Your Router as Fitbit: Health Monitoring with Network Traffic

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Introduction. In today's digital age, there is an increasing interest in using non-invasive and usable solutions to monitor the health of the elderly. Traditional patient monitoring methods, such as wearable sensors, cameras, and interviews/surveys, face various challenges, e.g., the lack of adherence and compliance [1], privacy invasiveness [2], and susceptibility to recall/self-report bias [3].

Our research mitigates these issues by developing an always-on, non-invasive health monitoring system that transforms everyday routers as health sensors. Our system goes beyond traditional sensor- or app-based methods [4]; it continuously collects and analyzes the often encrypted network traffic of mobile devices (including apps), computers, and various IoT devices on the elderly participant's home network. Based on the network traffic, we develop machine learning models to identify patterns of human behaviors at home, including but not limited to the sleep/nap/awake schedule, screen time, and the presence/absence of the elderly participant and any visitors at home, all of which could be indicative of potential health conditions [5]. Figure 1 shows a real-world example. Our models can also identify anomalies in behaviors that may suggest changing health conditions.

Our method, based on IoT Inspector [6], is software-only; it runs on commodity computers and does not require reconfiguring the home network. Our hardware-free setup potentially allows clinicians to scale home-monitoring ethnographic studies more so than traditional methods at lower costs. As the network traffic (albeit encrypted) reveals sensitive health conditions, we protect the privacy of the participants using federated learning and hostname-based whitelisting.

Potential use cases. ❶ *Longitudinal health monitoring*: monitoring cognitive decline through screen time analysis (e.g., phones and TVs) [7]; tracking Alzheimer's or Parkinson's disease progression by examining changes in sleep patterns; identifying signs of depression and anxiety by monitoring social media usage; estimating time spent outdoors by tracking the presence/absence of the participant's phone on the network. Figure 1 illustrates some of these human behaviors as inferred from one of the author's real-world network traffic. ❷ *Assessing caretakers' quality*: verifying caretakers' absence/presence and their punctuality by monitoring their phone's network traffic on the network (assuming that the caretakers join the WiFi network of the elderly). ❸ *Just-in-time interventions:* notifying clinicians and/or caretakers of anomalies in the elderly behavior, e.g., increase in screen time (due to depression) or absence of screen time (because the elderly fell in the bathroom and lost access to the phone).

Method. ❶ *Establishing a baseline:* Track network usage to establish distinct profiles for each application and device.

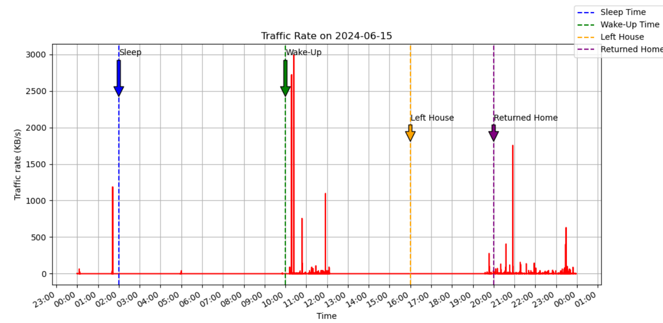

Fig. 1. Real-world uplink traffic rate (KB/s) of an author's phone on June 15, 2024, illustrating the correlation between network activity and daily events. Key moments include going to sleep at approximately 2 AM, waking up at 11 AM, leaving the house at 4 PM, and returning home at 8 PM, as indicated by corresponding fluctuations in the phone's traffic. We will apply the same method to monitor traffic patterns of phones and other devices in an elderly person's household.

We will leverage the existing IoT Inspector infrastructure [6], which uses ARP spoofing, to enable hardware-free, software-based network traffic collection. ❷ *Anomaly Detection:* Actively monitor for deviations from established patterns using both unsupervised and supervised learning methods to identify anomalies that may indicate worsening health or emergencies. ❸ *Ensuring user privacy:* Implement federated learning and hostname-based whitelisting to exclusively monitor authorized devices and applications. ❹ *Verifying inferences:* Compare detected usage patterns with self-reported data from caregivers, and assess changes in health metrics, such as sleep patterns and cognitive function, to verify intervention impacts. Issue real-time notifications to caregivers for immediate action upon detection of significant anomalies.

References

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