Modeling Behavioral Deviations in ADLs Using Inverse Reinforcement Learning

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ABSTRACT

The detection of abnormalities in Activities of Daily Living (ADLs) has garnered significant attention in recent studies, with many employing deep learning techniques. This paper introduces a novel approach to analyzing ADLs sequences, aimed at identifying meaningful deviations from an individual's routine behavior. Our method offers several benefits for older adults, including timely care, early detection of health conditions to prevent deterioration, reduced monitoring burden on family members, and enhanced self-sufficiency without disrupting daily activities. We propose an Inverse Reinforcement Learning (IRL)-based method to detect behavioral abnormalities in older adults by analyzing ADLs sequences. Our approach models the problem of abnormality detection in behavior sequences as a higher-order Markov Chain model. By applying the IRL method, we infer the reward function that motivates individuals to perform ADLs from observed behavior trajectories. This inferred reward function is then used to identify potential behavior abnormalities through a threshold-based mechanism, where sequences with rewards below a specified threshold are flagged as potential abnormalities.

1. Introduction

As the world's population ages, there is an increasing need to develop technologies that can support healthy aging and enable older adults to live independently in their homes for as long as possible. One of the challenges of aging is that it often leads to changes in behavior, which can be early indicators of cognitive decline or other health issues. Detecting these changes in behavior can help caregivers and healthcare professionals intervene early, potentially improving health outcomes and quality of life for older adults.

Activities of Daily Living (ADLs) data, which includes information about daily activities such as eating, sleeping, and personal hygiene, can be used to track changes in behavior over time. However, detecting behavior changes from ADLs data can be challenging due to the complexity and variability of human behavior. The monitoring of ADLs has been promoted by advancements in sensor technologies. Decreased ADLs performance has been found to be associated with the progression of chronic diseases, including cognitive impairment, in older adults Stineman, Xie, Pan, Kurichi, Saliba, and Streim [2011]. A study comparing two groups of older adults found that the activity maps of dementia patients displayed disorganized behavior patterns, and there was a notable difference in heterogeneity between the healthy group and the group with the disease. Urwyler, Stucki, Rampa, Müri, Mosimann, and Nef [2017]. Therefore, the study of life patterns in older persons can be used to quantify changes relevant to ADLs in the course of diseases. Although there is plenty of research on ADLs recognition and ADLs impairment detection, studying irregularities in the pattern of daily life has not been studied enough. The existing research on behavior anomaly detection in older adults has primarily focused on point anomalies, neglecting the potential of utilizing temporal features to their fullest extent. While these studies have successfully identified anomalies where individual data points deviate from the norm, they have overlooked collective anomalies that can only be detected by analyzing the sequential nature of the data. Moreover, some investigations have been limited to identifying abnormalities within specific activity classes, failing to account for higher-level analysis of activities. Thus, it is crucial to consider appropriate behavior granularity in developing effective anomaly detection methods. Additionally, it is desirable for the method to offer a generalizable solution that can be adjusted for different target users within a reasonable timeframe, enabling it to leverage pre-learned models and accelerate the learning process.

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In this work, we propose an IRL-based model for behavior abnormality detection in older adults, where the reward function is inferred from the observed behavior of an expert, which is called trajectories. To be specific, observed sequences of ADLs performed by an individual are fed into the model as trajectories to learn the reward function.

The proposed model takes advantage of Inverse Reinforcement Learning for training the agent to learn the behavior of the older adult through a semi-supervised task. Inverse Reinforcement Learning is a machine learning technique that has shown promise in modeling human behavior and inferring underlying motivations Lin and Cook [2020]. Inverse reinforcement learning is particularly beneficial in cases where defining the reward function is challenging due to its complexity. Additionally, the reward function has been demonstrated to exhibit greater transferability compared to the policy function Russell [1998], leading to the development of more generalizable models. Unlike supervised methods that require labeled data for training, IRL-based models learn from trajectories that are observations of an expert performing the task. The proposed model learns a reward function that captures the underlying motivations behind the observed ADLs data and uses this function to detect changes in behavior. The model can adapt to changes in behavior over time, making it well-suited for detecting early indicators of cognitive decline or other health issues.

The main contributions of this research are as follows: (1) A novel representation of the abnormality detection in ADLs sequences as a higher-order Markov Chain model. (2) A semi-supervised IRL-based model for detecting behavior changes in older adults from sequences of ADLs data. (3) An evaluation of the proposed model on a real-world dataset of ADLs data from older adults.

2. Related Works

Abnormal behavior can be defined as "actions that are unexpected and often evaluated negatively because they differ from typical or usual behavior" Durand and Barlow [2003]. Because the concept of an anomaly is difficult to define precisely and is closely tied to patient behaviors and the types and course of pathologies, artificial intelligence, and more specifically machine learning techniques, have been used to learn to recognize those anomalies.

Scholars have used machine learning methods extensively to analyze ADLs with the goal of providing on-time care and predicting older adults' health conditions. Many studies benefit from the availability of datasets for daily activities, including the use of machine learning methods for predicting/detecting anomalous behavior Arifoglu and Bouchachia [2019a], Lotfi, Langensiepen, Mahmoud, and Akhlaghinia [2012], Riboni, Bettini, Civitarese, Janjua, and Helaoui [2015], Suryadevara, Mukhopadhyay, Wang, and Rayudu [2013], Freitas, de Aquino Piai, Dazzi, Teive, Parreira, Fernandes, Pires, and Leithardt [2022].

Fahad et al. Fahad and Tahir [2021] propose a method for detecting behavior anomalies by taking into account two types of abnormality: missing or extra sub-events in an activity and unusual durations of the activity. They trained an H2O model to classify events using labeled activities (normal, anomaly). The main problem with such supervised models is that they must be trained using labeled data, which is time-consuming and difficult to generate.

Casagrande et al. Casagrande, Tørresen, and Zouganeli [2018] have used recurrent neural networks to forecast the future values of the activities for each sensor. When abnormal behavior is anticipated in the near future, the caregiver is informed using the projected values. Investigations into data gathering, classification, and prediction were conducted in actual homes with dementia-affected elderly residents.

In assisted living settings, temporal characteristics of ADLs are taken into consideration to forecast the next activity. Nazerfard Nazerfard [2018] presents an association rule mining module that identifies associations among ADLs that are grouped according to the start time and duration of the related ADLs. The sequence of the activities is also taken into account.

Karakostas et al. Karakostas, Briassouli, Avgerinakis, Kompatsiaris, and Tsolaki [2016] present an anomaly detection approach in which the predicted user activity is represented by a task model. The predicted and actual behavior are then compared to see if any variance (anomaly) has occurred. The problem with such model-based anomaly detection approaches is that they fail to detect anomalies that have not previously occurred. Ismail et al. Ismail, Hassan, and Alsalamah [2019] propose a context-aware framework for learning and predicting human behavior. Behavior contexts such as weekdays and the time of day are collected from residents' real-life data to improve the accuracy of activity prediction.

Cook et al. Cook and Schmitter-Edgecombe [2009] have developed algorithms for automatically learning separate Markov models for each of the five classes of activity (Telephone Use, Hand Washing, Meal Preparation, Eating and Medication Use, and Cleaning). These models are used to both categorize the activities that are carried out in smart homes and to identify errors and inconsistencies in those activities.