Adaptive Mobile Behavior Change Intervention Using Reinforcement Learning

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***Abstract*—As smartphones become increasingly intimate and continuous companions, many opportunities are arising in human behavior sensing, modeling, and coaching. This position paper explores opportunities and challenges for mobile-based deployment of behavior change interventions. We suggest the adoption and extension of reinforcement learning for addressing these challenges, and we identify several key areas of future research that, on the basis of prior results, appear ripe for extending the benefits of reinforcement learning to human behavior change. These areas include stronger grounding of states in theories of human behavior, RL agent adaptation and decomposition, cooperative reinforcement learning, and in situ evaluation.**

***Keywords*—Behavior change intervention, mobile health, reinforcement learning, human-in-the-loop.**

I. Introduction

Behavior change interventions (BCIs) aim to effect positive outcomes through sequential deployment of treatments targeting underlying behavioral determinants (e.g., perceptual and self-efficacy biases). The ubiquitous adoption of mobile devices with broad sensing capabilities and nearly continuous connectivity creates opportunities to deploy BCIs in mobile settings; however, there are several theoretical and practical challenges that impede the deployment of mobile BCIs (MBCIs). First, existing behavior theories (e.g., those in health [1]) are underutilized in the design of MBCIs, which may result in low efficacy. Second, the prolonged process of behavior change requires a framework that coevolves with users' complex and unpredictable behaviors, changing levels of motivation, and varied tolerance for interruption and interaction. Third, effective BCI requires the involvement of multiple parties beyond the end user (e.g., researchers, health care providers, and policy makers in the domain of health BCIs), thus requiring MBCIs to support principled mechanisms whereby each party gathers essential information and takes action to effect positive change within the BCI end user. In response to these challenges, a successful MBCI should incorporate current behavioral theories, be robust to within- and between-subject variation in motivators and mobile-interaction preferences, support coordinated multiparty interaction, and be evaluated in ecologically valid settings. In this position paper, we propose reinforcement learning (RL) [2] as the basis for successful MBCI. We review key points of related work and highlight several areas of RL theory and practice that are ripe for research aimed at the MBCI challenges noted above.

II. Related Work

MBCI is one aspect of the evolving mobile health (mHealth) field, in which commodity mobile technology (predominantly smartphones and tablets) have been used to promote a range of healthy behaviors (e.g., exercise, smoking cessation, and dietary coaching), facilitate medication adherence and disease management (e.g., for diabetes and HIV), and deliver mental health assessments and treatments (e.g., for depression, schizophrenia, and bipolar disorder) [3], [4]. MBCIs often take the form of notifications, text messages, and phone-based counseling, and they can be coupled with other resources such as Internet-based education programs [4].

Past work on modeling human behavior has adopted a diary approach administered through paper- and/or phone-based surveys [5]. More recently, cellular tower data and Bluetooth footprints that record users' approximate location trajectories were used to study human movement patterns [6]. Current mobile technology affords a broad range of passive sensing capabilities via onboard sensors whose primary purpose is to create an engaging user experience. As a byproduct, mHealth stakeholders are able to unobtrusively monitor users' spatiotemporal (via GPS) and activity (via triaxial accelerometer) trajectories, which can be augmented with momentary self-reports that are actively elicited [4]. These technological developments provide opportunities for behavior change practitioners to understand their users in situ and interact with them to provide individualized BCIs.

Reinforcement learning (RL) is a general-purpose family of methods for addressing sequential decision making problems characterized by nondeterministic dynamics, delayed decision-outcome pairings, and a lack of ground truth regarding optimal decisions [2]. Given the presence of these characteristics in MBCIs, as well as recent successes of RL across a diverse range of applications (e.g., autonomous vehicle/flight control and adversarial games historically dominated by human players), we suggest that MBCIs can be effectively formulated as RL systems in which incomplete knowledge of human behavior and learning dynamics are addressed through systematic exploration of the MBCI deployment space.

III. Proposed Research Areas

Our position on RL as a potential framework for MBCI delivery highlights several areas of future research. Below, we describe four areas that we are actively pursuing.

Theory-Informed State Estimation and Dynamics To date, few studies have grounded the end-to-end process of mobile-based behavior change in existing theories of human behavior (e.g., those described in [1] for health). We suggest that many aspects of RL-based MBCI deployment can be informed by these theories. For example, theories of human behavior should guide the design of state features used by the RL agent to estimate the value of a particular MBCI action at each point in time. These theories should then guide the scheduling of passive sensors and development of momentary self-report questions deployed to fill out the end-user's state representation. Such grounding will provide a sound basis for evaluating and improving RL-based MBCI, ultimately resulting in improved behavior change outcomes.

State/Action Adaptation and RL Decomposition Reports of successful RL usage have come predominantly from applications where (1) the action and state spaces are known and unchanging over time, and (2) it is relatively inexpensive for learning agents to obtain a large amount of experience. It is unlikely that MBCI will afford RL-based approaches either of these conveniences. Regarding (1): Human behaviors, their underlying motivational systems, and associated inroads for change evolve over time. Thus, it is unlikely that a static, effective MBCI action space can be defined. Correspondingly, the states (or features thereof) used to guide the selection of MBCI actions will likely require modification over time. Research indicates that human-in-the-loop modifications of the action and state spaces can be accomplished by domain experts (e.g., clinicians) [7], and we propose that end users might also provide similar adaptations for RL-based deployment of MBCIs. Regarding (2) above: We envision an MBCI deployment process in which, initially, a single RL agent accumulates all experience for a task within the MBCI (e.g., intervention delivery timing). As sufficient experience accumulates, this agent is decomposed into multiple agents that tailor the task to specific subpopulations. This approach balances the need for large amounts of experiential data in early phases with personalized MBCI delivery strategies. Research is required to identify optimal decomposition strategies.

Heterogeneous Multi-Agent Reinforcement Learning Successful MBCI deployments will involve coordinated interactions among multiple, often heterogeneous parties (e.g., patients and clinicians in a health care setting). Rather than positing a single, monolithic RL agent capable of interacting with all agents in this heterogeneous environment, we propose the use of multiple cooperative RL agents [8] that interact with the various parties (e.g., delivering health interventions to end users and information to clinicians) as well as with each other.

In Situ Evaluation As noted above, RL has traditionally been employed in data-rich settings (e.g., simulated environments) that produce large amounts of data for optimizing and evaluating RL agents. The MBCI setting, being rooted in human behavior, precludes the use of simulation, and the statistical dependence between successive decision-outcome pairings complicates the use of retrospective data for optimization and evaluation of RL agents for MBCI deployment. Thus, we suggest that live, in situ deployment of RL-based MBCIs in group- and micro-randomized trials is the appropriate design and evaluation setting for future research.

IV. Architecture and Ongoing Work

We are currently developing the lines of research suggested above. Our implementation is based on mobile sensing technology (Sensus [9]) that we have previously deployed to approximately 300 participants in studies of student depression and anxiety (e.g., [10]). Sensus is a general purpose Android/iOS system for active (via momentary self-report) and passive sensing. It integrates with Amazon Web Services for storage via S3, and we are working to augment the base Sensus system with EC2-hosted RL agents that learn from collected data and push MBCI deployment policies to Sensus end users for execution. This architecture will be reusable across the studies indicated in the prior section, and the entire framework will be made publicly available under an Apache v2 license.

V. Conclusion

The deployment of mobile-based behavior change interventions presents several challenges that we believe can be effectively addressed by adopting reinforcement learning as the underlying methodological approach. We have proposed four areas of future research that, on the basis of prior results, appear ripe for extending the benefits of reinforcement learning to the complex and theory-rich domain of human behavior change.

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