.

Ground truth: This is required for the following reasons: (*i*) When a significant behavioral change is observed, it may not always be possible to sense the factors influencing this change through the mobile phone sensors. For example, an emotional stress on a user might be due to the user receiving a lower grade in exams, and if we do not have access to ground truth, then it is difficult to map behavioral changes to facts. (*ii*) Assuming the factors influencing this behavioral change can be sensed through the mobile phone sensors, the sensor sampling may have to be performed on a continuous basis in order not to miss the ground truth events. However, due to limited battery resources of mobile phones this is not pragmatic.

Users forget to carry phones: It is a common case that users forget their phones on their desks or in their bags. It is difficult to detect this case and may result in data-holes in the studies. Motivating users to always carry their phones helps in capturing continuous data and leads to better modeling of behavior of the users.

Privacy concerns: Finally, privacy is an important design factor in the systems that capture behavior of the users. Data from some sensors like GPS, microphone is extremely sensitive, and unless a system has schemes for protecting privacy of the users, they may not be willing to use it.

3. EXAMPLE MOBILE SOCIAL SENSING SYSTEMS

Mobile social sensing systems capture various aspects of behavior of the users using mobile sensor systems like smart phones. We have addressed many of the challenges mentioned in the previous section in the social sensing systems: EmotionSense [8] and SociableSense [6]. We provide a brief description of these systems in this section, and then based on the experiences from design and deployment of these systems, we provide a set of high level design guidelines for building social sensing systems in the next section.

EmotionSense: This system is based on off-the-shelf smart phones and captures user behavior in terms of emotions, speech patterns and then correlates them with user's co-location, location, and physical activity. Microphone sensor data is used for emotion recognition and speaker identification. Co-location is sensed through Bluetooth radio, location through GPS sensor, and physical activity through accelerometer sensor. EmotionSense is a tool for social psychologists to capture behavioral data autonomously, and helps in understanding user behavior and the impact of external factors like co-location, location, and physical activity on it. In terms of system design, the key characteristics are *programmability* (social scientists can describe the sensing tasks using a declarative language), and *run-time adaptation* (social scientists can write rules to activate and deactivate sensors according to the user's context). Detailed system design, implementation, and evaluation are presented in [8].

SociableSense: This is a smart phones based social sensing system with the aim of providing real-time feedback to participants in order to help them in fostering their interactions and strengthening their relations with colleagues. SociableSense implements solutions for adaptive sensor sampling and intelligent distributed computation based on the user's context and mobile phone status. More specifically, a *sensor sampling component* adaptively controls the sampling rate of accelerometer, Bluetooth, and microphone sensors while balancing accuracy-energy-latency trade-offs based on the *reinforcement learning* mechanisms. A *computation distribution component* based on the *multi-criteria decision theory* dynamically decides where to perform computation of tasks such as data analysis and classification, by considering the importance given to each of the dimensions: data sent over the network, energy consumption, and latency. Finally, a *social feedback component* determines the sociability of users (i.e., a quantitative measure of the quality of their relationships) based on co-location and interaction patterns extracted from the sensed data at run-time, and provides them with feedback about their sociability, strength of relationship with colleagues, and also alerts about opportunities to interact. More details about the system design, implementation, and evaluation are presented in [6].

4. DESIGN GUIDELINES

In this section, we provide a set of design guidelines for building social sensing systems based on the experiences from the design and deployment of systems described in the previous section.

Architecture: The general architecture of social sensing systems described in the previous section is as shown in Figure 1. It consists of a sensor sampling layer that is responsible for querying data from the sensors of mobile phone. This data is then sent to an inference layer that is responsible for classifying and inferring events based on raw data from the sensors. A framework for defining inference rules helps social scientists to define their own inference rules and also to trigger other rules if some activities are sensed. Finally, social psychology applications can be built on top of these services, which may range from passively collecting data to assisting users by providing real-time information or interventions.

Sensor sampling: The sensor sampling layer queries data from the mobile phone sensors, for example, X, Y, Z axes data of the accelerometer sensor, or audio data from the microphone sensor. To achieve energy-efficiency, it is crucial to design algorithms that adapt the sensor sampling rate to the user's context and not sense the sensor data continuously from the sensors of the phone. In general, most of the sensed data may not contain interesting events, therefore, it is not generally recommended to sense data continuously. Instead, the systems should aim at learning the user's behavior and adapting the sampling rate to the his/her life. For example, in [7], when there are interesting events detected continuously, the sensors are sampled at an aggressive rate, and when there are no interesting events detected, the sensors are sampled conservatively. Another example is, if the system has observed in the past that the user tends to talk more when he/she is with a specific set of friends, then the microphone can be sampled at a higher rate when the system detects the presence of these friends (maybe through Blue-

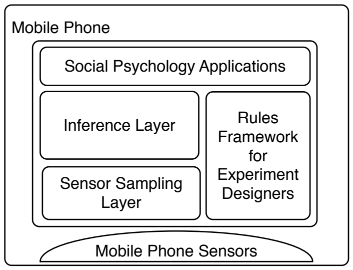

Figure 1: General architecture of mobile social sensing systems.

tooth). Another way of achieving energy-efficiency is using low powered sensors to trigger high powered sensors [8]. For example, instead of continuously sensing the GPS sensor to track the user's movement, the basic change in state can be monitored using accelerometer sensor and if a change is detected then GPS sensor can be activated.

Not all sensors are similar: The optimum sampling rates and duty cycling periods varies with respect to sensors and classifiers [7]. Since, the amount of data sensed and the energy consumption is different for each of the sensors, it would be effective to use sensor specific sampling rates instead of using a global sampling rate for all the sensors.

Correlation of data across sensors: A way of finding behavioral eccentricities of users is by capturing data through multiple sensors and correlating them. For example, by correlating microphone data with GPS sensor data, it is possible to find the emotional changes of user with respect to locations. Moreover, since it is difficult to collect fine-grained ground truth data, correlating multiple sensor data can also help in fathoming a complex observed phenomenon.

Ground truth: One way of capturing this is through multimodal sensing but is not always feasible due to lack of sensing infrastructure or complexity of integration with sensing systems that are not necessarily controlled or owned by the users. Another and more practical way is through experience sampling mechanisms [3]. For example, through accelerometer sensor if the system has detected that user is stationary for most of the time in the morning, then to correlate this observed phenomenon with facts, a simple question might help: *Were you stationary most of the time this morning or did I detect this because you were not carrying phone?*. However, the challenges are when to trigger these questions, and how frequently.

Protecting privacy of users: Privacy protection schemes increase confidence of the users in the system and thereby helps in increasing the participation numbers. In EmotionSense, the recorded audio files are discarded immediately after extracting the speaker and emotion information from it, and by computing everything locally, the audio data of users is not transmitted to the cloud. However, in some cases like speaker recognition, it is efficient in terms of energy consumption to compute high intensive tasks in the cloud and audio data need to be transmitted to the cloud for processing. SociableSense utilizes both the local and cloud resources effectively, however, the system can be configured to perform computations only locally, thereby avoiding transmission of any sensed data to the cloud. Users should be provided with fine-grained options to configure the systems in terms of protecting their privacy.

Requirements of social scientists: In a social sensing system there should be an easy way for social scientists or experiment designers to express their own inference rules. Social scientists may not have the required programming expertise to customize the system according to their requirements, and a rules framework may serve as an easy way to configure/define their own custom rules and inferences. For example, they might want to write a rule to sense data from the microphone sensor only when the user is at a particular location, or to send them an SMS message when the system detects that the user is angry for a threshold number of times. These frameworks, in a way, act as bridge between the computer sciences and the social sciences.

Making users to always carry phones: A practical way to make users always carry phones is through incentives. The SociableSense system provides incentives to users in terms of feedback about strength of their relations and opportunities to interact with colleagues. Incentives play a big role in increasing the user participation levels and also retaining them.

Application stores: Finally, with the advent of application stores like Android market [1] and Apple app store [2], social experiments can be preformed at an unprecedented scale. Some systems have taken advantage of this methodology but not many. The first step evaluation can be with a smaller set of people, so that experiment designers have more control over the experiment, and as a next step, the designers may consider deploying it over the application stores.

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