Creating Interpretable Data-Driven Approaches for Remote Health Monitoring

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Abstract

We are at a turning point to address the unprecedented challenges we are facing in healthcare systems. With the aging of the population and increasing health disparities in rural areas, healthcare needs assistance from technologies to provide quality care for these populations. In collaboration with clinicians, we seek to meet this need by creating data-driven methods that provide interpretable healthcare models from ubiquitous ambient and wearable sensor data. My doctoral research goal is to introduce novel ways to help clinicians understand patients' health status by developing new visualization tools and interpretable models that analyze human health and behavior from sensor data.

Introduction

There is an urgent need for a remote health monitoring system to help with aging-in-place. In 2019, one in eleven people in the world were over the age of 65, and by 2050, it will be one in six [1]. Older adults require substantial healthcare time and resources because 80% have at least one chronic health condition (CDC 2011). The disparity of services among different geographical areas contributes additional concerns (Weaver and Roberto 2020). Further, social distancing due to COVID-19 has caused an increase in the lack of health checkups (Kim, Marrast, and Conigliaro 2020). While multiple studies have confirmed that family caregivers have lower mortality rates than non-caregivers, caregivers often experience physical and psychological distress (Roth et al. 2018). A remote health monitoring system may empower clinicians to provide care to a larger group of people without geographical boundaries and reduce the impact on caregivers' lives.

The vast accessibility of inexpensive wearable devices and ubiquitous sensor-filled environments has revolutionized the amount of individualized behavior and physiological data that can be collected for a person. While ambient and wearable sensors provided data-rich information without the privacy intrusion that accompanies cameras and microphones, data collected from these sensors do not provide direct health indicators. My dissertation aims to create interpretable time series classifiers wherein their explanations are tailored to meet clinician needs. To meet this goal, we are pursuing three research tasks. We investigate the feasibility of extracting health-specific indicators from time series sensor data. Further, we develop clinician-interpretable machine learning models. Finally, we provide clinicians with intelligible interfaces to visualize raw data, inferences, and the corresponding health status of patients.

[1] United Nations, world population ageing 2019: highlights

Discovery of Health Indicators

We start by extracting behavior markers that provide indicators of current health status and health trends. In collaboration with professional nurses, we designed a data-driven dashboard for monitoring older adults' health trajectories living in homes equipped with smart home in the box (SHiB) kits (Cook et al. 2012). ShiB offers a convenient data collection approach since users do not need to carry or charge any devices. Clinicians and our team work together to extract a set of features for tracking patients' health from the data. Extracted features include the number of bed-to-toilet transitions, activity level, sleep duration, and relative walking speed. Through an iterative design process with the help of 60 experienced nurses, we developed the Clinician in the Loop Visualization tool (CIL-Vis) for assisting nurses in tracking patient health and identifying anomalies (Ghods et al. 2018). CIL-Vis is a caregiver aid tool that illustrates a collection of carefully chosen behavior markers. All of the graphics are selected through multiple rounds of collaborative design with the end-user clinicians.

The resulting interface helps nurses identify behavior patterns that indicate chronic health conditions and unexpected health events. In one home, nurses use the visualization to recognize prostate issues resulting from a large number of nighttime toileting and low nighttime sleep in the bed due to possible pain. In another case, nurses associate a greater than normal daily amount of sleep and little time out of the house with depression. Also, nurses identified a decrease in walking speed would result in wheelchair use. CIL-Vis offers the potential to support self-management and chronic conditions, especially for older adults living alone. CIL-Vis provides a snapshot history of users' behavioral patterns that help caregivers take appropriate action regarding the care users need. CIL-Vis provides an opportunity for the nurses to check patients who live in remote locations readily without invading patients' privacy.

In a related project, we collaborated with oncologists to investigate extracting behavioral markers from a smartwatch for gastrointestinal cancer patients. Patients with cancer spend most of their time in their homes experiencing constant change. Oncologists assess patient health status by asking them to complete forms describing their physical and physiological state after visiting clinics. Previous studies indicate that these assessments are not reliable due to low agreement between clinicians, nurses, and patients' scores. Further, these assessment forms do not provide a continuous view of patient health. We monitored 27 consenting patients by asking them to wear a smartwatch seven days before receiving chemotherapy treatment and fourteen days after (Ghods et al. 2020). Smartwatches are readily available to the public and can continuously collect user data. Our study reveals that daily step counts can reliably monitor patients with cancer and replace traditional form-based assessment. The daily number of steps and fluctuation in daily step counts are directly correlated with patients' physical and physiological states. The continuous view of patients' health status will help doctors make better decisions about treatment plans.

Interpretable Models for Health Monitoring

While deep neural networks are regarded as highly accurate models, their use for high-stake problems is not recommended because of their black-box nature. I surveyed the recent advancements of deep learning classifier technologies that are being used outside of deep neural networks to design highly accurate and interpretable models for time series classification (Ghods and Cook 2020b). Compared to other types of data, such as images or tabular i.i.d. data, time series data do not intuitively convey specific concepts to non-experts. Further, the complexity of the clinical setting and its requirement makes designing an interpretable model much more challenging.

We developed PIP (*Pictorial Interpretable Prototype Learning for Time Series Classification*) (Ghods and Cook 2020a), a novel deep learning architecture that jointly learns classification models and meaningful visual class prototypes. PIP is an intrinsic interpretable model that learns a set of prototypes. Because the prototypes are learned in a flexible latent space, they are not interpretable on their own. Simultaneously, PIP learns a function that transforms the encoded into meaningful pictures. The users provide these pictures, thus they can be meaningful visual class representations for specific end-users. We hypothesize that a pictorial description is an effective way to communicate a learned concept to non-expert users. We recruited 35 end-user participants to evaluate the interpretability of PIP. The participants are from different backgrounds: STEM (n=19), clinical (n=10), and other (n=6). Participants compare the interpretability of PIP to other baseline models for a variety of tasks. The result of our study reveals that clinicians and people from other disciplines preferred the PIP pictorial representation. Further, end-users more accurately and quickly predict class values from PIP information than other baselines such as decision trees. Participants also have more confidence in PIP because it offers a combination of predictive accuracy and interpretability.

For the future, I am interested in designing an interpretable model that can describe the time series data using text or visual explanation. We develop Activity2vec (Ghods and Cook 2019), which appears in the KDD DSHealth workshop. Activity2vec is a sequence-to-sequence model with the goal of learning better features. In the next step, we want to interpret the latent space of Activity2vec to generate time series captions. We also want to develop an interpretable model for predicting the future in time series data. We often describe future events as if-then rules (e.g., if you grab a cup then you drink water). Our goal is to develop a model that can discover rules in multivariate or different modalities of time series in an interpretable manner.

References

CDC. 2011. Healthy aging: Helping people to live long and productive lives and enjoy a good quality of life. *Centers for Disease Control and Prevention* .

Cook, D. J.; Crandall, A. S.; Thomas, B. L.; and Krishnan, N. C. 2012. CASAS: A smart home in a box. *Computer* 46(7): 62–69.

Ghods, A.; Caffrey, K.; Lin, B.; Fraga, K.; Fritz, R.; Schmitter-Edgecombe, M.; Hundhausen, C.; and Cook, D. J. 2018. Iterative design of visual analytics for a clinician-in-the-loop smart home. *IEEE Journal of Biomedical and Health Informatics* 23(4): 1742–1748.

Ghods, A.; and Cook, D. J. 2019. Activity2vec: Learning adl embeddings from sensor data with a sequence-to-sequence model. *KDD Workshop on Applied Data Science for Healthcare* URL http://arxiv.org/abs/1907.05597.

Ghods, A.; and Cook, D. J. 2020a. PIP: Pictorial Interpretable Prototype Learning for Time Series Classification. *arXiv* .

Ghods, A.; and Cook, D. J. 2020b. A survey of deep network techniques all classifiers can adopt. *Data Mining and Knowledge Discovery* URL https://doi.org/10.1007/s10618-020-00722-8.

Ghods, A.; Shahrokni, A.; Ghasemzadeh, H.; and Cook, D. J. 2020. The remote monitoring of gastrointestinal cancer patients' performance status and burden of symptoms via a consumer-based activity tracker. *JMIR Preprints* doi: 10.2196/preprints.22931.

Kim, E. J.; Marrast, L.; and Conigliaro, J. 2020. COVID-19: Magnifying the Effect of Health Disparities. *Journal of General Internal Medicine* 1.

Roth, D. L.; Brown, S. L.; Rhodes, J. D.; and Haley, W. E. 2018. Reduced mortality rates among caregivers: Does family caregiving provide a stress-buffering effect? *Psychology and Aging* 33(4): 619.

Weaver, R. H.; and Roberto, K. A. 2020. Location Matters: Disparities in the Likelihood of Receiving Services in Late Life. *The International Journal of Aging and Human Development* .