Interpretable AI for Well-Being Using Mobile Health

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Abstract

Mobile health (mHealth) and other highly pervasive, interactive and adaptive digital systems offer an enormous opportunity for enabling theory-based health behavior-change interventions that are replicable, scalable, and sustainable. Such advances could have great impact, and they offer great opportunities for advances in artificial intelligence (AI), psychology, and social science. Unfortunately, the technical challenges of developing AI to support healthier behaviors generally fall into the category of "not suitable for machine learning." This presentation will summarize recent research with the Fittle+ mHealth systems and predictive models of the daily effects of individual-level mHealth interventions. The models are developed in a computational cognitive architecture and rely on Instance Based Learning Theory and ACT-R learning mechanisms.

Introduction

Mobile health (mHealth) systems offer an opportunity for pervasive support of health behavior change in the actual ecology of people's everyday environments. Such advances could have vast impact since individual and social behavior, including poor diet, sedentary lifestyle, and social isolation are central to the etiology and management of many health outcomes, and yet are typically resistant to change (Klein et al., 2014). It is estimated that 70% of health care costs are due to changeable behavior, and behavioral and environmental factors account for more deaths than genetics (Riley, Nilsen, Manolio, Masys, & Lauer, 2015).

However, the mHealth field is still relatively new and lacks integrated theories of long-term behavior change that address multiple interventions and a multiplicity of individual, social, and environmental factors. As with digital health interventions in general, mHealth systems suffer high attrition rates (Eysenbach, 2005). However, recent research suggests that mHealth systems that adapt to the individual (Konrad et al., 2015; Pirolli, 2016), use evidence-based interventions (Pirolli et al., 2018), and include online social support (Du, Venkatakrishnan, Youngblood, Ram, & Pirolli, 2016; Du, Youngblood, & Pirolli, 2014) reduce attrition and improve achievement of behavior change goals. Intelligent mHealth systems that utilize multiple approaches, automate personalization, and increase social support can be a scalable approach to current healthcare challenges.

Novel computational theories of the psychological and social mechanisms of behavior change are needed in order to accelerate the development of mHealth systems so that they can help people build healthier lifestyles (Riley et al., 2011; Spruijt-Metz et al., 2015). In turn, we could use mHealth systems as experimental platforms for accelerated development of such theories. These theoretical and empirical foundations would then provide a basis for intelligent interactive agents that reason about causal models of the dynamics of individual human behavior--models that enable the planning and delivery of interventions and assessments that optimize the acquisition and maintenance of healthy habits.

Human Goal-Striving and Habit Formation

An unhealthy lifestyle can be viewed, in part, as a complex set of interrelated habits that need to be switched out for healthy ones, a few tiny habits at a time (Fogg & Hreha, 2010). Commercial and health-care provider weight loss programs can often involve months to years of counseling, which suggests thousands to tens of thousands of elementary habits being acquired (Feltovich, Prietula, & Ericsson, 2006). The working assumption for our own mobile health research is that to master the complex fabric of a new healthy lifestyle, one must master and weave together a new set of elementary habits

Unfortunately, modeling human behavior change and intervening in ways that shape healthier habits is enormously challenging and not suitable for current machine learning approaches (Brynjolfsson & Mitchell, 2017). This presentation gives a theoretical approach and several computational models that provide an integrated account of multiple mechanisms associated with people striving to achieve healthier behavior and their long-term habit formation. Interestingly, the mechanisms modeled in health-behavior change are also implicated in well-known human cognitive biases (Lebiere et al., 2013) and, in a sense, the success of the interventions we have studied appears to be the result of taking advantage of those biases.

I will present an overview of the Fittle+ mHealth systems (Pirolli et al., 2018) that have been used to study several evidence-based behavior change interventions. These systems provide *scaffolding interventions:* Behavior-change techniques and associated mHealth interactions (e.g., SMS reminders; chatbot dialogs; user interface functionality; etc.) that support the acquisition and maintenance of healthy habits.

I will present models developed in the ACT-R computational cognitive architecture (Anderson, 2007) that address data collected about individual-level daily achievement of behavioral goals for improved eating and exercise using Fittle+ mHealth applications. The models refine the psychological constructs of perceived *goal difficulty*, *self-efficacy* (Bandura, 1998) and *intended effort* (a kind of motivation) (Kukla, 1972). The models provide a plausible account of how intentions can lead to the initial effortful striving to carry out goals, how repeated execution of behaviors can become automated habits, and how specific intervention techniques support the development of habits. Together the models map a trajectory from initial effortful pursuit of a behavior-change goal to new stable habits.

The motivation for developing these models is that they may serve as a foundation for intelligent mHealth interaction algorithms. By developing these in a cognitive architecture, the models are not only predictive, but provide insight as to the underlying causal mechanisms, which is necessary for reasoning about optimal personalized interventions that help people achieve healthy lifestyles.

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