Investigating Causality in Mobile Health Data through Deep Learning Models

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***Abstract*—Mobile health has emerged as a practical alternative in treating and managing one's health problems. However, most of the mobile health data are observational data collected through sensors, which makes it difficult to analyze the causality of the delivered interventions through standard regression methods. In this work, we review deep learning models that can be used to estimate the causal effect in raw mobile health data. These models are capable of handling multivariate time series data in estimating the unbiased causal effect given a sequence of treatments.**

***Keywords*-causal inference, mobile health, digital therapeutics**

I. Introduction

The widespread use of mobile devices such as smartphones has led to the emergence of actionable healthcare through such digital platforms. For example, digital therapeutics (DTx), which seek to treat diseases and improve the patient's conditions through actions delivered through smartphones and other digital devices, has recently been actively used to treat and manage chronic diseases such as diabetes [1]. Similar to any other types of disease treatments such as pills, mobile healthcare methods must be thoroughly analyzed via a formal causal framework to acknowledge their effectiveness as a cure.

Together with the development of mobile healthcare methods, various experimental designs and their complementary analysis techniques suited for their causal analyses have been extensively proposed [2], [3]. Although experimental methods such as randomized control trials are the gold standard for causal inference, conducting experiments is often too costly and sometimes even infeasible. Hence, most of the collected mobile healthcare data are observational, in which the data are collected without controlling for any factors. However, estimating causal (treatment) effects on observational data through standard regression methods may lead to incorrect causal conclusions because of potential sources of bias including confounders (variables that are common causes of both treatment and outcome).

A typical characteristic of mobile healthcare data is that the data are collected by various sensors and logs in smartphones. Thus, mobile healthcare data naturally consist of multiple time series. Although it is possible to remove the temporality of the data by using various summary statistics instead of the raw data and analyze causality correspondingly [4], [5], a great amount of information is lost in doing so. For example, one of the primary interests in mobile healthcare causal inference is the collective effect of the multiple interventions given as treatment [6]. In mobile health, because individual interventions can be relatively cheaply delivered, multiple actions can be taken to treat the patient [7]. Because each intervention is given with respect to time and thus has a time-varying effect as a treatment, performing causal inference after removing the temporality of the data may result in a limited or distorted view of the causality of the intended action. In addition, mobile data generated by smartphones are often high-dimensional and complex, which may be difficult to handle using simple models.

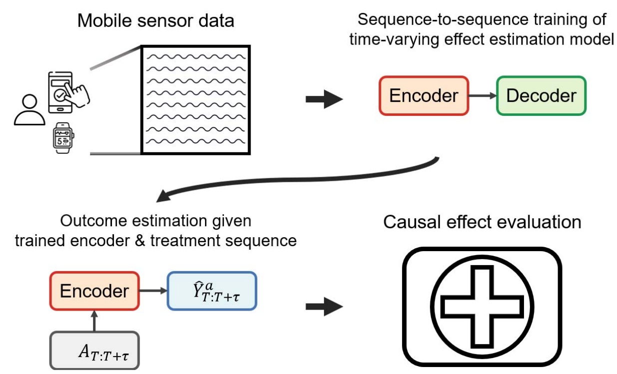

Figure 1. Pipeline of mobile health data causal analysis using sequential deep learning models

In this work, we briefly review two deep learning-based methods, namely the recurrent marginal structural network (R-MSN) [8] and the counterfactual recurrent network (CRN) [9], and outline how these methods can be used to estimate causal effect in temporal mobile healthcare data (Fig. 1). Both methods build on recurrent neural networks (RNN) and introduce modifications to remove bias to accurately estimate the causal effect size.

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II. Deep Learning-based Time-varying Treatment Effect Estimation Models

We describe two RNN-based treatment effect models that can be used for causal analysis in mobile healthcare. Both models are sequence-to-sequence architectures capable of handling multivariate temporal data which utilize the high-performance computation of neural networks to model complex causal relationships that comprise the input data.

A. Recurrent Marginal Structural Network

The recurrent marginal structural network (R-MSN) [8] builds on the marginal structural model (MSM) for time-dependent effect estimation [10] to estimate a sequence of responses given a sequence of treatments. In order to remove bias in estimating the causal effect, MSMs create a pseudo-population by weighting samples using the inverse of the propensity score. The effect size is estimated via taking the difference between the outcomes of the treated samples and that of the untreated samples in the pseudo-population. The MSM can be applied to temporal data as well by constructing weights for the joint treatment that incorporate time.

The R-MSN is comprised of three RNNs: the propensity network, encoder, and decoder. The propensity network is first trained with binary cross entropy loss to estimate the propensity score at each time step, which is used to generate a sequence of stabilizing weights. The encoder is then trained to estimate the outcome at time $t+1$ given the treatment and covariate values at time t, which produces a representation of the history of the subject. The encoder is trained using a mean-squared error weighted by the stabilizing weights obtained using the propensity network. Finally, the decoder takes the representation created by the encoder as input to generate a sequence of outcomes given a treatment sequence. The decoder is also trained with a similar weighted loss using the obtained stabilizing weights.

B. Counterfactual Recurrent Network

The counterfactual recurrent network (CRN) is also an RNN-based model designed to generate a causally unbiased outcome sequence given a treatment sequence. Contrary to the R-MSN which aims at removing bias through propensity score-based weighting, the CRN achieves the goal by creating a treatment-balanced representation. Using such representation to estimate the outcome removes the effect of time-dependent confounders and effectively allows the model to capture the direct causal effect of the treatment on the outcome.

The CRN follows a sequence-to-sequence architecture, in which the encoder RNN is used to build a treatment-balanced representation and the decoder RNN uses the encoder representation to estimate the outcome. First, the encoder is trained to be predictive of the outcome but not predictive of the treatment assignment, which is implemented by placing a gradient reversal layer in the treatment prediction module. This encourages the representation to predict the outcome regardless of what the assigned treatment was, resulting in a treatment-balanced representation. Once the encoder is fully trained, the resulting representation given by the final hidden state of the encoder RNN is given as the input to the decoder RNN, which is trained to predict the observed outcome given treatment at each time step.

III. Application to Mobile Health Data

A unique characteristic about mobile health compared to traditional medicine is that interventions are relatively cheap and thus frequent. In addition, the effect of individual interventions is weaker than that of physical treatments. For example, the effect of a mental health tips delivered by one's mobile phone would have a much weaker effect on relieving depressive symptoms than directly administered medications. Therefore, it is important in mobile health to simulate the effect of multiple possible treatment schemes and to assess not only the effect of individual interventions but also the joint effect of the entire treatment sequence.

The deep learning-based models reviewed in this work meet this purpose, in which the models are able to estimate the causal effect of treatment schemes by training on observed data. As the models are sequential models, they are naturally able to handle raw mobile sensor data. In addition, once a model is trained, it can be used to easily simulate the effect of dozens of treatment schemes which allows us to effectively narrow down the options to be physically experimented on. For example, we could use the models to compare the outcome of the case when treatment is given at all time points versus the case when treatment is not given at all to highlight the effect of the intervention. In other cases, we could simulate A/B tests to identify the more effective treatment schemes by generating the respective outcome sequences using the models.

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