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Innovative Applications of O.R.

Behavioral modeling in weight loss interventions

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ABSTRACT

Designing systems with human agents is difficult because it often requires models that characterize agents' responses to changes in the system's states and inputs. An example of this scenario occurs when designing treatments for obesity. While weight loss interventions through increasing physical activity and modifying diet have found success in reducing individuals' weight, such programs are difficult to maintain over long periods of time due to lack of patient adherence. A promising approach to increase adherence is through the personalization of treatments to each patient. In this paper, we make a contribution toward treatment personalization by developing a framework for predictive modeling using utility functions that depend upon both time-varying system states and motivational states evolving according to some modeled process corresponding to qualitative social science models of behavior change. Computing the predictive model requires solving a bilevel program, which we reformulate as a mixed-integer linear program (MILP). This reformulation provides the first (to our knowledge) formulation for Bayesian inference that uses empirical histograms as prior distributions. We study the predictive ability of our framework using a data set from a weight loss intervention, and our predictive model is validated by comparison to standard machine learning approaches. We conclude by describing how our predictive model could be used for optimization, unlike standard machine learning approaches that cannot.

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1. Introduction

Effective design of systems involving human agents often requires models that characterize the agents' varied responses to changes in the system's states and inputs. Most operations research (OR) models quantify agent behavior as decisions generated by optimizing static utility functions that depend upon time-varying system states and inputs. In contrast, researchers in the social sciences have found that the motivational psychology of agents changes in response to past states, decisions, and inputs from external agents (Ajzen & Fishbein, 1980; Bandura, 2001; Gonzalez, Goepfinger, & Lorig, 1990; Janz & Becker, 1984; Joos & Hickam, 1990; Kanfer, 1975); however, these social science models are primarily qualitative in nature, making them challenging to incorporate into OR design and optimization approaches. In this paper, we focus on developing a predictive modeling framework that incorporates time-varying motivational states (which describe the changing efficiency or preferences of the agent) – thereby quantifying agent behavior

as decisions generated by optimizing utility functions that depend upon time-varying system states, system inputs, and motivational states, all evolving according to some modeled process based on qualitative social science models of behavior change.

Our ultimate goal is to solve optimization problems to more effectively allocate resources in systems with human agents; to do this we need to develop behavioral models that can be integrated as constraints in standard optimization approaches. In this paper, we develop a modeling framework that inputs noisy and partially-missing data and uses this to estimate the parameters of a predictive model consisting of (a) a utility-function describing the decision-making process that depends upon time-varying system states, system inputs, and motivational states, and (b) temporal dynamics on agent's system state and motivational state (i.e., often referred to as the type of the agent). We consider two distinct but related kinds of estimates: estimation of the set of parameters for the utility function and dynamics, and separately, estimation of the distribution of future states.

The framework we develop in this paper is described within the context of modeling the behavior of individuals in a weight loss program; specifically, we are interested in using a short time-span (e.g., 15–30 days) of physical activity and weight data from an individual participating in a weight loss program in order to effectively

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characterize the likelihood of whether or not that individual will achieve clinically significant weight loss (i.e., 5% reduction in body weight) after a long period of time (e.g., 5 months). While machine learning approaches such as support vector machines (SVMs) (Hastie, Tibshirani, & Friedman, 2009; Oztekin, Al-Ebbini, Sevkli, & Delen, 2018; Wang, Zheng, Yoon, & Ko, 2017) and artificial neural networks can be used to make binary predictions of significant weight loss based on a short time span of data (Hastie et al., 2009) they have two significant limitations: first there is no obvious way to integrate them into an optimization model, and second these approaches are generally limited in their interpretability (Breiman et al., 2001). Here, we show that in contrast to these machine learning methods, our approach is interpretable since the equations are based on models from the social sciences, and can be incorporated into optimization models since it is posed as a mixed integer linear program (MILP), while maintaining comparable prediction accuracy.

1.1. Personalized Treatments and Obesity

Obesity is a significant problem in the United States. About 70% of American adults are overweight or obese (Flegal, Carroll, Kit, & Ogden, 2012), and its annual cost to the health care system is estimated to be \$350 billion (Valero-Elizondo et al., 2016). Currently, the most effective treatments for obesity are weight loss interventions composed of counseling sessions by clinicians and daily goals for physical activity and caloric consumption. The Diabetes Prevention Program Research Group (2002, 2009) showed that participating in these types of treatments results in significant weight loss of 5–7% and can prevent the onset of type-2 diabetes with few side effects. However, adherence to these clinician-set goals decreases over time (Acharya et al., 2009), and these programs are labor-intensive and expensive to sustain (Diabetes Prevention Program Research Group, 2003; McDonald, Garg, & Haynes, 2002). Making these interventions more *effective and efficient* will require designing treatments personalized to each individual's preferences.

While individualized goal-setting and personalized interventions are crucial to the success of these programs, these features are expensive to provide. Cost efficient programs will need automation of goal-setting and scheduling of counseling resources for individuals to succeed in reducing their weight. Such approaches will likely involve digital/mobile/wireless technologies, which already have high adoption rates (Bender et al., 2014; Lopez, Gonzalez-Barrera, & Patten, 2013) and have shown promise for improving the quality of and adherence to weight loss programs (Fukuoka et al., 2011). These technologies allow clinicians and researchers to remotely collect real-time health data and communicate with individuals participating in the program. However, healthcare data sets generated by mobile devices have been underutilized to date, and little research has focused on effective ways to utilize individuals' health-related data patterns to improve and personalize weight loss interventions (Azar et al., 2013; Fukuoka et al., 2011; O'Reilly & Spruijt-Metz, 2013; Pagoto, Schneider, Jovic, DeBasse, & Mann, 2013).

1.2. Overview

Ultimately, effective automated approaches will depend upon nuanced models to predict the effects different interventions (i.e., changes in activity and caloric goals, or specific types of counseling) will have on the weight loss trajectories of different individuals. In this paper, we present an initial step – specifically, we develop an approach for using a short time-span (e.g., 15–30 days) of physical activity and weight data from an individual participating in a weight loss program to effectively characterize the likelihood of whether or not that individual will achieve clinically sig-

nificant (i.e., 5% reduction in body weight) weight loss after a long period of time (e.g., 5 months) as a function of the physical activity goals and amount of counseling given to the individual. (The Diabetes Prevention Program Research Group (2002, 2009) showed 5% weight loss provides substantial health benefits.) As discussed above, this type of predictive tool will ultimately enable the adaptive design of more effective and cost efficient interventions. Toward this end, we also show how our predictive model is able to predict the impact of changes in the intervention treatment on the weight loss trajectory of a specific individual.

A key feature of predicting future behavior is the inherent uncertainty due to having limited data. As a result, it is natural to consider predictive modeling approaches that generate ranges or intervals of predictions. Though frequentist approaches can be used to construct confidence intervals, we instead propose a Bayesian approach that constructs a range of predictions characterized by a *posterior* distribution. An important benefit of our Bayesian (as compared to a frequentist) approach is that it can incorporate data from individuals that have been in the program for a longer period of time or have even completed a fixed duration (e.g., 5 months) of the program. We quantitatively show in Section 6 that incorporating the information of other individuals using a nonparametric Bayesian prior distribution improves the accuracy of predictions versus not using a Bayesian framework.

Our resulting predictive modeling approach is presented in Section 5. In the preceding sections, we develop essential elements for constructing the model. We first describe the structure of mobile phone-based weight loss interventions in Section 2. Section 3 describes our utility-maximizing model of the decisions of an individual participating in a weight loss intervention. Mathematically, we represent prior information in the Bayesian framework as histograms of parameter values for the utility functions of individuals that have completed the fixed duration of the program. To compute these parameters, we solve a maximum likelihood estimation (MLE) problem, which is the focus of Section 4. Our predictive modeling approach in Section 5 uses the utility-maximizing framework and corresponding histograms of parameter values to predict the weight loss trajectory of a single individual. Both the MLE in Section 4 and predictive model in Section 5 are computed by solving a mixed integer linear program (MILP).

To validate our predictive modeling approach, we use a longitudinal data set collected from a 5-month randomized controlled trial (RCT) of a mobile phone-based weight loss program. Section 6 begins with an overview of this RCT, and additional details are available in Fukuoka, Gay, Joiner, and Vittinghoff (2015). Next, we evaluate the effectiveness of our approach for predicting whether or not an individual will achieve clinically significant (i.e., 5% or more) weight loss at the end of the intervention. We validate our approach by showing its binary predication accuracy is comparable to standard machine learning methods (i.e., linear SVM, decision tree, and logistic regression) in terms of prediction quality. In contrast to these machine learning methods, our predictive model is also able to determine the impact of changing intervention parameters for a specific individual on that individual's weight loss trajectory, and we conclude with a discussion of this aspect of our model and how it can be used to perform optimization.

1.3. Literature Review

Statistical classification methods (which include logistic regression, support vector machines, neural networks, and random forests) predict a binary $\{-1, +1\}$ output label based on an input vector (Denoyel, Alfandari, & Thiele, 2017; Hastie et al., 2009). In the context of weight loss interventions, these approaches could predict whether (+1) or not (−1) an individual will achieve 5% weight loss after 5 months, based on 30 days of an individual's

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