THE SCIENCE OF HOME AUTOMATION

By

BRIAN LOUIS THOMAS

A dissertation submitted in partial fulfillment of
the requirements for the degree of

DOCTOR OF PHILOSOPHY

WASHINGTON STATE UNIVERSITY
School of Electrical Engineering and Computer Science

JULY 2017

To the Faculty of Washington State University:

The members of the Committee appointed to examine the dissertation of BRIAN LOUIS THOMAS find it satisfactory and recommend that it be accepted.

Diane J. Cook, Ph.D., Chair

Matthew E. Taylor, Ph.D.

Anurag K. Srivastava, Ph.D.

Aaron S. Crandall, Ph.D.

ACKNOWLEDGMENTS

First and foremost, I would like to thank my advisor, Dr. Diane J. Cook, for her invaluable help, guidance, and encouragement during my research. I would like to thank my parents Cam and Debbie for always being there for me and encouraging me to be inquisitive about the world, as long as I went outside to do it. Mr. True, you not only taught me pre-calculus and AP calculus but also showed me how I could use my analytical mind to approach problems and understand them. To my friends and family in the Seattle Cascades, you helped me push through pain to achieve my dreams, and find confidence in myself.

Clint Cole, EE214 was the first time that I controlled a physical object with my code when I turned on a LED, the first of many. Andy O'Fallon, I can not thank you enough for all that you taught me about embedded processors and the Cerebot robot. It was my work with microcontrollers and your recommendation that introduced me to the CASAS Lab. I also have to thank Carl Hauser for his help outside of class, and his course on concurrency, which I utilize in my research and continued work with the CASAS Lab.

Aaron Crandall, Jim Kusznir, and Randall Svancara, I always enjoyed our lab engineering meetings and planning of middleware systems. Megan, Marshall, Will, Jen, Kyle, Bryan, Parisa, Dave, Leah, and Shirin, thank you for the fun times and helping me keep my sanity throughout grad school. Gene Whelan, it was my sunset discussion with you that finally pushed me over the edge to apply for grad school, thank you for being such a good role model and friend growing up. Lastly, I would like to thank Alyssa Dalbeck for her continued love, support, and encouragement as I finished my research.

THE SCIENCE OF HOME AUTOMATION

Abstract

by Brian Louis Thomas, Ph.D.
Washington State University
July 2017

Chair: Diane J. Cook

Smart home technologies and the concept of home automation have become more popular in recent years. This popularity has been accompanied by social acceptance of passive sensors installed throughout the home. The subsequent increase in smart homes facilitates the creation of home automation strategies. We believe that home automation strategies can be generated intelligently by utilizing smart home sensors and activity learning.

In this dissertation, we hypothesize that home automation can benefit from activity awareness. To test this, we develop our activity-aware smart automation system, CARL (CASAS Activity-aware Resource Learning). CARL learns the associations between activities and device usage from historical data and utilizes the activity-aware capabilities to control the devices. To help validate CARL we deploy and test three different versions of the automation system in a real-world smart environment.

To provide a foundation of activity learning, we integrate existing activity recognition and activity forecasting into CARL home automation. We also explore two alternatives to using human-labeled data to train the activity learning models. The first unsupervised method is Activity Detection, and the second is a modified DBSCAN algorithm that

utilizes Dynamic Time Warping (DTW) as a distance metric. We compare the performance of activity learning with human-defined labels and with automatically-discovered activity categories.

To provide evidence in support of our hypothesis, we evaluate CARL automation in a smart home testbed. Our results indicate that home automation can be boosted through activity awareness. We also find that the resulting automation has a high degree of usability and comfort for the smart home resident.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Dedication

To everyone who encouraged me to strive for more, thank you.

CHAPTER 1. INTRODUCTION

In recent years, smart homes have been enhanced by the notion of context-aware and activity-aware computing. Sensing and representing the current situation can improve the design of the physical system and strengthen its real-time system resiliency and responsiveness. In this research, smart homes are pushed to this level by introducing the notion of activity-aware home automation systems. Deploying activity-aware smart homes requires several computational components to make them aware of user activities.

Context, concerning context-aware [1], is first defined as "information about located objects and how those objects change over time." Additional context-aware systems quickly developed with the introduction and use of mobile computing devices [2, 3], middleware technologies [4], and smart home research [5–7]. Using the following definition of context [8]:

> Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves.

and the definition of context-aware [8]:

> A system is context-aware if it uses context to provide relevant information and/or services to the user, where relevancy depends on the user's task.

a definition of activity-aware systems can be built using the foundation of context-aware systems.

Activity-aware systems utilize activity recognition methods to provide additional information on broader behavioral patterns and activities in environments such as offices [9] to operating rooms [10]. Taking advantage of recent advances in live activity recognition on streaming sensor data [11] can allow a more diverse deployment of activity-aware systems in real-world situations. To minimize confusion, activity-aware systems will be defined as follows:

> An *activity-aware system* utilizes knowledge of the current activity being performed, in addition to other contextual information, to adapt the system and its related services.

The minimal activity-aware system will only utilize the current activity, but the more activity-related information that is included in the context (previous activity, the start time of current activity, etc.), the greater the level of awareness and expected performance improvement.

It should be noted that "context-aware" is a superset of "activity-aware." Existing context-aware systems do not use knowledge of activities, instead only utilizing location, time, or interaction with specific objects [1]. To differentiate this earlier work from systems that also incorporate information about the user's activities in the present, past, and/or future, the term activity-aware system has been introduced. Activity-aware systems are valuable when creating adaptive, intelligent, smart homes because services such as building automation can now adapt to the needs of individual users.

This dissertation hypothesizes that building automation can benefit from being activity-aware. Validation of this hypothesis is achieved by utilizing technology developed at CASAS (the Center for Advanced Studies in Adaptive Systems) to create a real smart home that automates building control for energy efficiency. The developed activity-aware smart automation system, CARL (CASAS Activity-aware Resource Learning), is based on the foundation of the CASAS smart environment infrastructure. Data are collected from sensors embedded in everyday building settings found in smart cities such as smart offices, smart hospitals, and smart homes. The collected data are used to identify activities that residents are performing and to determine the devices that are utilized in the context of those activities. The goal of CARL is to automate a smart building by turning off devices that are not needed for the current activity and leaving on devices that are required. By recognizing the current activity, a building found in a smart city is sensitive to its residents and does not turn off devices that they need. User adaptation is then further enhanced by forecasting when the current activity will end and the next begin. By providing this activity-aware energy-efficient building automation, smart buildings can realize energy savings while still meeting the needs of the individuals who live and work there.

To validate the notion of an activity-aware automated home, CARL is implemented and evaluated on real-time and historical smart home data to determine its ability to automate an actual smart building without disrupting resident activities efficiently. In particular, the resulting research contributions include the following:

- Design and implementation of the CASAS sensor-filled smart home (Chapter 3)

- Design and implementation of an automatable CASAS smart home called navan (Chapter 3)

- Incorporation of activity learning algorithms, including activity recognition, activity forecasting, and activity clustering, into the design of a home automation system (Chapter 4 and Chapter 5)

- Design of the CARL building automation algorithm (Chapter 6)

- Evaluation of CARL based on actual home automation using navan and simulated automation using historical smart home datasets (Chapter 7)

This research offers a new perspective on home automation. By implementing the ideas in the context of an actual automated home, a basis is provided for future researchers and developers to envision and create activity-aware smart homes for a greater range of applications. The next chapter provides background and related research on current building automation systems.

CHAPTER 2. ENERGY-EFFICIENT BUILDING AUTOMATION

The automation of the home is known as domotics [12], generally referring to a house equipped with mechanical and electronic automation facilities. These homes are now known as smart homes [13], drawing from popular culture and movies to describe an equipped living space that is designed to assist residents with daily activities. To make decisions about automation in the smart home, an intelligent agent must be aware of the environment in the smart home. This awareness brings forward questions of sensing and resident privacy which are addressed in the next sections.

2.1 Automation

Until recently, occupant behavior has been difficult to capture accurately. Self-report of behavior and energy consumption is error prone [14], and whole-home meter monitoring does not capture the behaviors in the home that influence use. As a result, there is an urgent need to develop technologies capable of examining energy usage in homes, relating behavior to power consumption, and providing energy reduction support through activity-aware home automation.

Numerous approaches have been utilized to explore the influences and motivation for residential energy use and the gap between the minimum amount of consumption that is needed for daily activities and the consumption that is observed. Four broadly defined perspectives to explain this difference are economics, technology adoption and decision science, environmental psychology, and sociology [15–17]. The underpinnings of these various approaches are based on models of the individual or household decision making to advance underlying well-being, values, attitudes, or social norms within the context of different constraints including available choices, incentives, and existing technologies. Some studies also consider the link between consumption and household composition, including geography and political ideology [18].

On the other hand, many studies are based on economic theory that centers on person-driven household utility optimization in response to financial incentives aimed at either reducing total electricity consumption or shifting consumption from peak demand periods to off-peak periods. Recent surveys find that household responses to economic incentives are relatively small [19]. The effectiveness of time-of-use pricing policies designed to shift consumption to off-peak periods appears to be mixed [20–23]. This limited consumer response may be due in part to little information about household consumption. Since users mostly receive monthly utility bills reporting aggregate use, it may be difficult for them to respond to incentives. Consumers might be unaware of both electricity consumption associated with particular tasks or activities and of cumulative use through a billing cycle. A 2010 survey of 15 experiments [16] found that critical-peak pricing is far more effective when incentives are accompanied with enabling technologies providing details on the nature of their consumption and allow remote control of electricity consumption.

Recently, some authors have investigated the effectiveness of information intervention on electricity consumption. One company, Opower [24], mails reports to households every few months containing personalized feedback, comparisons, and conservation tips. Researchers found that families receiving the Opower report reduce electricity use within days of receiving reports [25], but that responses decay rapidly. However, the reaction-and-backsliding cycle decreases after receiving repeated reports. The authors speculate that when intervention is repeated, people develop new behavior habits making treatment effects permanent. One implication is that it is important to repeat an intervention until participants develop habits or knowledge to develop a persistence effect lasting beyond the treatments.

Also, studies have shown that social interfaces can be effective at promoting behavior change, leading to a reduction in resource consumption. Some of the mechanisms that have been tried are collective group goals, team play, and the feeling of responsibility for the social group's consumption status [26, 27].

Researchers claim that providing users with knowledge about the relationship between their activities and energy consumption and automation support for energy reduction will result in substantial decreases in overall consumption. This view is underpinned by an increasing body of work that links awareness of energy consumption and its impact on behavioral routines and behavioral change [28–30]. Until recently, validating this hypothesis was not possible. However, with the convergence of technologies in ubiquitous computing and machine learning, gathering data on human behavior is now automatable. Data can be collected from sensor-filled smart homes [31] and smartphones [32] unobtrusively while individuals perform their normal daily routines. Because these sensor modalities operate in a continuous mode, feedback and interventions repeat ad infinitum, thereby maximizing the persistence effect.

Technologies to unobtrusively monitor energy consumption are now beginning to emerge at the consumer level. Non-intrusive appliance load monitoring [33] has been designed to detect the use of individual devices. Several academic studies focused on this topic to estimate residential energy levels based on appliance usage [34, 35]. Concerning energy conservation, some industrial products concentrate on providing energy information services and savings tips to residents. The Nest thermostat attempts to make energy reduction hip and approachable [36–38]. Google PowerMeter provided a free energy monitoring tool for saving energy by providing energy information via smart meters. Other companies, such as Microsoft Hohm, C3 Energy, and Opower apply statistical methods and data mining algorithms to analyze a home's raw utility data and give customers practical energy saving tips. However, these projects are orthogonal to the CASAS automation infrastructure, in which automation technologies are provided that are related to resident behavior in the home.

Several studies exist that predict building energy consumption at a highly aggregated level for an extensive collection of buildings [39], but these studies differ from current work considering human behaviors in an individual building as primary features for predicting energy usage. Some early work has focused on linking resident activity with energy consumption [40], and this work builds on these earlier projects to provide automation that does not disrupt these sensed activities.

Recently, research groups have increasingly ventured into the area of home control for energy efficiency. Much of this work focuses on the control of HVAC systems. Remote control of HVAC systems has been facilitated and fine-tuned with automation control and user-friendly app interfaces [41]. Researchers have built upon this foundation to investigate probabilistic models to predict home occupancy [42, 43].

Building on these earlier technologies and findings, CARL has been developed to go beyond building occupancy, and instead learns and recognizes the range of activities that are performed in a smart environment. This information is then used to determine what devices and consumption are needed in support of the activities, and to turn off what is not required.

2.2 Smart Thermostats

The presence of occupants and their behavior in buildings has been shown to have substantial impacts on energy requirements for lighting, appliances, building controls, and HVAC systems [44]. For the average U.S. residential home, heating, ventilation, and air conditioning (HVAC) alone account for 43% of the total energy consumed in a year [45]. In an effort to reduce energy costs, programmable thermostats were introduced as a method to reduce energy requirements for an HVAC system. Programmable thermostats can utilize a setback schedule to significantly reduce the energy needed for heating and cooling a home. A setback schedule is a schedule of provided times during the day that the thermostat can relax temperature setpoints, typically when no one is usually home or when residents are sleeping. Figure 2.1a visualizes the setback behavior of a programmable thermostat. This thermostat is programmed to use the relaxed setpoint at 10 am and return to normal comfort levels later in the evening.

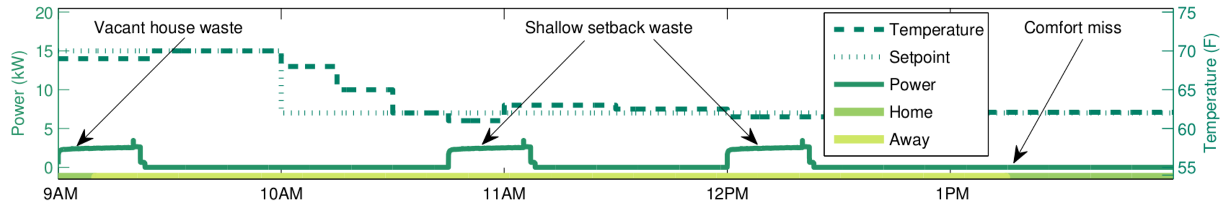
Reactive thermostats were developed in an attempt to improve programmable thermostats. By reacting to the residents, reactive thermostats were supposed to provide a method of energy saving that would better match a resident's changing behaviors. Instead of following a pre-programmed schedule, reactive thermostats react to input from sensors in the surrounding environment. Motion sensors, door sensors, or key-card access systems are often used as data to these thermostats. In Figure 2.1b the thermostat can be observed reacting an hour after the departure of the resident and setting a shallow setback temperature. Unfortunately, when the resident returns just after 1 pm the reactive thermostat must use much more energy to quickly return the temperature to the resident's comfort levels as it reacts to the resident's sudden return.

A study by the Environmental Protection Agency (EPA) found that when properly used, an exact setback schedule can reduce the energy required to heat and cool a home by as much as 10%-30% [45]. Unfortunately, the same study also found that less than 50% of U.S. households have a programmable thermostat installed, and in addition to that, 30% of the households with programmable thermostats installed are either disabling the programmable feature or have them programmed incorrectly. Building on the previous problem, it was discovered that many homes with programmable thermostats have higher energy consumption on average than homes with manual controls due to the incorrectly programmed or disabled thermostats [46]. Resulting from this, the EPA decided to suspend the Energy Star certification program for all programmable thermostats, effective December 31, 2009 [47].

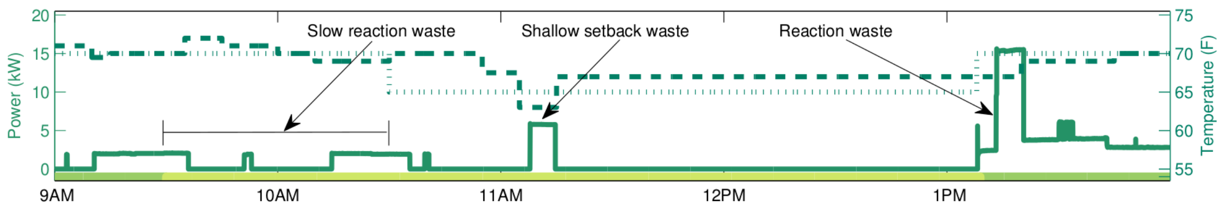
With the loss of the Energy Star certification for the programmable thermostats, several researchers took up the challenge to research new techniques that could improve the energy efficiency of thermostats. There is lots of research focusing on predicting occupancy patterns for HVAC control [42, 48–55], yet only a small portion of the research evaluates their energy saving potential in a real test-bed or actual experiments [42, 56–58]. Presented here are the Smart Thermostat from the University of Virginia, and a second system that builds upon many ideas from the Smart Thermostat, called PreHeat.

2.2.1 The Smart Thermostat

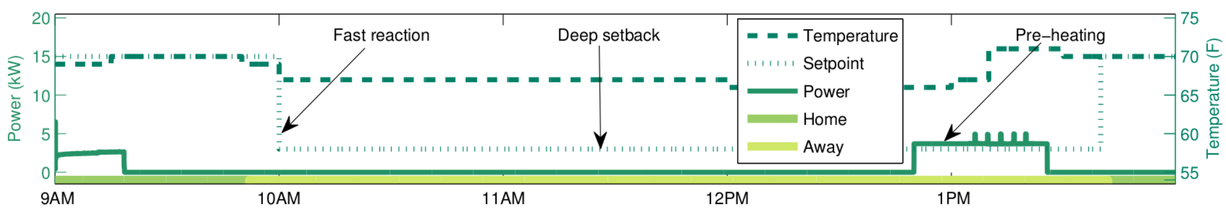
The Smart Thermostat [42] is a thermostat designed to use occupancy sensors to automatically turn off the HVAC system when residents are sleeping or away from home. If the average U.S. home were to reduce HVAC energy usage by 20%-30%, the monthly energy bill would decrease by approximately $15. It has been argued that this small financial gain does not justify the difficulties in optimizing HVAC control on a daily basis [42]. At the national scale, these savings would be approximately 100 billion kWh at the cost of $15 billion annually and prevent 1.12 billion tons of pollutants from being released into the atmosphere every year [59]. With this in mind, the Smart Thermostat was developed to use off the shelf sensors that are easy to install and inexpensive enough that the energy savings would recoup their cost within 2-3 months. By using X10 motion and door sensors,



(a) Programmable Thermostat



(b) Reactive Thermostat



(c) Smart Thermostat

Figure 2.1: While both programmable and reactive thermostats can waste energy and cause discomfort, a smart thermostat can use a deep setback temperature while residents are gone and preheat immediately before their return [42].

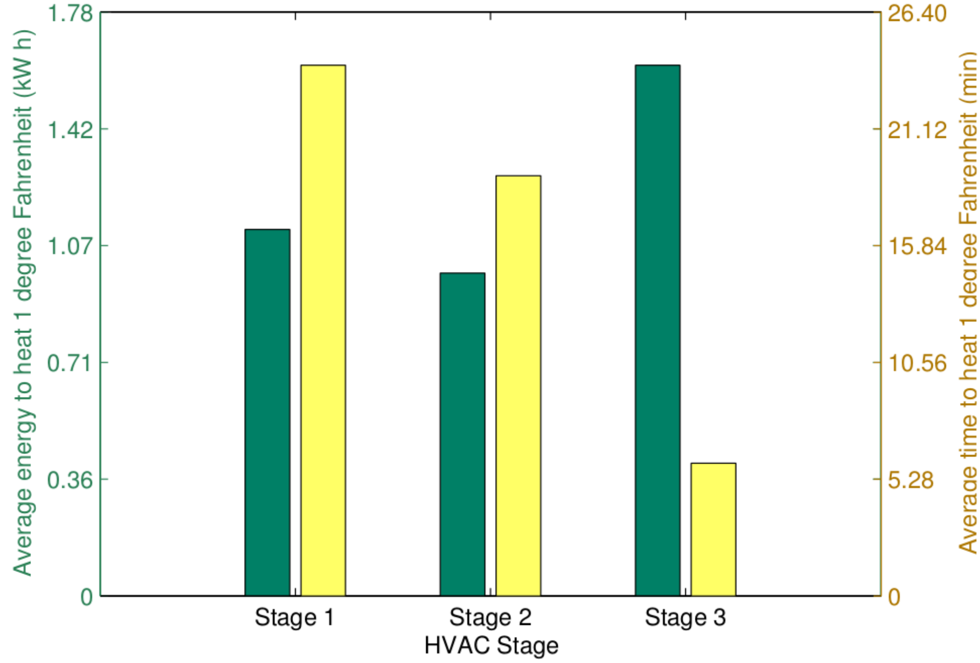


Figure 2.2: Energy efficiency and lag time for three stages of a standard HVAC system [42].

each costing approximately $5 [60], the sensors required for an average home with nine rooms would cost around $50 to $100. A motion sensor would be placed in every room and a door sensor in most doorways. However, analysis and simulations with several publicly available smart home datasets would show that using a *select* set of sensors (3-5 sensors) carefully placed throughout the home instead of the planned 12-20 sensors resulted in negligible differences in occupancy detection. The ability to install this system with the *select* sensors and still get significant energy saving for less than $25 puts it in a place that just might outweigh the initial cost and installation to reach the benefits from continued use [42].

To make decisions about turning on and off the HVAC system, a Hidden Markov

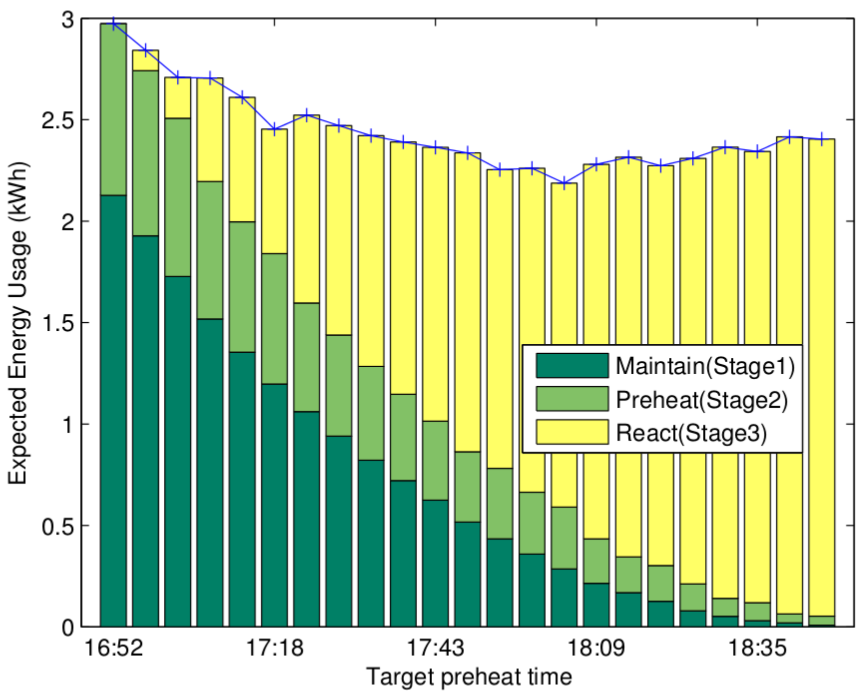


Figure 2.3: Target preheat times are chosen to minimize the expected energy use, in this case, the smart thermostat would start to preheat at 18:04 [42].

Model (HMM) is trained to estimate the probability of the home being in each of three defined states: (1) *Away* for when the house is unoccupied, (2) *Active* for when the home is occupied, and at least one resident is awake, and (3) *Sleep* for when all residents that are home are sleeping. Turning off the HVAC system is easier to determine than when it should be turned on. Preheating the home too early can waste energy when maintaining the higher setpoint for too long. Figure 2.2 depicts the three stages found in most HVAC systems. In many homes, there is a 2-stage heat pump and a third stage electric heater that can condition the space in significantly less time, but with a significantly higher rate of energy use. The Smart Thermostat algorithm balances this delicate trade-off by choosing the optimal preheat time.

By plotting the targeted preheat time against the long-term expected energy usage, shown in Figure 2.3, the algorithm can use the observed capacities and efficiencies of the different HVAC system stages to calculate the optimal time that will use the least energy in preheating the space in time for the predicted return of the residents. This plot demonstrates that if the thermostat preheats too early (left side), energy is wasted from maintaining the high setpoint temperature too long, and if the thermostat preheats too late (right side), energy is lost because it must react with the fast-yet-inefficient Stage3 (electric heater) if the residents return before preheating is complete.

When calculating the setback temperatures for *away*, shallow setbacks are typically used to reduce the risk of comfort loss, in case of the resident returning unexpectedly and the home is still at the setback limit. If the setback period is plotted against the depth of the setback temperature, as in Figure 2.4, one can see that the deeper setback

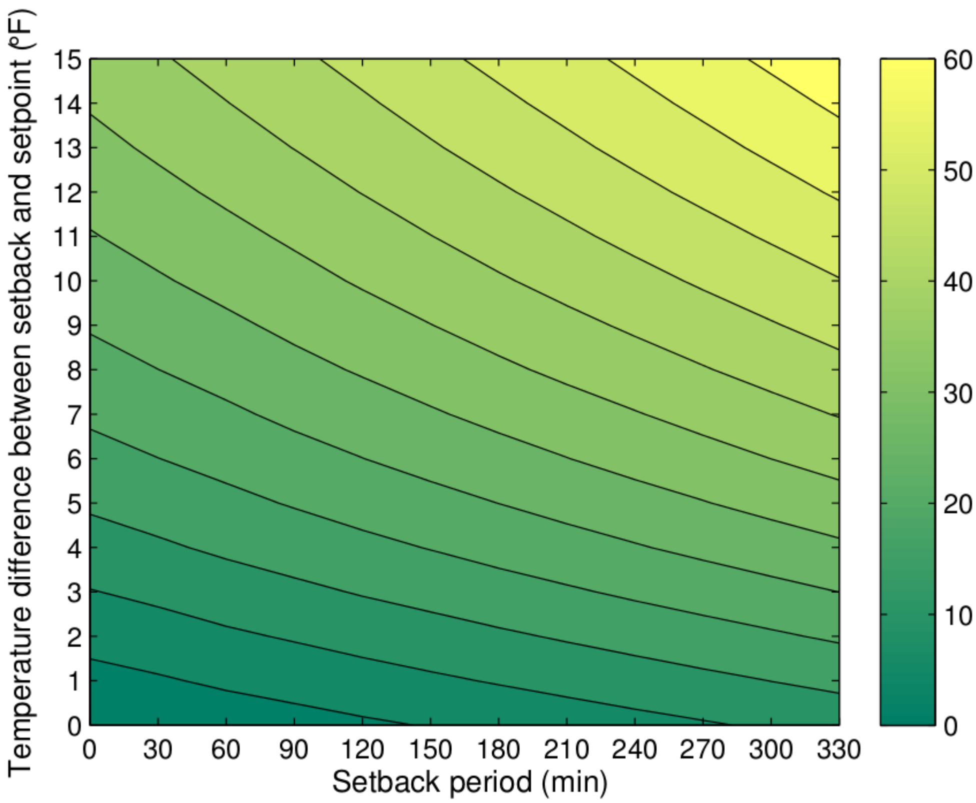


Figure 2.4: A comparison of deeper setback degrees to longer setback periods [42], demonstrating that a deeper setback provides greater energy savings than a longer setback.

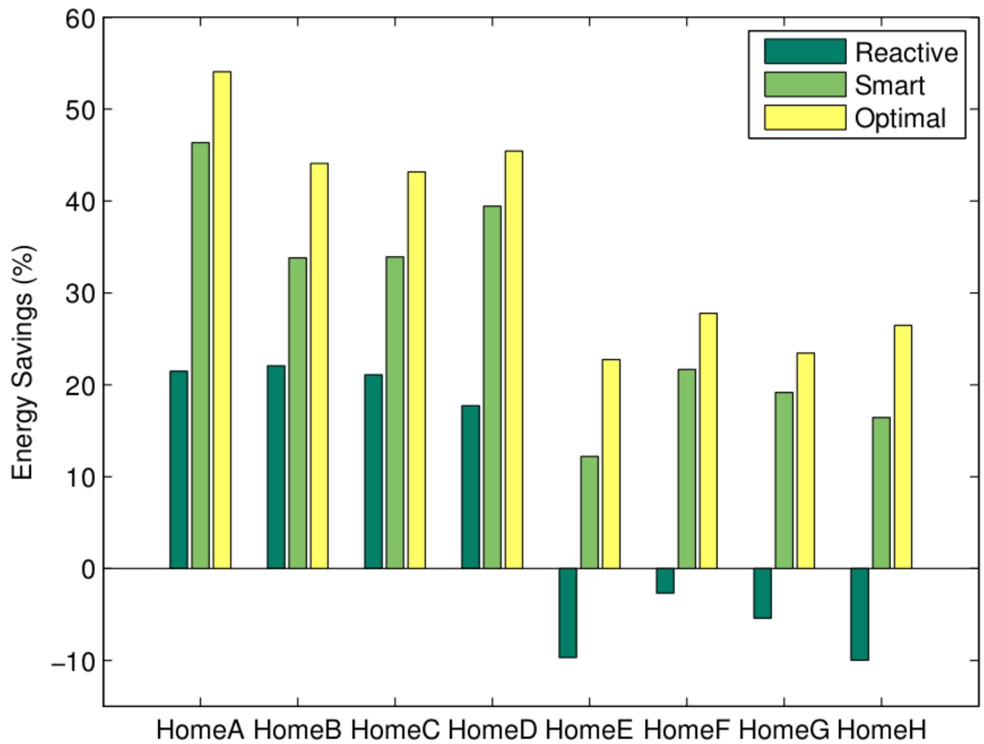


Figure 2.5: Results on data collected in 8 homes, each having run for 14 days [42].

temperatures have larger impacts on energy savings than longer setback periods. From this graph, it can be calculated that increasing a setback temperature by five degrees for an hour is equivalent in energy expenditure as holding the standard setback temperature for five hours.

To start evaluating algorithms and models, a framework was built around the U.S. Department of Energy's EnergyPlus simulator [61]. By utilizing the whole-house thermal simulation modeling, evaluations were run over several different algorithms with different housing conditions and climates. Comparisons were made between an optimal algorithm that was designed to provide the theoretical upper bound on energy savings, a reactive thermostat with a five-minute threshold, and the Smart Thermostat. The optimal algorithm knows the complete state of the home at all times and has no lag time when heating, implying that the optimal miss time will always be zero. Results on the data collected from 8 homes are presented in Figure 2.5. The depicted energy savings is defined as the percentage of saving by the scheme over the cost of continuously maintaining the setpoint temperature. The Smart Thermostat outperforms the reactive thermostat in all 8 homes and maintaining the setpoint even beats the reactive thermostat in homes E-H. On average the Smart Thermostat saves 28% of the energy used by residential HVAC systems.

2.2.2 PreHeat

PreHeat [43] was primarily a Microsoft supported research project that attempted to improve upon the work done with the Smart Thermostat by improving occupancy

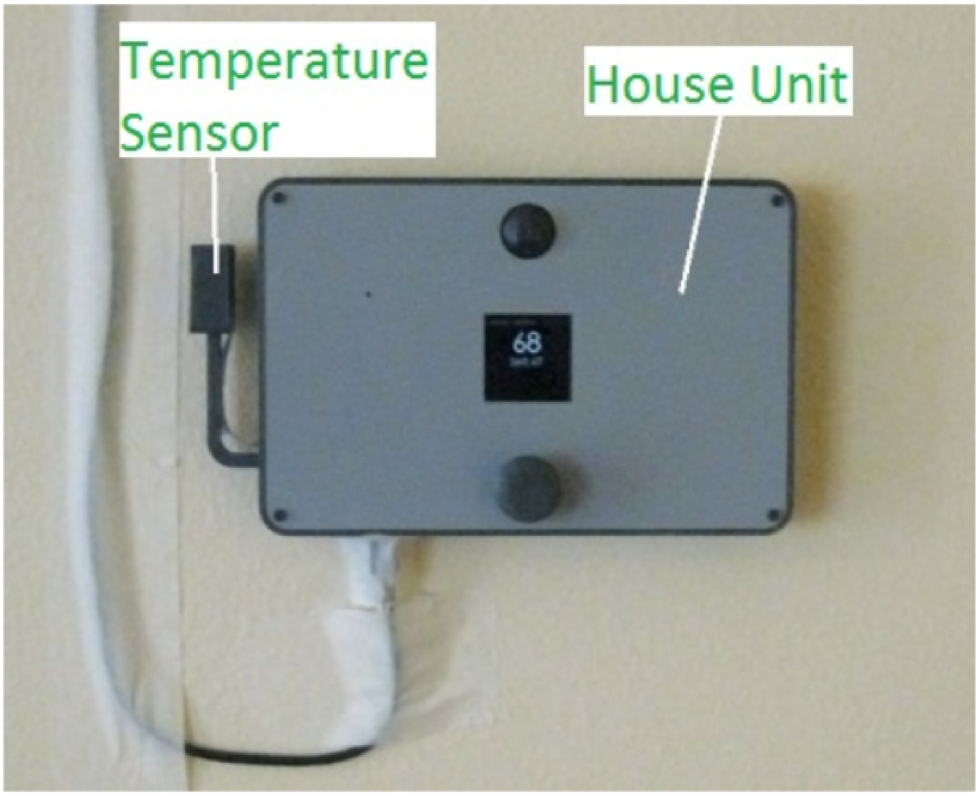


Figure 2.6: House Unit in U.S. deployment replacing the preexisting thermostat [43].

prediction. The experimental thermostat was installed in five homes, three in Seattle, USA and two in Cambridge, U.K. from January through April of 2011. Images of the installed hardware may be found in Figures 2.6, 2.7, and 2.8. All U.S. homes had whole-house forced air HVAC systems, so a single House Unit (Figure 2.6) was installed, replacing the existing thermostat. The U.K. homes were equipped with per-room heating and fitted with Room Units (Figure 2.7) and a Control Unit (Figure 2.8) for controlling per-room under-floor heating valves or the house boiler.

Occupancy detection was performed using two different methods between the U.S. and U.K. installs. In the U.S., occupancy was detected with RFID tags given to the

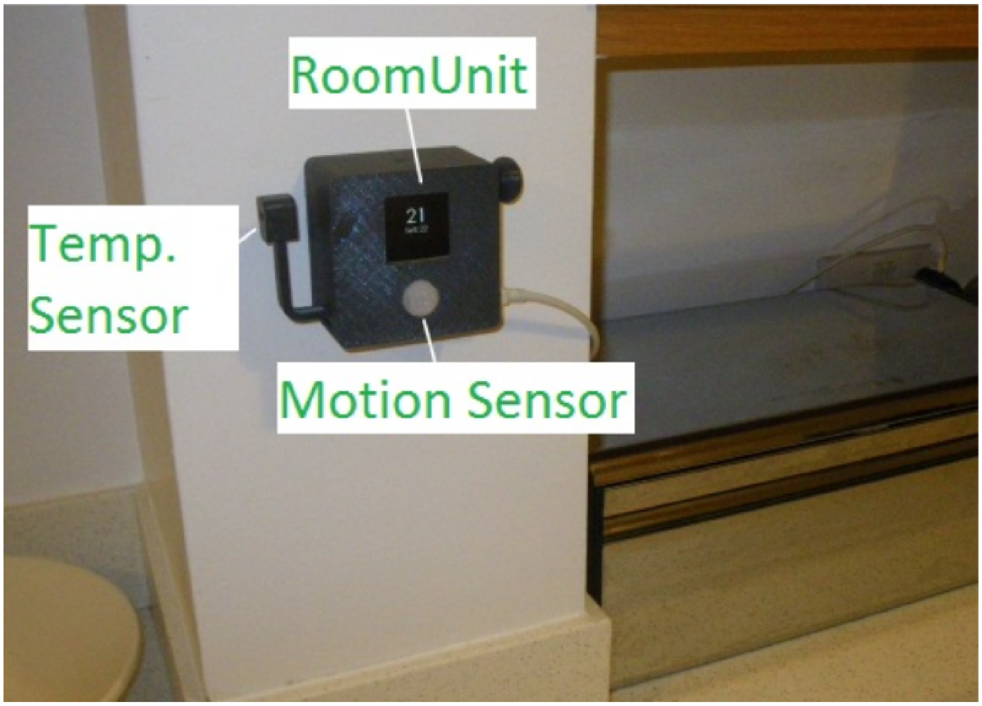


Figure 2.7: Room Unit from a U.K. installation [43].

residents to put on their keys. The U.K. homes had motion detectors installed because heating could be controlled on a per-room basis. U.K. residents did have RFID tags as well, but they were only used during system evaluation and not for prediction.

The PreHeat prediction algorithm first utilizes occupancy-reactive heating when a given space is occupied. When a given space is unoccupied, the algorithm then predicts when the given space will next be occupied by comparing historical occupancy data to what it has observed for the current day. A binary vector represents occupancy in the spaces, where each element is a 15-minute interval, shown in Figure 2.9. The pattern for the current observed partial day is compared to past partial days, and the five most similar are then selected. Probabilities for the future occupancy are then computed by taking the

Figure 2.8: Control Unit from the U.K. wired into old boiler control circuitry [43].

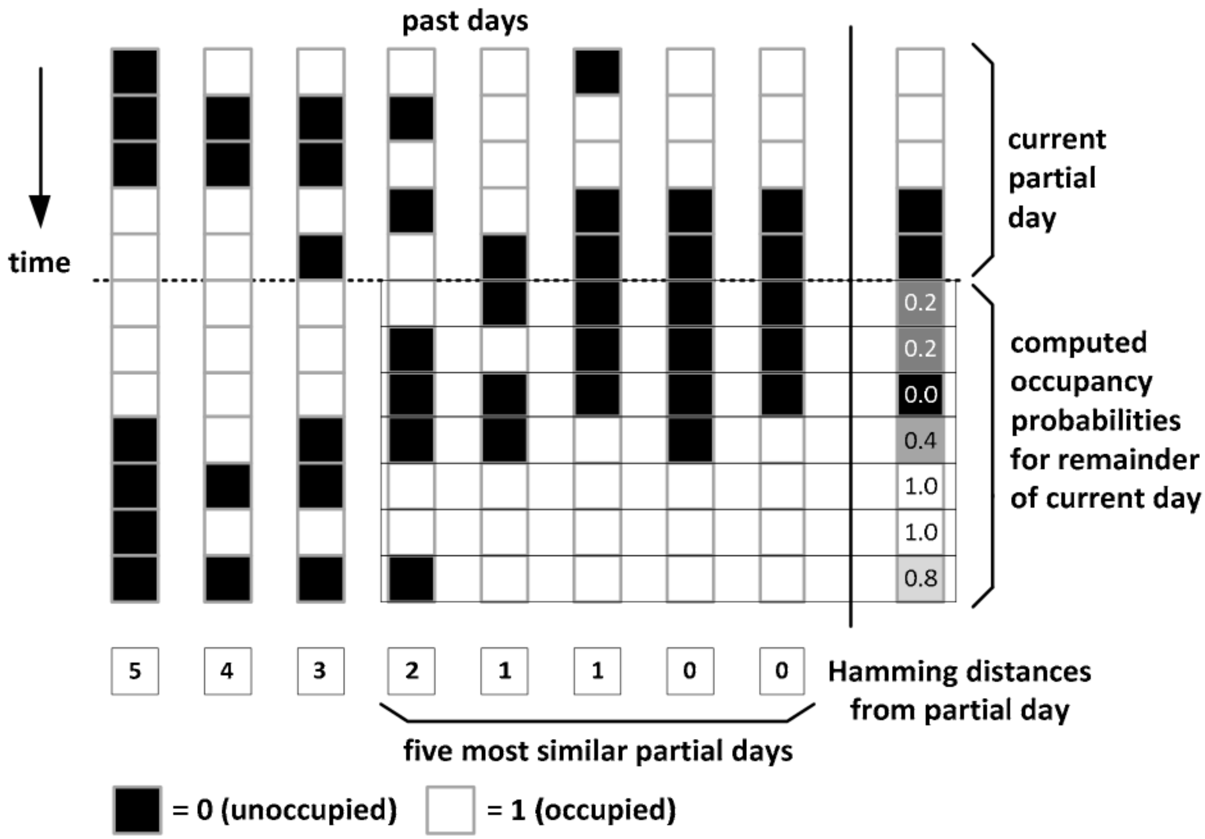


Figure 2.9: The PreHeat prediction algorithm. Every day is split into 15-minute windows, so for a partially observed day (on the right) the algorithm searches for the five best matches found in the past, computing probabilities for future occupancy from the averages of what happened the remainder of those days [43].

average of the five selected past days for each interval.

Two variations of the PreHeat algorithm were implemented in an attempt to improve accuracy. The first variation added a field to the binary vector identifying the day as a weekday or a weekend. Weekend predictions were then only computed from other historical weekend observations and the same for weekday predictions. This improved accuracy because residents normally have different occupancy patterns between weekends and weekdays. There is a noted flaw in this assumption if the residents did not have regular white-collar jobs, such as a position in retail, and instead took their two days off at differing times during the week. This issue could be overcome by allowing weekends to compute predictions from weekdays, or vice versa if conditions are similar enough to warrant overriding that flag. The second variation of the PreHeat algorithm augments the beginning of each occupancy vector with four hours of occupancy data from the previous day, giving predictions near the start of a day a little more help in comparing to historical observations. Four hours of observations are also added to the end of each day, allowing the avoidance of complexities in making predictions that span midnight.

Deployment of the PreHeat system collected data across three phases. Phase 0 lasted a minimum of a week and was used for debugging and allowing residents to get used to the RFID tags and adjust their preferred setpoints. The preexisting thermostat (if programmable) was used as a baseline schedule and residents were asked to update the program if necessary. Phase 1 was the initial data collection and lasted 14 days without occupancy prediction. The schedule provided during Phase 0 was used as a programmable thermostat during this time. This schedule also allowed the collection of enough historical occupancy data so the prediction system in Phase 2 could work accurately. Phase 2 compared the PreHeat prediction algorithm against the scheduled system and lasted between 48 and 72 days. To regulate for schedule changes, each day alternated between the PreHeat algorithm and the scheduling algorithm.

While per-room heating was not directly studied through a direct comparison, an

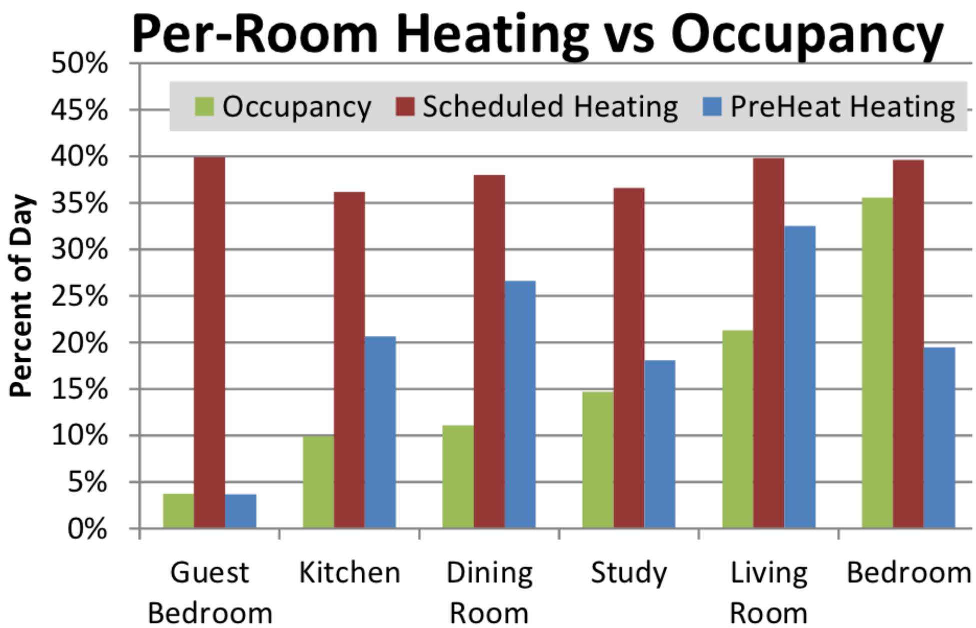


Figure 2.10: PreHeat can adapt and heat several rooms with differing-occupancy much more efficiently than a scheduled thermostat [43].

example of how well PreHeat was able to adapt to each room's occupancy settings is still fascinating. Figure 2.10 shows how often each of the algorithms ended up heating each room for one of the U.K. deployments. From examining data collected in Phase 2, it was found that 91% of the time the system needed 90 minutes or less notice for each daytime heating instance. A 90-minute look ahead time was then chosen as the evaluation for the rest of the assessment. Prediction accuracies for the 90-minute look ahead can be found in Figure 2.11. The manually programmed schedule thermostat performed worse than the PreHeat algorithm by a median ten percentage points. The general population can expect even greater improvements as many do not use the programming feature in their thermostats, or have it poorly programmed.

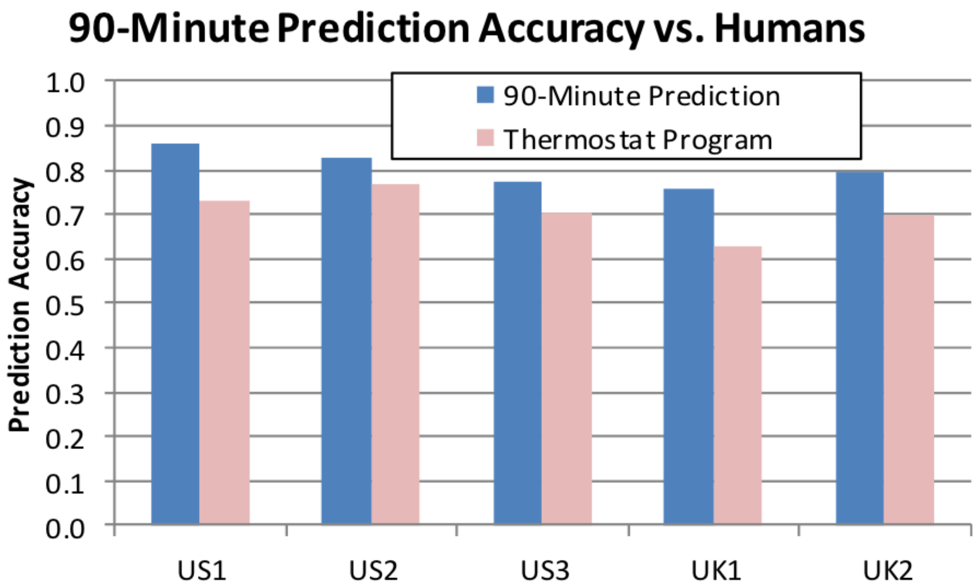


Figure 2.11: PreHeat consistently outperformed thermostats that were carefully programmed [43].

After living with PreHeat for some time, the researchers provide some anecdotes about their experiences. PreHeat handles weekend chaos better than expected, programming the thermostat for the weekend was always a challenge and PreHeat did a better job without requiring manual effort or interventions from the residents. PreHeat supports more complicated occupancy patterns than programmable thermostats allow and prediction on a per-room basis was a relief to U.K. residents as maintaining multiple thermostats throughout the home can be quite the hassle. PreHeat adapts to changing schedules with ease, a schedule change in one of the U.S. homes only took a few observations of the new pattern before PreHeat was correctly predicting occupancy again.

2.3 Energy-Efficient Smart Buildings

The impacts of lifestyle choices on energy usage and the environment are becoming increasingly noticeable, and therefore a focus of resources on building automation and smart cities. Vast and attractive opportunities exist to reduce a building's energy use at lower costs and higher returns than in other sectors [62]. Research on office environments has shown a positive correlation between occupant productivity and lighting satisfaction [63]. Continuing on this trend of financial incentives, further studies report on potential savings of 58% [64], 48% [65], and 33% [53] of energy used in office lighting. These reductions are fundamental to supporting achievement of the International Energy Agency's (IEA) target of a 77% decrease in the planet's carbon footprint against the 2050 baseline to reach stabilized CO_2 levels called for by the Intergovernmental Panel on Climate Change (IPCC). As a result, research attention is being directed toward green technology, environmentally-friendly building design, and active demand response within the smart grid. This work examines the behavior side of sustainability and introduces ubiquitous computing technologies that may aid in reducing energy consumption. In particular, an activity-aware intervention is described that promotes energy efficient, sustainable building automation.

Research by the World Business Council for Sustainable Development (WBCSD) in 2009 demonstrates that energy used in buildings can be cut dramatically, saving as much energy as the entire transport sector currently uses. In 2015, the United States consumed 97.651 quadrillions BTU of energy, a 300% increase from 1949 [66]. The growth of energy usage is not entirely due to manufacturing plants and automobiles: residential and commercial buildings are responsible for 40% of the energy consumption [67]. There exists evidence that residential consumer behavior can be influenced to be more sustainable. For example, home residents have reduced consumption by as much as 15% in response to just viewing raw usage data [68]. Changing behavioral patterns in these environments can influence usage by as much as 90% in commercial buildings and 100% in household settings [25].

Until recently, occupant behavior has been difficult to capture accurately. Self-reports of behavior and energy consumption are error prone for some populations [69], and whole-home meter monitoring does not capture the behaviors in the home that influence consumption. Approaches have been utilized to explore the gap between the minimum amount of consumption that is needed for daily activities and the consumption that is observed [15]. Some early work has focused on linking resident activity with energy consumption. The hypothesis that providing users with knowledge about the relationship between their activities and power consumption and automation support for energy reduction will result in substantial decreases in overall consumption is supported by an increasing body of work that links awareness of energy consumption and its impact on behavioral routines and behavioral change [29, 30, 70]. Until recently, validating this hypothesis was not possible. However, with the convergence of technologies in ubiquitous computing and machine learning, gathering data on human behavior is now automatable. Data can be collected from sensor-filled smart buildings and smartphones unobtrusively while individuals perform their normal daily routines. Because these sensor modalities operate in a continuous mode, feedback and interventions repeat ad infinitum, thereby maximizing the persistence effect.

Automating control of buildings for energy efficiency has been explored by other groups [62, 71–77]. However, this work represents the first known approach in which activity awareness is used to automate the environment more intelligently.

2.4 Smart Environments

Computers are commonly embedded in familiar objects such as home appliances and mobile devices, gradually pervading almost every level of society. In the last decade, machine learning and pervasive computing technologies have matured to the point where this power is not only integrated into the lives of most consumers, but it can provide activity-aware, automated support in an everyday environment. One physical embodiment of such a system is a smart home. In the home or other smart building environments, computer software that plays the role of an intelligent agent perceives the state of the physical environment and residents using sensors, reasons about the configuration of the environment using artificial intelligence techniques, and then takes actions to achieve specified goals.

Activity-aware building automation can be accomplished with any sensor-filled physical environment (see Figure 2.12). One physical embodiment of such a system is a smart home. In the home environment, computer software that plays the role of an intelligent agent perceives the state of the physical environment and residents using sensors, reasons about this state using machine learning and data mining, and then takes actions to achieve specified goals.

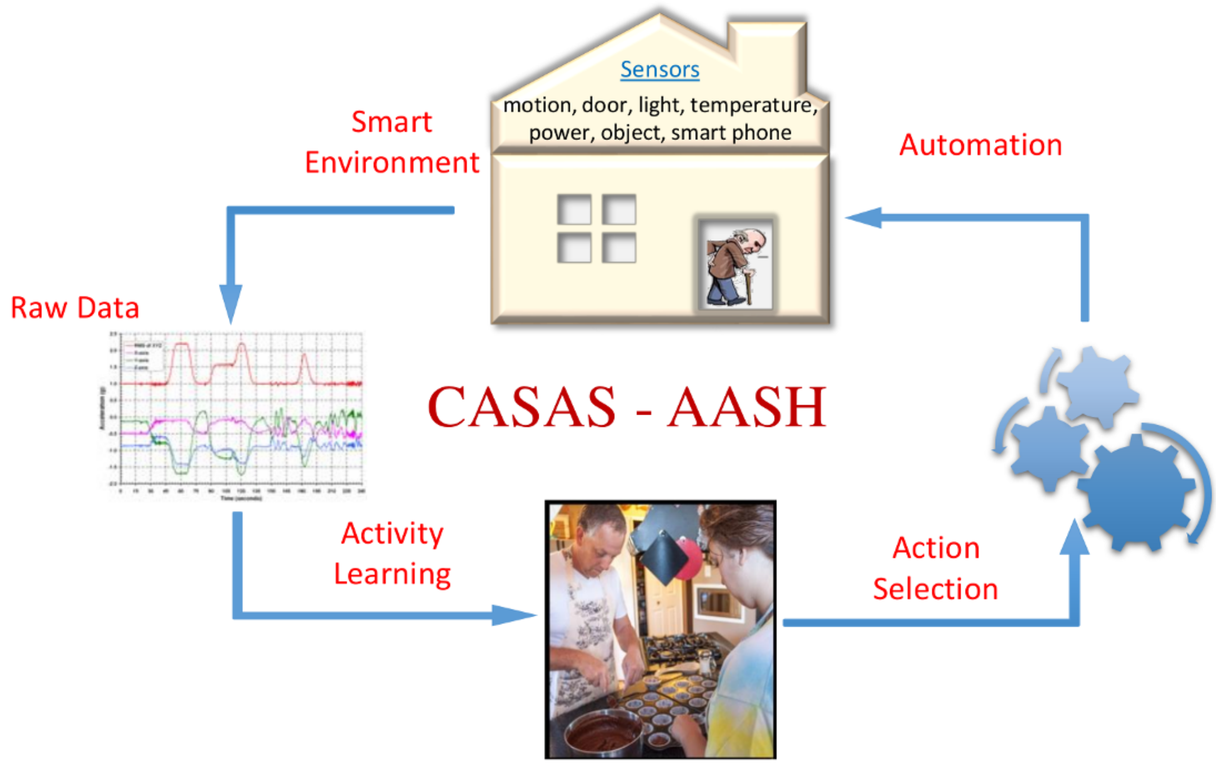


Figure 2.12: The physical systems (sensors, home) work together with humans and computational components (activity learning) to provide activity-aware automation.

Smart home technology is being increasingly recognized valuable for applications including health monitoring and home automation [78]. Smart home projects, including the Aware home [79], the Gator Tech Smart home [80], and the MavHome [81], demonstrated the capabilities of using sensors and computers to create a home that reasons about its state and takes actions to make the home more comfortable. Smart homes have recently been a focus for companies including GE, Intel, iControl, Control4, Brillo, and Google, who are creating smart home operating systems, interfaces, developer platforms, and maintenance plans for the consumer. Many of these projects provide a necessary infrastructure for collecting sensor data and automating devices. The key to making such environments intelligent is the software that reasons about the home using techniques, such as activity recognition and activity forecasting.

CHAPTER 3. SMART HOMES

The CASAS smart home technology is designed for in-home monitoring of ADLs (Activities of Daily Living) as well as home automation applications. Over the last decade, much progress has been made in the area of smart homes and smart environments. This chapter defines the particular CASAS smart home framework utilized in this research and describes in detail one CASAS smart home that was designed with automation in mind and later employed in live experiments with the activity-aware smart automation system, CARL.

3.1 The CASAS Smart Home Framework

The CASAS "Smart Home in a Box" software architecture components are shown in Figure 3.1. During perception, control flows up from the physical components through the middleware to the software applications. When taking action, control moves down from the application layer to the physical components that automate the work. The core goal is that each of the layers is lightweight, extensible and ready to use as is, without additional customization or training.

The CASAS physical layer contains hardware components including sensors and actuators. The architecture utilizes a ZigBee wireless mesh which communicates directly with the hardware components. The middleware layer is governed by a publish/subscribe

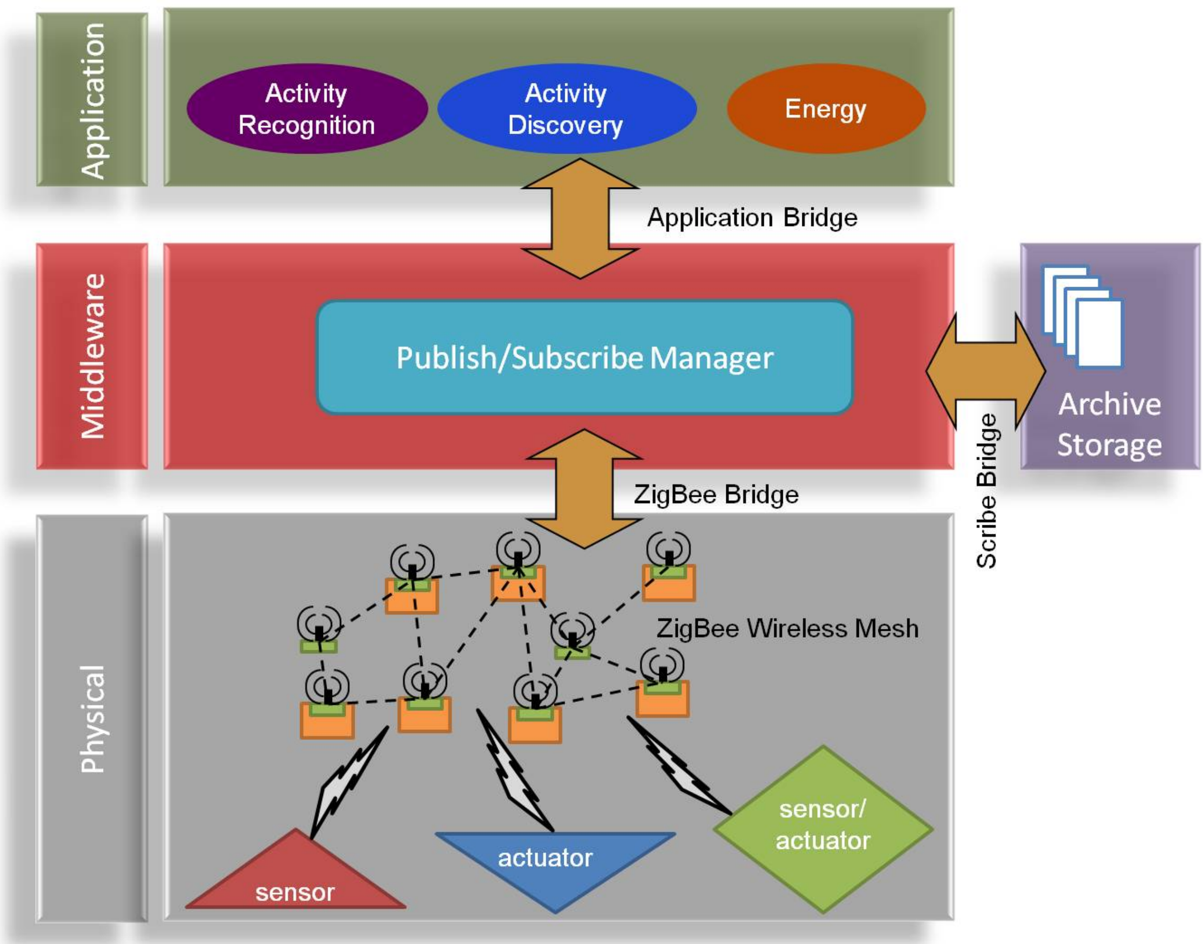


Figure 3.1: CASAS smart home components.

manager. The manager provides named broadcast channels that allow component bridges to publish and receive messages. Additionally, the middleware provides valuable services including adding time stamps to events, assigning UUIDs, and maintaining site-wide sensor state. Every component of the CASAS architecture communicates via a customized XMPP bridge to this manager. Examples of such bridges are the ZigBee bridge, the Scribe bridge which archives messages in permanent storage, and bridges for each of the software components in the application layer. While each site runs independently, the smart building site also securely uploads events to be stored in a relational database in the cloud.

The CASAS architecture is easily maintained, easily extended, and easily scaled. This design is easily maintained because the communication bridges use lightweight APIs that support a wide variety of messages in a free-form manner. As a result, the middleware is compact and stable - it has had only one update in seven years. CASAS is extendable because new bridges can be configured and integrated without changing or even restarting the middleware. Bridges that link multiple smart homes together were recently designed and implemented, allowing CASAS to scale to communities of smart homes.

All of the CASAS components fit within a single small box, as is shown in Figure 3.2. The current box contains physical elements in the form of sensors that are pre-labeled with the intended location. Additional sensors and controllers can be included when needed. The middleware, database, and application components reside on a small, low-power computer with an ITX form factor server. While this layout is designed to allow each smart home to run independently and locally, smart homes can also securely upload events to be stored in a relational database or the cloud.

For this research, the system is implemented and evaluated in the context of a CASAS smart home. Due to the difficulty of creating a fully-functional smart environment infrastructure, many of the early smart home projects described in the previous chapter are tested on simulated or lab-based data [82, 83]. To support the scaling of smart environment research, a streamlined "Smart Home in a Box" (SHiB) was designed [84], shown in Figure 3.2.

Data has been collected in over 100 smart environment sites to date. The CARL home automation system is evaluated using data from a number of these testbeds. One particular testbed, called navan, is additionally equipped for automation and provides a real-time testbed for the complete home automation system. The next section provides details on this testbed.

3.2 The navan Smart Home

The navan testbed is a single-resident apartment with a floor plan, shown in Figure 3.3. The testbed is equipped with 118 sensors. To track the location of smart home residents, infrared motion sensors are placed on the ceilings with removable adhesive strips. Most of the motion sensors are focused on sensing an area in a one-meter diameter circle immediately below the sensor. However, additional motion sensors are placed in each major room, which has a much broader coverage to indicate whether human (or pet) movement is occurring anywhere in the observable space. The circles in Figure 3.3 represent

Figure 3.2: Smart Home in a Box.

the positions of the motion sensors. The square icons in the illustration indicate the presence of magnetic door sensors, which register the open/shut status of external doors as well as cabinets in the kitchen and bathrooms. Coupled with these are additional sensors that monitor ambient light and ambient temperature, which are useful for recognizing key activities such as bathing and cooking and for sensing internal (and to an extent, external) weather conditions. Additionally, navan also includes temperature-only sensors (represented as stars in the figure) that are placed in pairs throughout the apartment at 8" from the ceiling and 12" from the floor to identify temperature gradients. Electricity usage data are collected in navan using a Ted5000 power meter that provides instantaneous usage wattages every few seconds. Arduino-based WiFi thermostats (represented by hexagonal icons in the figure) were designed, built, and installed to monitor use of the baseboard heaters in individual rooms and to log temperature setpoints.

The sensors in the smart home are discrete event sensors. When a state change is sensed (e.g., there is motion in the area, a cessation of motion in the area, a significant temperature change, or a change in door status), the sensor generates a reading that is sent (as a text message) to the smart home middleware. The middleware logs the ID of the sensor generating the reading together with the date and time of the reading and the state of the sensor. Table 3.2 shows a sample of the readings that are generated by one such smart home.

To facilitate control of devices inside navan, ZigBee light switches are installed to control lights and the bathroom fan. Also, custom electrical boxes are designed with ZigBee light switches, as shown in Figure 3.4, to monitor and control additional devices

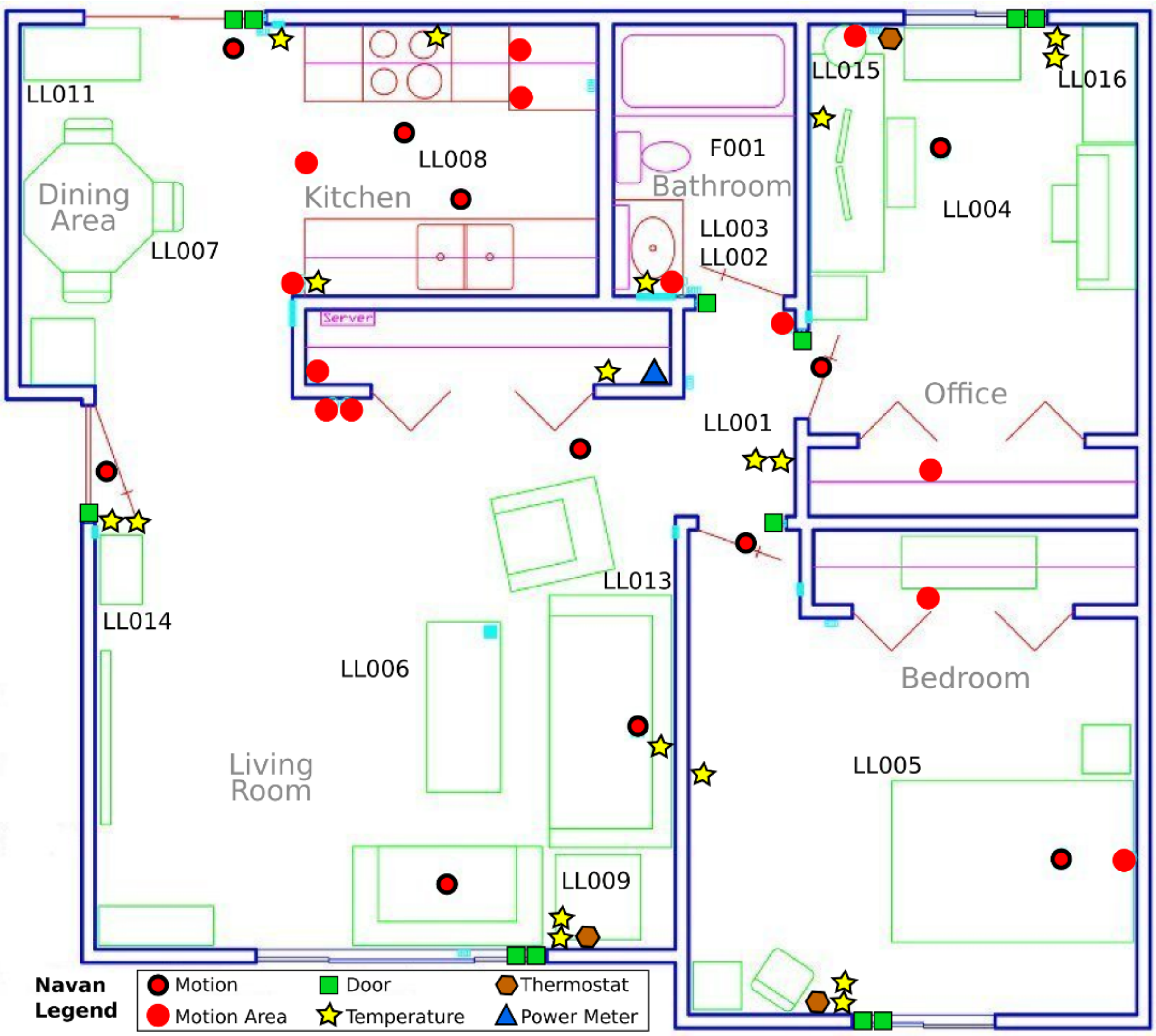


Figure 3.3: navan automated smart home testbed.

Figure 3.4: A ZigBee light switch is used to control devices and provide user feedback.

including reading lamps and speakers. Each light switch reports changes in the state of the device as well as button taps and tap counts. These taps provide a mechanism for the resident to provide feedback to the home automation system. In Figure 3.3, the locations of devices that are controlled by the ZigBee light switches are indicated by the name of each device. All of the mentioned devices represent lights or lamps except for F001 (the bathroom fan) and LL014 (the television speakers). A more detailed sensor map of navan can be found in Appendix A.

Device	Watts	Description
F001	30	Bathroom exhaust fan
LL001	60	Hallway light
LL002	120	Bathroom light
LL003	250	Bathroom heat lamp
LL004	120	Office light
LL005	120	Bedroom light
LL006	120	Living room light
LL007	120	Dining room light
LL008	80	Kitchen light
LL009	98	Accent lighting
LL011	49	Accent lighting
LL013	180	Living room light
LL014	75	Television speakers
LL015	60	Desk light
LL016	25	Desk halogen lamp

Table 3.1: Device descriptions and wattages for the navan testbed.

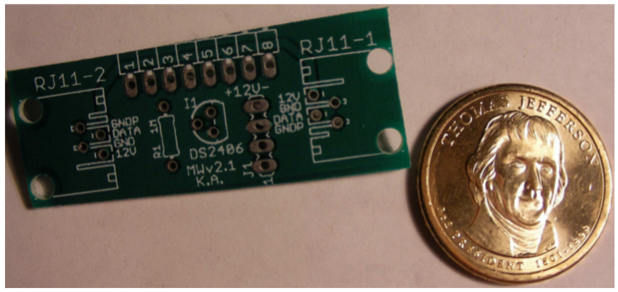


Figure 3.5: OneWire LentilBoard.

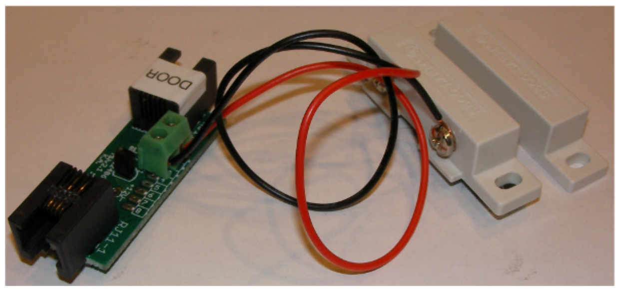


Figure 3.6: OneWire Door Sensor.

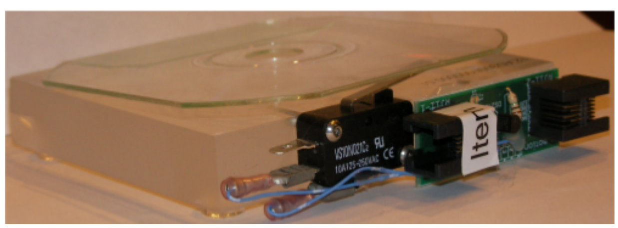


Figure 3.7: OneWire Item Sensor.

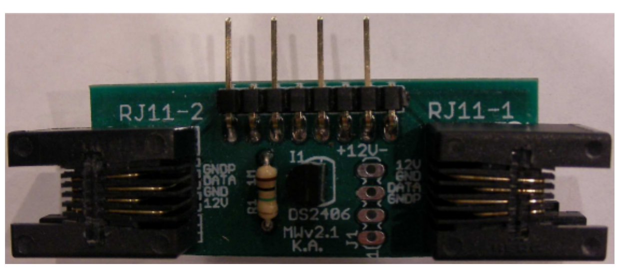


Figure 3.8: OneWire PIR Sensor.

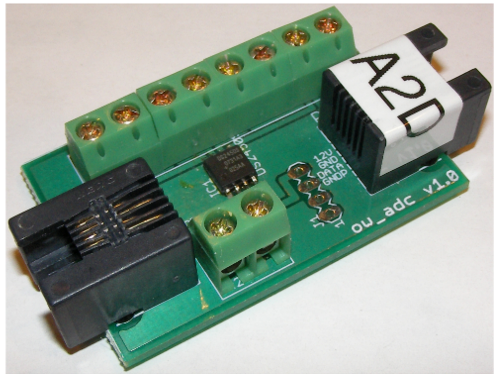


Figure 3.9: OneWire A2D (Analog to Digital) Sensor.

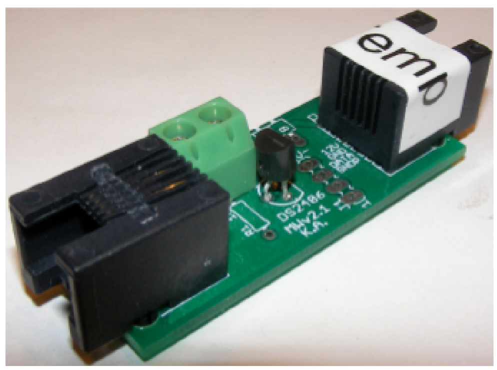


Figure 3.10: OneWire Temperature Sensor.

Figure 3.11: OneWire Motion Sensor.

Figure 3.12: Magnetic contact relay (1 internal, up to 2 external) and temperature (1 internal, up to 1 external probe) sensors. Used to sense door activity.

Figure 3.13: Externally powered ZigBee Pro Extender. Internal magnetic contact relay and temperature only.

Figure 3.14: Ceiling mounted infrared motion and light sensor. The lens is usually partly blocked, so only motion in a small region is observed.

Figure 3.15: Wall mounted infrared motion and light sensor. The lens is often left unblocked to act as an "occupancy" sensor for a large region.

Figure 3.16: Passive Control4 sensors in the second generation sensor network at CASAS. These wireless ZigBee Pro devices (except for 3.13) connect to a permanently powered Control4 device (see Figure 3.17, or 3.13) to transmit sensed events along the mesh to the base station as they can only be leaves in the mesh due to a power saving feature that turns off the radio for minutes at a time.

(a) Light switch, on/off or dimming options

(b) 3 button keypad

(c) 6 button keypad

Figure 3.17: Active Control4 sensor/actuator devices in the second generation sensor network at CASAS. These permanently powered devices make up the core mesh structure of the Control4 ZigBee Pro network, all wireless devices (see Figure 3.16) connect and pass messages through these active devices.

Date	Time	Target	Message	Tag
2008-03-03	14:13:58.873547	M014	ON	Cook Begin
2008-03-03	14:13:58.997577	M013	ON	
2008-03-03	14:13:59.144543	M009	OFF	
2008-03-03	14:13:59.984724	D007	OPEN	
2008-03-03	14:14:01.033088	M014	OFF	
2008-03-03	14:14:04.578001	I008	ABSENT	
2008-03-03	14:14:09.120758	M013	OFF	Cook End
2008-03-03	14:14:09.622629	M016	ON	Eat Begin
2008-03-03	14:14:12.413874	M016	OFF	

Table 3.2: Example format of sensor data with annotation tags.

Testbed	Description
hh101	2 months of data collection, with single resident.
hh102	2 months of data collection, with single resident.
hh103	2 months of data collection, with single resident.
hh104	2 months of data collection, with single resident.
hh105	2 months of data collection, with single resident.
hh106	2 months of data collection, with single resident.
hh107	1 month of data collection, with 2 residents.
hh108	2 months of data collection, with single resident.
hh109	2 months of data collection, with single resident.
hh111	2 months of data collection, with single resident.
hh112	3.5 months of data collection, with single resident.
hh113	15.5 months of data collection, with single resident.
hh114	1 month of data collection, with single resident.
hh115	10 months of data collection, with single resident.
hh116	2 months of data collection, with single resident.
hh117	11 months of data collection, with single resident.
hh118	1 month of data collection, with single resident.
hh119	1 month of data collection, with single resident.
hh120	2 months of data collection, with single resident.

Table 3.3: HH testbeds utilized in experiments.

Testbed	Description
hh122	1 month of data collection, with single resident.
hh123	1 month of data collection, with single resident.
hh125	2 months of data collection, with single resident.
hh126	1 month of data collection, with single resident.
hh127	1 month of data collection, with single resident.
hh128	2 months of data collection, with single resident.
hh129	1 month of data collection, with single resident.

Table 3.3: HH testbeds utilized in experiments.

Testbed	# Motion	# Door	# Temperature	# Light Switches
hh101	16	3	5	-
hh102	25	6	5	5
hh103	11	3	4	5
hh104	27	6	7	6
hh105	21	5	5	9
hh106	25	6	6	9
hh107	24	3	9	-
hh108	24	5	4	7
hh109	19	5	6	2

Table 3.4: Sensor types and counts for the HH testbeds.

Testbed	# Motion	# Door	# Temperature	# Light Switches
hh111	23	5	9	8
hh112	16	4	4	3
hh113	23	6	5	10
hh114	14	3	4	8
hh115	15	5	6	9
hh116	16	5	6	8
hh117	13	4	3	6
hh118	20	5	6	10
hh119	16	4	6	6
hh120	20	3	4	7
hh122	24	4	9	-
hh123	18	2	7	-
hh125	24	3	7	-
hh126	15	2	4	-
hh127	15	2	5	-
hh128	18	2	5	-
hh129	18	2	5	-

Table 3.4: Sensor types and counts for the HH testbeds.

3.3 Additional Testbeds

In addition to the navan testbed, we utilized data from an additional 26 testbeds. All of these testbeds are listed in Table 3.3, along with the number of months of data from each site and the number of residents in the home. As all of these testbeds are called hh101, hh102, through hh129, we will refer to this group as the HH testbeds.

Each HH testbed is an apartment with a kitchen, a dining area, at least one bedroom, and at least one bathroom. Every testbed utilizes ZigBee Pro motion sensors with built-in brightness sensors, door sensors, and temperature sensors. Many of the HH testbeds are also equipped with ZigBee Pro light switches that we can monitor for use. The counts of each sensor type deployed in each testbed can be found in Table 3.4. Floorplans for these sites can be found in Appendix A.

CHAPTER 4. ACTIVITY LEARNING FOR HOME AUTOMATION

Learning and understanding observed activities is at the center of many fields of study and is essential for smart environments such as smart buildings that are sensitive to the needs of the humans they serve. Smart environments that operate in complex real-world applications such as building automation require the depth of information that is provided by activity learning algorithms because activity labels and models provide a rich vocabulary for expressing behavior within a system. In the past, theories about behavior and activity patterns were formed based on limited observation and self-reports. More recently, the maturing of technologies, such as the SHiB, has made it possible to automate activity learning. Learning activities, in turn, enrich smart homes because the home's intelligent agent can reason at a high level about the resident's activities and take appropriate actions.

In the CARL activity-aware building automation approach, activity learning plays two roles. Firstly, activity recognition is used to identify activities as they are performed in a smart building environment. Secondly, activity forecasting is used to forecast whether a particular activity will occur within the upcoming time window. Together, activity recognition and activity forecasting provide a basis for building automation that supports current and future tasks the residents will perform in the building. The next three sections give details for these two critical components of activity-aware home automation.

4.1 Activity Learning Features

Many of our features were initially described by Cook [85], then expanded and enhanced as outlined in this section. All of our features utilize a sliding window length of 2400 seconds, a context derived from the ten past windows, and sample the current value of each sensor every 10 seconds. Every sensor reading, together with the date, time, and sensor identifier, is considered a sensor event. We categorize sensor events based on the type of sensor that generated the reading. If an individual interacted with a sensor, thus triggering the event, we refer to the event as an *entity* event. Similarly, events generated by motion, door, item, button or light sensors are entity events. On the other hand, events produced by light sensors, temperature sensors, or power meters are referred to as *non-entity* events. The set of features that are extracted from our smart home sensor data is summarized in Tables 4.1 and 4.2. The features in Table 4.3 are only used in activity forecasting.

Feature	Description
lastSensorEventHour	The hour (0-23) of the most recently observed sensor event.
lastEntitySensorEventHour	The hour (0-23) of the most recently observed entity sensor event.

Table 4.1: Base Features

Feature	Description
lastSensorEventSecondsPastMidnight	The number of seconds past midnight that the most recent sensor event occurred, with a range of (0-86,400).
lastEntitySensorEventSecondsPastMidnight	The number of seconds past midnight that the most recent entity sensor event occurred, with a range of (0-86,400).
windowSecondsDuration	The size, in seconds, of the current window.
secondsSinceLastSensorEvent	The number of seconds since the most recent sensor event was observed, with a range of (0-86,400).
secondsSinceLastEntitySensorEvent	The number of seconds since the most recent entity sensor event was observed, with a range of (0-86,400).
dominantSensor	The dominant sensor in the window.
dominantEntitySensor	The dominant entity sensor in the window.
dominantMotionSensor	The dominant motion sensor in the window.

Table 4.1: Base Features

Feature	Description
pastDominantSensor$_i$	The dominant sensor in past window i.
pastDominantEntitySensor$_i$	The dominant entity sensor in past window i.
pastDominantMotionSensor$_i$	The dominant motion sensor in past window i.
currentSensorId	The current or most recent sensor observed.
lastEntitySensorId	The most recently observed entity sensor.
lastMotionSensorId	The most recently observed sensor of type motion.
numberDistinctSensor	The number of distinct sensors in the sliding window.
numberDistinctEntitySensors	The number of distinct entity type sensors in the sliding window.
numberDistinctMotionSensors	The number of distinct motion type sensors in the sliding window.

Table 4.1: Base Features

Feature	Description
sensorState_i	The current numeric value of sensor i.
$\text{sensorEventCount}_i$	The number of events for sensor i in the sliding window.
$\text{weightedSensorEventCount}_i$	The weighted number of events for sensor i in the sliding window using mutual information.
$\text{weightedEntitySensorEventCount}_i$	The weighted number of events for sensor i in the sliding window using mutual information with entity sensors.
$\text{sensorEventElapsedTime}_i$	The number of seconds since an event was last generated by sensor i, with a range of (0-86,400).
maximumValue_i	The maximum value of sensor i in the sliding window.
minimumValue_i	The minimum value of sensor i in the sliding window.
sum_i	The sum of the sampled sensor values for sensor i across the sliding window of length W. S is the set of sampled sensor values from sensor i.

Table 4.2: Features generated for each sensor.

Feature	Description
	$sum(S) = \sum_{j=0}^{W} S_j \qquad (4.1)$
mean_i	The mean of the sampled sensor values for sensor i across the sliding window.
	$mean(S) = \mu = \frac{Sum(S)}{W} \qquad (4.2)$
$\text{meanAbsoluteDeviation}_i$	The mean absolute deviation of the sampled sensor values for sensor i across the sliding window.
	$meanAbsoluteDeviation(S) = \frac{1}{W} \sum_{j=0}^{W} \lvert S_j - Sum(S) \rvert \qquad (4.3)$
$\text{medianAbsoluteDeviation}_i$	The median absolute deviation of the sampled sensor values for sensor i across the sliding window.
	$medianAbsoluteDeviation(S) = \frac{1}{W} \sum_{j=0}^{W} \lvert S_j - Median(S) \rvert \qquad (4.4)$
$\text{standardDeviation}_i$	The standard deviation of the sampled sensor values for sensor i across the sliding window.
	$standardDeviation(S) = \sqrt{\frac{1}{W} \sum_{j=0}^{W} (S_j - \mu)^2} \qquad (4.5)$

Table 4.2: Features generated for each sensor.

Feature	Description
coefficientVariation$_i$	The coefficient variation of the sampled sensor values for sensor i across the sliding window.

$$coefficientVariation(S) = \frac{StandardDeviation(S)}{\mu} \tag{4.6}$$

Feature	Description
zeroCrossings$_i$	The number of zero crossings in the sampled sensor values for sensor i across the sliding window.

$$zeroCrossings(S) = |S_j < Median(S) < S_{j+1}| + |S_j > Median(S) > S_{j+1}| \tag{4.7}$$

Feature	Description
percentile10$_i$	The value below the top 10% percent of the sampled values for sensor i in the sliding window.
percentile25$_i$	The value below the top 25% percent of the sampled values for sensor i in the sliding window.
percentile50$_i$	The value below the top 50% percent of the sampled values for sensor i in the sliding window.

Table 4.2: Features generated for each sensor.

Feature	Description
percentile75$_i$	The value below the top 75% percent of the sampled values for sensor i in the sliding window.
percentile80$_i$	The value below the top 80% percent of the sampled values for sensor i in the sliding window.
squareSumOfLessThanPercentile10$_i$	The square sum of values that fall below the top 10% of the sampled values for sensor i in the sliding window.
$$squareSumOfLessThanPercentile10(S) = \sum\{S_j^2 \mid S_j < Percentile10(S)\} \quad (4.8)$$	
squareSumOfLessThanPercentile25$_i$	The square sum of values that fall below the top 25% of the sampled values for sensor i in the sliding window.
$$squareSumOfLessThanPercentile25(S) = \sum\{S_j^2 \mid S_j < Percentile25(S)\} \quad (4.9)$$	
squareSumOfLessThanPercentile50$_i$	The square sum of values that fall below the top 50% of the sampled values for sensor i in the sliding window.

Table 4.2: Features generated for each sensor.

Feature	Description
$$squareSumOfLessThanPercentile50(S) = \sum \{S_j^2 \mid S_j < Percentile50(S)\} \quad (4.10)$$	
squareSumOfLessThanPercentile75$_i$	The square sum of values that fall below the top 75% of the sampled values for sensor i in the sliding window.
$$squareSumOfLessThanPercentile75(S) = \sum \{S_j^2 \mid S_j < Percentile75(S)\} \quad (4.11)$$	
squareSumOfLessThanPercentile80$_i$	The square sum of values that fall below the top 80% of the sampled values for sensor i in the sliding window.
$$squareSumOfLessThanPercentile80(S) = \sum \{S_j^2 \mid S_j < Percentile80(S)\} \quad (4.12)$$	
interQuartileRange$_i$	The difference between the 25th and 75th percentiles.
$$interquartileRange(S) = abs(Percentile75(S) - Percentile25(S)) \quad (4.13)$$	

Table 4.2: Features generated for each sensor.

Feature	Description
Ratio$_i$InBin$_j$	The sampled sensor values for sensor i are split into $j = 10$ bins containing a linear spread of values. The ratio of values in each bin is then calculated and output as the feature values.
skewness$_i$	The skewness of the sampled sensor values for sensor i across the sliding window.

$$skewness(S) = \frac{\frac{1}{W}\sum_{i=0}^{W}(S_i - \mu)^3}{(\frac{1}{W}\sum_{i=0}^{W}(S_i - \mu)^2)^{\frac{3}{2}}} \tag{4.14}$$

Feature	Description
kurtosis$_i$	The kurtosis of the sampled sensor values for sensor i across the sliding window.

$$kurtosis(S) = \frac{\frac{1}{W}\sum_{i=0}^{W}(S_i - \mu)^4}{(\frac{1}{W}\sum_{i=0}^{W}(S_i - \mu)^2)^3} - 3 \tag{4.15}$$

Feature	Description
signalEnergy$_i$	The signal energy of the sampled sensor values for sensor i across the sliding window.

$$signalEnergy(S) = \sum_{i=0}^{W} S_i^2 \tag{4.16}$$

Feature	Description
logSignalEnergy$_i$	The log signal energy of the sampled sensor values for sensor i across the sliding window.

Table 4.2: Features generated for each sensor.

Feature	Description
	$$logSignalEnergy(S) = \frac{1}{W}\sum_{i=0}^{W} log_{10}(s_i^2) \quad (4.17)$$
signalPower$_i$	The signal power of the sampled sensor values across for sensor i the sliding window.
	$$signalPower(S) = \frac{1}{W}\sum_{i=0}^{W} s_i^2 \quad (4.18)$$
diffMaxMin$_i$	The difference between the max and min of the sampled sensor values for sensor i across the sliding window.
	$$diffMinMax(S) = abs(Max(S) - Min(S)) \quad (4.19)$$
avgTimeBetweenPeaks$_i$	The average time between peaks of the sampled sensor values for sensor i across the sliding window.
numberOfPeaks$_i$	The number of peaks of the sampled sensor values for sensor i across the sliding window.
slope$_i$	The slope of the sampled sensor values for sensor i across the entire sliding window.

Table 4.2: Features generated for each sensor.

Feature	Description
slopeOfSegment$_j$Sensor$_i$	The sampled sensor values for sensor i are split into 10 segments, and then the slope of each segment is calculated and output as the feature values.

Table 4.2: Features generated for each sensor.

4.2 Random Forests for Activity Recognition

The challenge of activity recognition is to map sensor events to a label that indicates the corresponding activity the individual is performing. There are activity recognition challenges that are unique among machine learning problems. The sequential nature of the input data, the ambiguous partitioning of data into activities, and the overlapping of activity classes mean that additional data processing must be performed. As Figure 4.1 shows, the recognition steps include collecting and preprocessing sensor data, dividing it into subsequences of manageable size, then extracting subsequence features. The final feature vectors are either labeled by an expert to use as training data or are input to an already-trained model to generate the corresponding activity label.

Let $A = \{a_1, a_2, \cdots, a_T\}$ be the set of all modeled activities, where a_i corresponds to the ith activity class. A smart home generates raw sensor data in the form of time-

Feature	Description
$\text{activityEventCount}_a$	The number of events with activity a as the label in the sliding window. Here S' is the current list of all sensor events in the sliding window with length W.

$$activityEventCount(S', a) = \sum_{j=0}^{W} \begin{cases} 1 & \text{if } S'_j \text{ is labeled with activity } a \\ 0 & \text{if } S'_j \text{ is not labeled with activity } a \end{cases} \tag{4.20}$$

Feature	Description
$\text{activityEventElapsedTime}_a$	The number of seconds activity a occurs in the sliding window.

$$actEvntElTime(S', a) = \sum_{j=0}^{W-1} \begin{cases} S'_{j+1}.epoch - S'_j.epoch & \text{if } S'_j \text{ has } a \\ 0 & \text{otherwise} \end{cases} \tag{4.21}$$

Feature	Description
currentActivity	The current observed activity.

Table 4.3: Activity features used in forecasting.

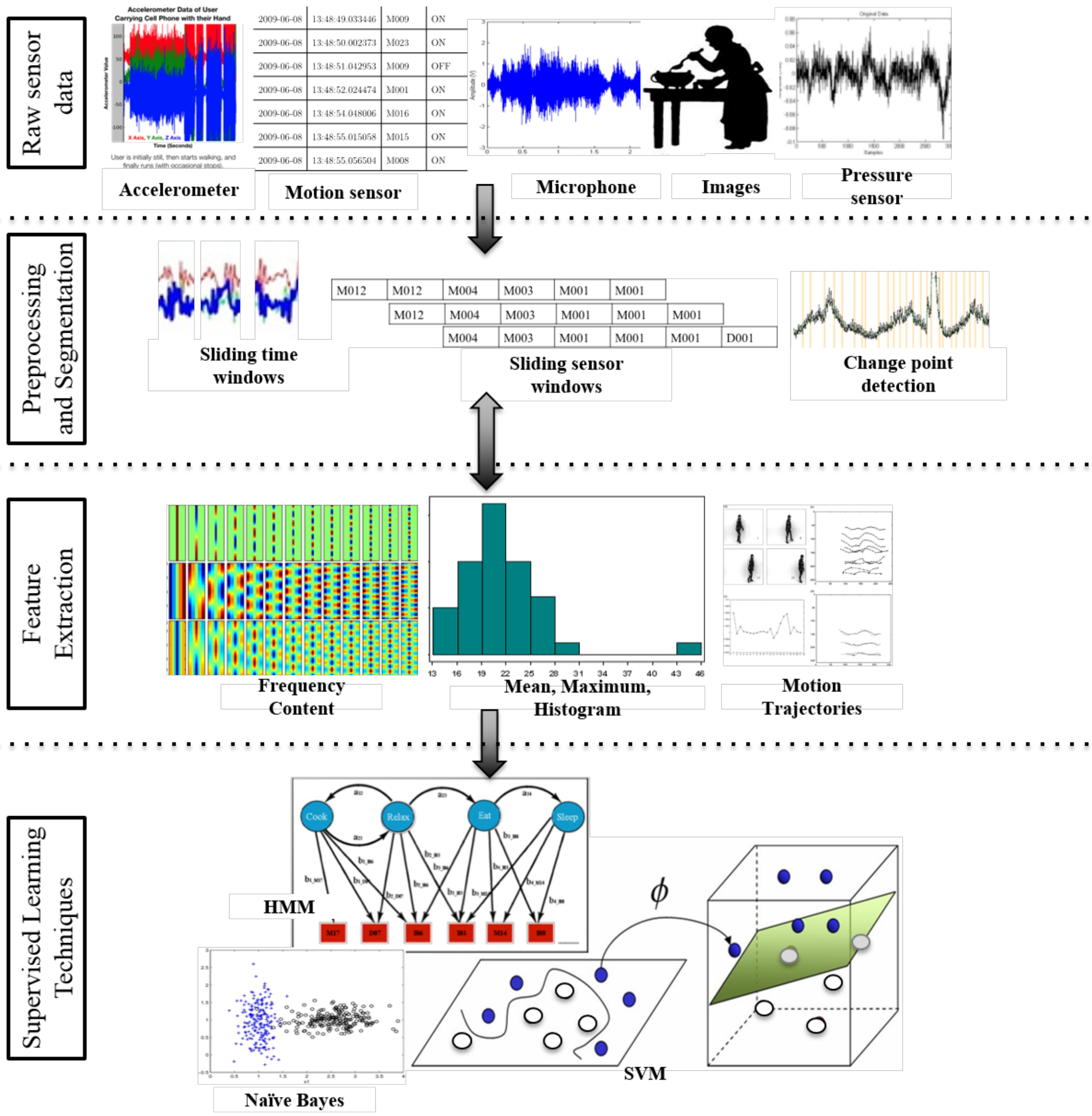


Figure 4.1: Activity recognition includes stages of raw sensor data collection, data preprocessing and segmentation, feature extraction, and supervised machine learning [86].

stamped sensor readings or events, $\Lambda = (\lambda_1, \lambda_2, \cdots, \lambda_N)$, where event λ_i corresponds to a sensor reading or sensor value generated at time t_i. The data are preprocessed to handle missing or noisy data, then, features $x \in \Re^d$ are extracted from the raw smart home sensor data. Finally, a supervised machine-learning algorithm learns a mapping from the feature vector X to an activity label.

This work builds upon work by the CASAS team to design algorithms that automatically build activity models from sensor data using machine learning techniques [11,86–88]. Other groups have also explored a large number of approaches to supervised activity recognition [13, 89–102]. These have been tested for a variety of sensor modalities, including environment [86, 103–105], wearable [106–108], object [109, 110], smartphones [32, 111], and video [112]. The learning methods can be broadly categorized into template, generative, discriminative, and ensemble approaches. Template matching techniques employ a k-Nearest Neighbor (kNN) classifier with dynamic time warping to a varying window size [113]. Generative approaches, such as naive Bayes classifiers, Markov models, and dynamic Bayes networks, have yielded promising results for behavior modeling and offline activity recognition when a large amount of labeled data is available [87, 114–117]. On the other hand, discriminative approaches that model the boundary between different activity classes offer an effective alternative. These techniques include decision trees, meta-classifiers based on boosting and bagging, support vector machines, and discriminative probabilistic graphical models such as conditional random fields [87, 117–132]. Other approaches combine these underlying learning algorithms, including boosting and other ensemble methods [133–136].

The home automation approach described here builds on the activity recognition algorithm called CASAS-AR [11] to label raw data with corresponding activity labels. Using a random forest [137] with 100 trees and a minimum split value of 15, we assembled a robust activity recognition algorithm. While many activity recognition algorithms have been proposed, they are typically designed for constrained situations with pre-segmented data, a single user, and no activity interruptions. Our activity recognition algorithm extends this to consider the generalization of activity models over multiple smart homes. In earlier work, a common vocabulary of sensor locations was defined to facilitate the design of algorithms that recognize activities even in new environments with no training data. Furthermore, the activity recognition algorithm provides real-time activity labeling on streaming data. To label streaming data, the activity recognition algorithm extracts features from a fixed-sized sliding window of sensor events, $\lambda_i \cdots \lambda_j$, and maps the feature vector onto an activity label, indicating the activity that was performed at the time of the last event in the window, or time t_j.

In our early experiments, described in Chapter 7, we implemented a single decision tree for classification. However, we discovered that a single decision tree was prone to overfit and subsequently replaced this approach with a random forest. To provide a robust classification method that could address the overfitting problem that is associated with high-dimensional data such as smart home data, we chose the Random Forest classifier [137]. A random forest is a voting ensemble of decision trees. We used 100 decision trees, as Breiman identifies that value as the optimal number of trees [137].

Using the features built from the smart home data, explained in detail in Section 4.1, we can train each of the 100 decision trees. Because the class distributions are heavily skewed, we undersample majority classes with a goal of achieving a more uniform class distribution. To accomplish this, we remove randomly-selected data points from majority classes. The number of points that are removed a proportional the difference between the majority class size and the mean class size. The result of this step is a data distribution that has a close-to-uniform class distribution.

When creating each decision tree in the forest, a parameter N is used to specify the number of data points that are modeled. Each decision tree randomly selects N samples from the training data with replacement. The random selection of training data allows for a data point to be represented multiple times in the training data for a single decision tree, or not represented at all.

Given the size of our feature vector, F, each tree in the random forest will randomly select $\log_2(F) + 1$ features at each node and choose the best feature to split. The best feature to split is the one that will provide the greatest information gain. Each node also has a minimum number of samples required to create a splitting node. We utilized two different values for this, $minimumSplit = 15$ for our activity recognition random forest, and $minimumSplit = 5$ for our activity forecasting random forest. These values were arrived at experimentally. In the case of activity forecasting, performance dropped dramatically for values of $minimumSplit$ greater than 5. Similarly, in the case of activity recognition values below 15 for $minimumSplit$ resulted in overfitting issues. Also, values below 15 result in a reduced performance for smaller datasets. Once the random forest is trained, it can classify a given sample utilizing voting from each of its trees to determine the dominant class and return that class value.

Utilizing the random forest described in Section 4.2, we can train our system to label the current activity that is observed in a smart home. We read in the sensor events and convert them to features as described in Section 4.1. We also read the labels on the annotated data. These labels are the classes that we will train our random forest to identify.

To train our activity recognition random forest, labels are provided for at least one month of sensor data from each smart building location. Human annotators label the sensor data in each dataset with corresponding activities based on interviews with the residents, photographs of the home, and a floor plan highlighting the locations of sensors in the space. Sensor events are labeled with the activity that was determined to be occurring in the home at that time.

Sensor events that do not fit into one of the core activity classes are labeled as Other_Activity and provide context for the activity recognition as well as for the activity forecaster. To maximize consistency of ground truth labels, multiple annotators look at the datasets and disagreements between labels are resolved via discussion. The annotators demonstrate inter-annotator agreement of $K = 0.85$ for our selected activities. Most of the activity classes utilized in the activity recognition are drawn from the Psychology literature describing Activities of Daily Living (ADLs) and Instrumental Activities of Daily Living (iADLs) [138–143].

In addition to summarizing the results of our activity recognition on previous smart home testbeds, activity recognition is also evaluated in detail on data collected in the navan smart home (described in Chapter 6). In the navan testbed, the activity recognition is trained on 14 core activities. 1.5 months of navan data were annotated with human annotators using these labels, shown in Table 7.5, to provide the ground truth dataset, referred to as *navan_2014*. The activity recognition random forest was evaluated on this set of activities using 3-fold partitioning validation with the human-annotated training data. The results, summarized in Section 7.2.1, are consistent with earlier findings and are important to observe because the strength of the home automation system relies on the accuracy of the activity learning algorithms.

4.3 Activity Forecasting

While a reactive home automation system can use activity recognition to turn needed devices on and unneeded devices off in real time, a proactive system can use activity forecasting to forecast upcoming activities and provide automation in anticipation of these activities.

Given the foundation of an activity recognition algorithm, the smart environment can then perform activity forecasting. In the context of building automation, activity forecasting consists of determining which activities will occur within the next 10 minutes. Smart home-based activity forecasting is a new area in the field and has not been used before this for home automation. Preemptive automation is the goal of building automation because the home can forecast activities rather than just react to them, thereby making the home more efficient in its use of resources such as energy. Specifically, this approach allows the CARL building automation system to avoid turning off devices that are currently in use (as determined by activity recognition) or will soon be in use (determined by activity forecasting).

While activity prediction is not as heavily investigated as these other areas of activity learning, there are some representative first efforts in this area. Many of these techniques focus on sequence prediction, which can be adapted to predict the label of the activity that will occur next in the sequence. This work includes the Active LeZi algorithm [144] which is used to predict the identifier of the sensor in a home that will generate the next event. Other researchers including Hawkins et al. [145], Kitani et al. [146], and Koppula and Saxena [147] have investigated the use of probabilistic graph models to predict next events in video data.

In contrast with activity recognition, the activity forecasting problem is to determine whether a particular activity will occur within the next time window (here, the size of the time window is 10 minutes). Our activity forecasting problem is viewed as a binary classification problem. As with activity recognition, the input consists of raw sensor events that are converted into the features described in Section 4.1 using the sliding window and creating a datapoint every 60 seconds. By training a random forest for each separate activity the class becomes a true/false output, identifying if the given activity will occur in the next 10 minutes. Throughout the remainder of the dissertation, we will refer to a *true case* for a particular activity as a point in time when the activity forecaster predicts the activity will occur within the next ten minutes. Similarly, we will refer to a *false case* for an activity as time points when the forecaster predicts it will not occur within the next ten minutes. After parsing the training data and identifying the ground truth for the classes, we then train the random forests to learn the mapping from the input feature vector and current activity to a binary label where 0 indicates that the activity will not occur in the next 10 minutes and 1 shows that the activity will occur. As with activity recognition, we initially implemented activity forecasting with a single decision tree and later replaced with the more robust random forest.

The activity forecasting problem is formulated and solved in the framework of imitation learning. In traditional imitation learning, the goal of the learner is to learn to imitate the behavior of an expert performing a sequential decision-making task (such as playing a game) in a way that generalizes to similar tasks or situations. Imitation learning techniques have been applied to a variety of natural language processing and computer vision prediction tasks [101, 148, 149]. For each time step, the activity forecasting algorithm computes the feature vector and uses the activity label provided by the activity recognition algorithm as the ground truth for the activity timings. If the algorithm can learn a function that is consistent with these imitation examples, then the learned function will generalize and perform well on new instances [150, 151]. In the next chapter we describe some unsupervised methods for labeling the data and how the unsupervised methods might be used to replace the human annotated data.

CHAPTER 5. UNSUPERVISED METHODS

Requiring human experts to label smart home data with activities to train models is something we do not need. In this chapter, we propose two potential methods for labeling smart home data in an unsupervised manner that could be utilized in home automation. This work is centered on the idea of activity-aware home automation. For many, this implies that predefined human activities are modeled and used to label sensor data for activity-sensitive automation. The activity classes utilized for this typically draw from the Psychology literature in which Activities of Daily Living (ADLs) and Instrumental Activities of Daily Living (iADLs) are specified based on their critical role in human health and functional independence. Here we propose to replace the use of predefined activity categories with automatically-discovered activity classes. Utilizing automatically-discovered activity classes offers two potential advantages for home automation. The first is that activity classes can be detected, modeled, and labeled without the need for human annotation. Second, the activity classes may be easier to recognize (if the method of detecting activity classes utilizes the same set of features as activity recognition) and this improved recognition accuracy can boost the automation performance.

Our approach to activity discovery builds on a rich history of research, including methods for mining frequent sequences [152, 153], mining frequent patterns using regular expressions [154], constraint-based mining [155], mining frequent temporal relationships [156], and frequent periodic pattern mining [157]. More recent work extends these initial approaches to look for more complex patterns. Ruotsalainen et al. [158] design the Gais genetic algorithm to detect interleaved patterns in an unsupervised learning fashion. Other approaches have been proposed to mine discontinuous patterns [159–161] in different types of sequence datasets and to allow variations in occurrences of the patterns [162]. Huỳnh et al. [163] explored the use of topic models and LDAs to discovery daily activity patterns in wearable sensor data.

Aspects of these earlier techniques are useful in analyzing sensor sequence data. In addition to finding frequent sequences that allow for variation as some of these others do, we also want for our purposes to identify sequences of sufficient length that may constitute an activity of interest. We are interested in characterizing as much of the sensor data as possible but want to minimize the number of distinct patterns to increase the chance of identifying more abstract activity patterns. We describe our approach to meeting these goals next.

5.1 Activity Detection

The first approach we consider for an unsupervised method is the CASAS Activity Discovery (AD) algorithm [86]. The AD algorithm first looks at the entire sequence of sensor events and identifies the pattern that best compresses the dataset. The AD algorithm then runs another iteration where the previous best pattern is replaced by a symbol, shown in Figure 5.1. It should be noted that new patterns can include AD generated symbols. The AD algorithm will run this way for as many iterations as it has been instructed.

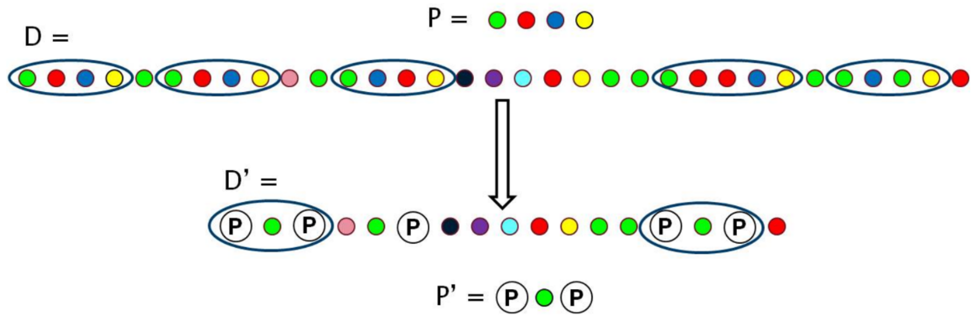


Figure 5.1: An example of the Activity Discovery algorithm working on a data sequence. P is defined on the first iteration, then on the second iteration P' is defined using P as part of the sequence [86].

For our AD experiments, we set the number of iterations to be 15. We found this to be a number that adequately captured the patterns inherent in the smart home data. The resulting sequence pattern labels were used as the activity label on the smart home data. As stated at the beginning of this chapter, the discovered activity classes can be utilized for activity-based home automation instead of relying on human-defined activity classes. In Chapter 7 we will evaluate the results of using these discovery methods in activity learning and automation.

5.2 DBSCAN with Dynamic Time Warping

Our first discovery method built on a foundation of sequence discovery algorithms. To contrast this approach with another traditional method, we next consider a second unsupervised machine learning method using clustering based on DBSCAN (Density-Based

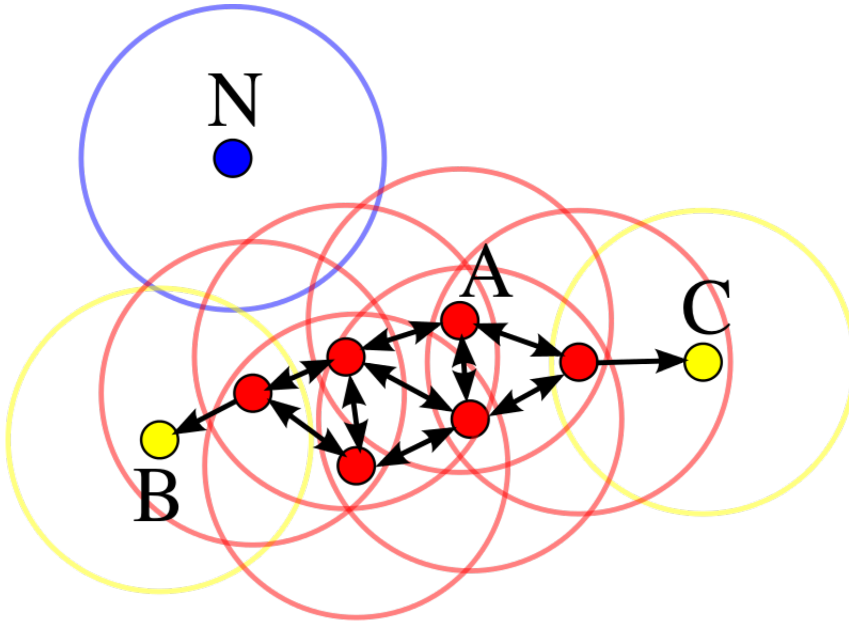


Figure 5.2: An example of the DBSCAN algorithm in action. Points B and C are part of the same cluster as A. N is too far from the given points to be part of the density region.

Spatial Clustering of Applications with Noise) [164]. DBSCAN is a clustering algorithm that looks at the density of regions of points and groups regions of points with sufficiently high density into clusters. As input, DBSCAN takes two values, ε and $MinPts$ (in addition to the dataset to cluster), shown in the pseudo code in Algorithms 1, 2, and 3. The $MinPts$ value is used to determine when to consider a group of points a cluster. When there are $MinPts$ data points that are each within ε distance of another in the same region, DBSCAN considers those points to be a cluster. This process is visualized in Figure 5.2, where A is part of the cluster, but N is too far away.

Based on preliminary experiments, we propose to utilize Dynamic Time Warping (DTW) as the distance metric [165]. While DTW has previously been only useful for

Algorithm 1 DBSCAN(D, ε, $MinPts$)

DBSCAN(D, ε, $MinPts$):
Given: D is the dataset consisting of points P.
Given: ε is the minimum distance between adjacent points.
Given: $MinPts$ is the minimum number of adjacent points required to create a cluster.
$C = \emptyset$
for each point P in dataset D:
    if P is visited:
        continue to next point
    mark P as visited
    $NeighborPts = regionQuery(P, \varepsilon)$ ▷ See Algorithm 2
    if $sizeof(NeighborPts) < MinPts$:
        mark P as $NOISE$
    else:
        C = next cluster
        $expandCluster(P, NeighborPts, C, \varepsilon, MinPts)$ ▷ See Algorithm 3

Algorithm 2 regionQuery(P, ε)

regionQuery(P, ε):
Given: P is the point to search from.
Given: ε is the distance to search.
return all points within the ε-neighborhood of P, including P

Algorithm 3 expandCluster(P, $NeighborPts$, C, ε, $MinPts$)

expandCluster(P, $NeighborPts$, C, ε, $MinPts$):
Given: P is the point to grow the cluster from.
Given: $NeighborPts$ is the set of points within the ε-neighborhood of P.
Given: C is the cluster to expand.
Given: ε is the distance to search.
Given: $MinPts$ is theminimum number of adjacent points required to create a cluster.
Add P to cluster C
for each point P' in $NeighborPts$:
    if P' is not visited:
        mark P' as visited
        $NeighborPts' = regionQuery(P', \varepsilon)$ ▷ See Algorithm 2
        if $sizeof(NeighborPts') \geq MinPts$:
            $NeighborPts = NeighborPts \cap NeighborPts'$
    if P' is not yet member of any cluster:
        add P' to cluster C
return all points within the ε-neighborhood of P, including P

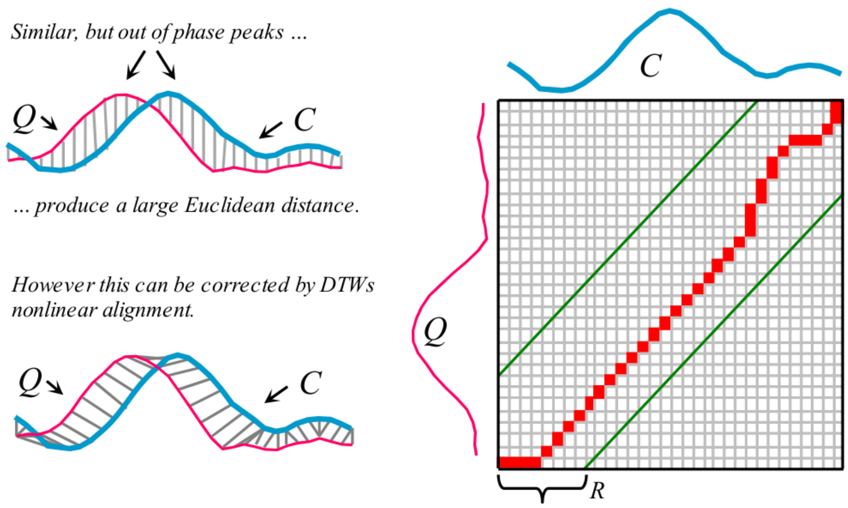


Figure 5.3: Two sequences, Q and C, are somewhat similar but shifted or phased out of alignment. At its simplest, DTW is the measure of the warping matrix (in red) that allows the two sequences to be compared for optimal similarity even if they are out of phase [179].

single-variate time series data [166–170], there is now work on applying DTW to multi-variate time series [171–175]. Additionally, there has been other research investigating clustering with DTW [176, 177]. Finally, DTW has a strong performance where patterns are distorting the time axis in time series data, while Euclidean distance performance degrades [178].

Dynamic Time Warping (DTW) measures a distance-like quantity between two given sequences, which can be of different lengths. Given two sequences, s of length n and t of length m, and a bounding window of size w, we can compute the DTW distance between s and t. As shown in Algorithm 4, the function $DTWDistance()$ first builds a 2-dimensional array, DTW, that is of size $n+1$ by $m+1$. We then update w if the difference in size

Algorithm 4 Dynamic Time Warping Algorithm

```
DTWDistance( s, t, w ):
Given: s is an array [1 ... n]
Given: t is an array [1 ... m]
Given: w is a window parameter, such that |n − m| ≤ w
DTW = array [[0 ... n], [0 ... m]]
w = max(w, abs(n − m))
for i = 0 to n:
    for j = 0 to m:
    DTW[i, j] = ∞
DTW[0, 0] = 0
for i = 1 to n:
    for j = max(1, i − w) to min(m, i + w):
        cost = abs(s[i] − t[j])
        DTW[i, j] = cost + min(DTW[i − 1, j], DTW[i, j − 1], DTW[i − 1, j − 1])
return DTW[n, m]
```

between the sequences is larger than the bounding window. The 2-dimensional array is initialized, so each value is ∞. Then the starting point, $DTW[0, 0]$, is set to 0. Moving along the sequence, s, we inspect a range of sequence t, identified as $max(1, i - w)$ to $min(m, i + w)$. This process is visualized by the red path in Figure 5.3. DTW then considers the minimum of three operators that can be applied to one sequence to better align it with the other: shrink, stretch, and delete. The cost to apply the operator is calculated as the difference between values $s[i]$ and $t[j]$, then added to the value of the chosen operator and stored in $DTW[i, j]$. We then update the DTW matrix by adding the cost to the minimum of 3 previous values. When we are done stepping through the sequences, we return the value found in $DTW[n, m]$ as the distance calculated.

We created a new version of the DBSCAN algorithm that incorporates dynamic time warping (DTW) [167] as the distance measure between points. Using a sliding window, we stored events for the last 600 seconds and created a new datapoint every 240 seconds.

Algorithm 5 DTW of Smart Home Data

Given: Array *Input* containing current events from sliding window.
Given: Array T
Given: $T_0 = 0$
for $i = 0$ to $len(Input)$**:**
    if $Input_i ==$ "M001"**:**
        $T_{i+1} = T_i + 3$
    else if $Input_i ==$ "M002"**:**
        $T_{i+1} = T_i + 2$
    else if $Input_i ==$ "M003"**:**
        $T_{i+1} = T_i + 1$
    else if $Input_i ==$ "M004"**:**
        $T_{i+1} = T_i - 1$
    else if $Input_i ==$ "M005"**:**
        $T_{i+1} = T_i - 2$
    else if $Input_i ==$ "M006"**:**
        $T_{i+1} = T_i - 3$

The window size is smaller than that used for forecasting as it is chosen to mitigate the computation requirements of the algorithm. Algorithm 5 displays a simple example of how we created our feature vectors for the DTW distance from the sliding window of sensor events. Our algorithm was inspired by an algorithm for converting DNA to time series data for clustering with DTW [179]. Each sensor is given a value such that the distribution is evenly spread above and below 0. As we step over the sensor events in the window, the sensor's value is added (or subtracted if negative) from the previous value in the sequence before being added to the sequence. Based on our parameter selection method for activity forecasting, we chose five as the minimum number of points required to create a dense region. That left us with the ε value for DBSCAN to explore. The results from the ε exploration can be found in Chapter 7.

In this chapter, we defined automated approaches to learning the activity classes that will form the foundation for building automation. In the following chapters, we will describe the algorithms that will form the building automation process itself.

CHAPTER 6. SMART HOME AUTOMATION

The CASAS Activity-aware Resource Learning (CARL) automation system controls all the devices in a smart building space using the smart building infrastructure described in Chapter 3 and the activity learning elements described in Chapter 4. The first version of CARL, CARLv1, automates only by turning off devices that are not needed for currently-detected activities. The second version of CARL, CARLv2, enhances the first version by adding activity occurrence forecasting and will not turn off devices that are associated with upcoming activities as determined by activity forecasting. The third version of CARL, CARLv3, builds upon the second version by additionally turning devices on that are currently off and associated with forecasted activities.

6.1 CARLv1

The initial strategy of CARLv1 is to turn off all devices that are not needed in support of the current set of activities. To do this, CARLv1 first identifies the given activities and determines the devices that are utilized during those activities.

Determining the set of current activities presents a particular challenge when processing data in real time. Segmentation algorithms can be used to mark the beginning point and end point for any particular activity. However, these typically handle historical data in offline mode. For real-time processing, a delay value is maintained for each activity

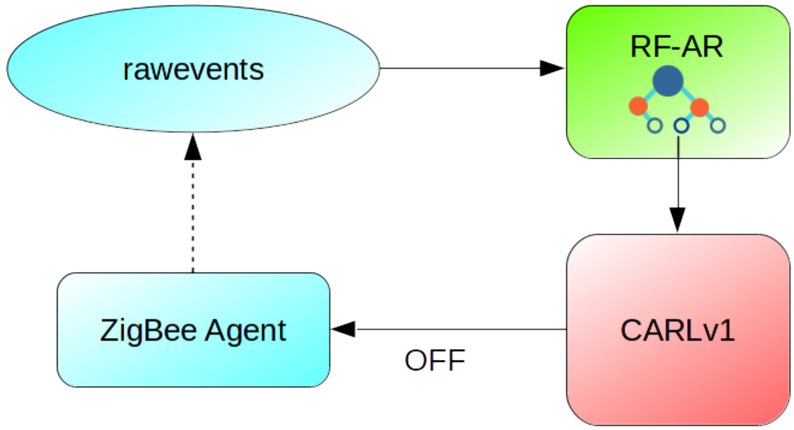


Figure 6.1: A visualization of the data flow for CARLv1.

class and device. The delay value $Delay_{A_i}$ represents the amount of time that has elapsed since a sensor event was observed that was labeled with activity label A_i. If the delay value for a particular activity is within a threshold number of time units, then the activity is considered current. The delay value $Delay_{D_j}$ represents the amount of time that has elapsed since device D_j was observed changing state to ON. Each device D_j has an associated $DeviceThreshold_j$ that is used to prevent the device from being turned off seconds after the resident turned the device on, allowing new activities to be initiated before the device is evaluated by CARLv1. Additionally, turning the device on with a double tap of the light switch informs CARLv1 that the automatic decision to turn it off was incorrect and $DeviceThreshold_j$ should be set to $LongThreshold$.

Next, for each activity A_i, the algorithm maintains a probability distribution over devices whose status is ON. Devices with a sufficiently significant likelihood of being associated with A_i are left untouched when activity A_i is current. On the other hand, any device D_j whose status is not typically ON for any of the current activities is a candidate for CARLv1 to turn off if $Delay_{D_j}$ is greater than $DeviceThreshold_j$. The CARLv1 activity-aware automation algorithm is summarized in Algorithm 6 and visualized in Figure 6.1.

A modification to the algorithm for the experiment was made after a short pilot test with the resident. A guard statement was added to prevent CARL from turning off lights in the bathroom while the bathroom door was closed. There are no windows in the bathroom so unexpectedly turning off the light could present an unsafe situation and raised safety concerns.

6.2 CARLv2

CARLv2 builds upon CARLv1 to also take into account activities that are forecast to occur within the next 10 minutes, and avoid turning off any devices associated with those activities. As a preliminary step, CARLv2 identifies the set of devices associated with each activity $a \in A$; these should not be turned off if a is a current or upcoming activity. Here, D_a represents devices that are associated with activity a, where D is a subset of the total set of devices, $D_a \subseteq D$.

Assuming that the device sets have been constructed, CARLv2 then performs a check for conditions to achieve device automation at every time step t. The goal is to identify each device that is being used by a current or forthcoming activity, denoted as $CurrentDevices$, and turn off every device, not in the set $CurrentDevices$. CARLv2

Algorithm 6 CARLv1 Automation

Input: A is the set of known activity classes
Input: D is the set of available devices
$LongThreshold = DelayThreshold * 4$
for $j = 1$ to $|D|$ **:** ▷ Set threshold for each device
  $DeviceThreshold_j = DelayThreshold$
$t = 1$
while observe new sensor event e_t **:**
  CurrentActivities = $\emptyset$
  CurrentDevices = $\emptyset$
  $A^t = AR(e_t, A)$ ▷ Get activity label for sensor event
  for $i = 1$ to $|A|$ **:** ▷ Update times for each activity
    if $A_i = A^t$ **:**
      $Delay_{A_i} = 0$
    else :
      $Delay_{A_i} = Delay_{A_i} + 1$
  for $j = 1$ to $|D|$ **:** ▷ Update times for each device
    if $e_t == D_j$ and $State(D_j, ON)$ **:**
      $Delay_{D_j} = 0$
      if $e_t == DoubleTapOn$ **:**
        $DeviceThreshold_j = LongThreshold$
      else :
        $DeviceThreshold_j = DelayThreshold$
    else :
      $Delay_{D_j} = Delay_{D_j} + \Delta_t$
  for $i = 1$ to $|A|$**:** ▷ Get the set of current activities
    if $Delay_{A_i} < DelayThreshold$ **:**
      Append($CurrentActivities$, A_i)
  for $j = 1$ to $|D|$**:** ▷ Get set of current devices
    if $D_j \in Devices(CurrentActivities)$ **:**
      Append($CurrentDevices$, D_j)
  for $j = 1$ to $|D|$ **:** ▷ Turn off not-needed devices
    if $State(D_j, ON)$ and $D_j \notin CurrentDevices$ **:**
      if $Delay_{D_j} > DeviceThreshold_j$ **:**
        ChangeState(D_j, OFF)
  t += 1

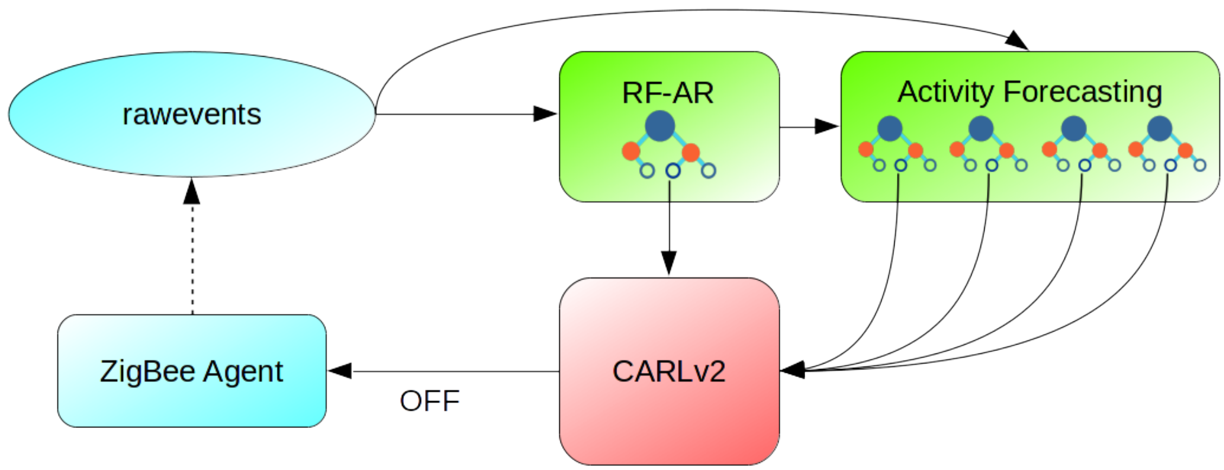


Figure 6.2: A visualization of the data flow for CARLv2.

must, therefore, identify the current activities occurring at time t ($CurrentActivities$) and those that will occur between t and $t + 10$ minutes ($ForecastedActivities$). The CASAS-AR activity recognizer is used to determine which activities are current at time t, or $CurrentActivities$. CARLv2's GetForecasted function is used to determine which activities will occur within the next 10 minutes (between time t and time $t + 10$ minutes, or $ForecastedActivities$).

Finally, a command is sent to turn off the device. In some cases, the smart home resident may want the device to remain on after CARLv2 decided it is not needed. User buttons are installed around the home. A double tap on the button indicates that the user is overriding CARLv2 to turn a device back on, as well as setting the delay to $LongThreshold$. A delay is imposed on the corresponding device called $DelayThreshold$, during which CARLv2 will not turn off the device. For the experiments, $DelayThreshold$ is set to five minutes, and $LongThreshold$ is set to twenty minutes. A summary of the

CARLv2 operations is given in Algorithm 7 and visualized in Figure 6.2.

6.3 CARLv3

As CARLv2 built upon CARLv1, so CARLv3 builds upon CARLv2. The third version of CARL, CARLv3, adds the behavior of turning devices on that are associated with a forecasted activity.

As an initial step, CARLv3 identifies the set of devices associated with each activity $a \in A$. The set D_a represents devices that are associated with activity a, and is a subset of the complete set of devices, $D_a \subseteq D$. These devices, D_a, will be turned ON and OFF by CARLv3.

Now that the initial setup is complete, CARLv3 will start listening for sensor events. For each new sensor event, CARLv3 will use activity recognition and activity forecasting to identify the current activity, A^t, and the set of forecasted activities, $ForecastActivities$. CARLv3 now updates the $Delay_{A_i}$ values for each activity, $Delay_{D_j}$ values for each device, and the current state of each device. For the set of activities A, if any activity a has been observed more recently than the $DelayThreshold$, then activity a is added to the set $CurrentActivities$. If activity a is in the set $ForecastActivities$, then activity a is also added to the set $CurrentActivities$. Next, for the set of devices D, if any device d has an associated activity a that is in $CurrentActivities$, then d is added to the set $CurrentDevices$. Additionally, for the set of devices D, if any device d has an associated activity a that is in $ForecastActivities$, then d is added to the set $ForecastDevices$.

Algorithm 7 CARLv2 Automation

```
Input: A is the set of known activity classes
Input: D is the set of available devices
LongThreshold = DelayThreshold * 4
for j = 1 to |D| :                                        ▷ Set threshold for each device
    DeviceThreshold_j = DelayThreshold
t = 1
while observe new sensor event e_t :
    CurrentActivities = ∅
    ForecastedActivities = ∅
    CurrentDevices = ∅
    A^t = CASAS-AR(e_t, A)                         ▷ Get activity label for sensor event
                                                           (described in Section 4.2)
    ForecastedActivities = GetForecasted(e_t, A)       ▷ Get set of activity forecasts
                                                           (described in Section 4.3)
    for i = 1 to |A| :                                ▷ Update times for each activity
        if A_i = A^t :
            Delay_{A_i} = 0
        else :
            Delay_{A_i} = Delay_{A_i} + 1
    for j = 1 to |D| :                                  ▷ Update times for each device
        if e_t == D_j and State(D_j, ON) :
            Delay_{D_j} = 0
            if e_t == DoubleTapOn :
                DeviceThreshold_j = LongThreshold
            else :
                DeviceThreshold_j = DelayThreshold
        else :
            Delay_{D_j} = Delay_{D_j} + Δ_t
    for i = 1 to |A|:                          ▷ Get the set of current activities
        if Delay_{A_i} < DelayThreshold or A_i ∈ ForecastedActivities :
            Append(CurrentActivities, A_i)
    for j = 1 to |D|:                                   ▷ Get set of current devices
        if D_j ∈ Devices(CurrentActivities) :
            Append(CurrentDevices, D_j)
    for j = 1 to |D| :                                ▷ Turn off not-needed devices
        if State(D_j, ON) and D_j ∉ CurrentDevices :
            if Delay_{D_j} > DeviceThreshold_j :
                ChangeState(D_j, OFF)
    t += 1
```

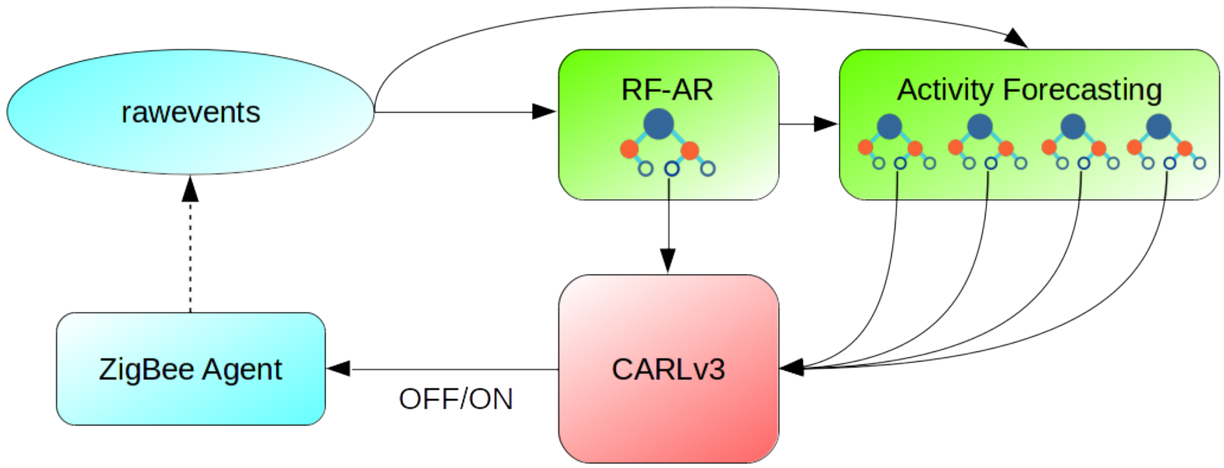


Figure 6.3: A visualization of the data flow for CARLv3.

Finally, CARLv3 iterates through each device d in the set of devices D. If d is ON, device d is not in the set $CurrentDevices$ or the set $ForecastDevices$, and the delay value for device d is greater than the device delay threshold, then CARLv3 sends the command to turn device d OFF at the next time step $t+1$. If d is OFF, and d is in the set $ForecastDevices$, then CARLv3 sends the command to turn device d ON at the next time step $t+1$. A summary of this CARLv3 behavior is outlined in Algorithm 8 and visualized in Figure 6.3.

There are a couple of timeout values associated with turning devices ON and OFF in CARLv3 to prevent devices from being turned on and off rapidly, creating random jitter. After CARLv3 sends a command to change the state of a device, it can not send another command to that device for 5 minutes. If a resident provides a double tap correction, then CARLv3 must wait 20 minutes before it can send new commands to that device.

An experiment with CARLv3 was performed in a live smart home environment right after the experiment for CARLv2. One anecdotal response from the experiment subject was that they could not provide the double tap correction to CARLv3 while they were away from home or asleep. This early experiment of CARLv3 did not utilize the random forest activity recognition and activity forecasting and was prone to a sort of feedback loop where CARLv3 would cause states in the environment that the resident had never created before (the state of lights being on and off). These errors were influenced by overfitting which was addressed by utilizing the random forest activity recognition and activity forecasting. In the next chapter, we explore how the performance of activity recognition and activity forecasting can influence the resulting performance of the different versions of CARL.

Algorithm 8 CARLv3 Automation

```
Input: A is the set of known activity classes, D is the set of available devices
LongThreshold = DelayThreshold * 4
for j = 1 to |D| :                                          ▷ Set threshold for each device
    DeviceThreshold_j = DelayThreshold
t = 1
while observe new sensor event e_t :
    CurrentActivities = ForecastActivities = ∅
    CurrentDevices = ForecastDevices = ∅
    A^t = CASAS-AR(e_t, A)                                  ▷ Get activity label for sensor event
    ForecastActivities = GetForecasted(e_t, A)              ▷ Get set of forecast activities
    for i = 1 to |A| :                                      ▷ Update times for each activity
        if A_i = A^t :
            Delay_{A_i} = 0
        else :
            Delay_{A_i} = Delay_{A_i} + 1
    for j = 1 to |D| :                                      ▷ Update times for each device
        if e_t == D_j and State(D_j, ON) :
            Delay_{D_j} = 0
            if e_t == DoubleTapOn :
                DeviceThreshold_j = LongThreshold
            else :
                DeviceThreshold_j = DelayThreshold
        else :
            Delay_{D_j} = Delay_{D_j} + Δ_t
    for i = 1 to |A|:                                       ▷ Get the set of current activities
        if Delay_{A_i} < DelayThreshold or A_i ∈ ForecastActivities :
            Append(CurrentActivities, A_i)
    for j = 1 to |D|:                                       ▷ Get set of current and forecast devices
        if D_j ∈ Devices(CurrentActivities) :
            Append(CurrentDevices, D_j)
        if D_j ∈ Devices(ForecastActivities) :
            Append(ForecastDevices, D_j)
    for j = 1 to |D| :                                      ▷ Turn off not-needed and on needed devices
        if State(D_j, ON) and D_j ∉ CurrentDevices and D_j ∉ ForecastDevices :
            if Delay_{D_j} > DeviceThreshold_j :
                ChangeState(D_j, OFF)
        else if State(D_j, OFF) and D_j ∈ ForecastDevices :
            ChangeState(D_j, ON)
    t += 1
```

CHAPTER 7. EXPERIMENTAL RESULTS

In this chapter, we present and discuss results from experiments on activity-aware home automation. There are several evaluation steps we perform below. Because activity-aware automation relies on robust activity awareness, we first evaluate the ability of our algorithms to perform activity learning. We evaluate activity recognition for our smart home testbeds both using predefined activities and automatically-discovered activities. Similarly, we assess activity forecasting performance on these datasets. Building on the activity learning foundation, we then evaluate the performance of CARL's activity-aware automation algorithms on the smart home datasets. To begin the discussion, we start with an overview of the datasets that were created and used in these evaluations.

7.1 Datasets

The experiments utilized several datasets from the navan testbed and others from the CASAS hh101 through hh129 testbeds. Details of these datasets can be found in Tables 7.1 and 7.2.

As we discussed in Chapter 5, an alternative to utilizing predefined activity labels for smart home datasets is to discover activity classes automatically. The first dataset we introduce is *navan_week*, which will be used to illustrate the techniques described in Chapter 5. The *navan_week* dataset contains one week of navan sensor data with human-

Dataset	Description
navan_week	A week of annotated data from the navan testbed.
navan_week.DTW	The *navan_week* dataset run through the DBSCAN-DTW clustering algorithm with $\varepsilon = 75$.
navan_2012	5 months of annotated data from the navan testbed. *navan_week* is contained within this dataset.
navan_2012.AD	The *navan_2012* dataset run through the Activity Discovery algorithm.
navan_2014	1.5 months of annotated data from the navan testbed.
navan_2014.AD	The *navan_2014* dataset run through the Activity Discovery algorithm.
navan_2014.DTW	The *navan_2014* dataset run through the DBSCAN-DTW clustering algorithm with $\varepsilon = 75$.

Table 7.1: Datasets from navan utilized in experiments and their descriptions. See Section 3.2 for details on the navan testbed.

Dataset	Description
*hh101**	2 months of annotated data.
*hh101.AD**	The *hh101* dataset with activity labels generated by the Activity Discovery algorithm.

Table 7.2: HH datasets utilized in experiments and their descriptions.

(* identifies testbeds only utilized in activity recognition and activity forecasting experiments)

Dataset	Description
hh102	2 months of annotated data.
hh102.AD	The *hh102* dataset with activity labels generated by the Activity Discovery algorithm.
hh103	2 months of annotated data.
hh103.AD	The *hh103* dataset with activity labels generated by the Activity Discovery algorithm.
hh104	2 months of annotated data.
hh104.AD	The *hh104* dataset with activity labels generated by the Activity Discovery algorithm.
hh105	2 months of annotated data.
hh105.AD	The *hh105* dataset with activity labels generated by the Activity Discovery algorithm.
hh106	2 months of annotated data.
hh106.AD	The *hh106* dataset with activity labels generated by the Activity Discovery algorithm.
*hh107**	1 month of annotated data, with 2 residents.
*hh107.AD**	The *hh107* dataset with activity labels generated by the Activity Discovery algorithm.
hh108	2 months of annotated data.

Table 7.2: HH datasets utilized in experiments and their descriptions.

(* identifies testbeds only utilized in activity recognition and activity forecasting experiments)

Dataset	Description
hh108.AD	The *hh108* dataset with activity labels generated by the Activity Discovery algorithm.
hh109	2 months of annotated data.
hh109.AD	The *hh109* dataset with activity labels generated by the Activity Discovery algorithm.
hh111	2 months of annotated data.
hh111.AD	The *hh111* dataset with activity labels generated by the Activity Discovery algorithm.
hh112	3.5 months of annotated data.
hh112.AD	The *hh112* dataset with activity labels generated by the Activity Discovery algorithm.
hh113	15.5 months of annotated data.
hh113.AD	The *hh113* dataset with activity labels generated by the Activity Discovery algorithm.
hh114	1 month of annotated data.
hh114.AD	The *hh114* dataset with activity labels generated by the Activity Discovery algorithm.
hh115	10 months of annotated data.

Table 7.2: HH datasets utilized in experiments and their descriptions.

(* identifies testbeds only utilized in activity recognition and activity forecasting experiments)

Dataset	Description
hh115.AD	The *hh115* dataset with activity labels generated by the Activity Discovery algorithm.
hh116	2 months of annotated data.
hh116.AD	The *hh116* dataset with activity labels generated by the Activity Discovery algorithm.
hh117	11 months of annotated data.
hh117.AD	The *hh117* dataset with activity labels generated by the Activity Discovery algorithm.
hh118	1 month of annotated data.
hh118.AD	The *hh118* dataset with activity labels generated by the Activity Discovery algorithm.
hh119	1 month of annotated data.
hh119.AD	The *hh119* dataset with activity labels generated by the Activity Discovery algorithm.
hh120	2 months of annotated data.
hh120.AD	The *hh120* dataset with activity labels generated by the Activity Discovery algorithm.
*hh122**	1 month of annotated data.

Table 7.2: HH datasets utilized in experiments and their descriptions.

(* identifies testbeds only utilized in activity recognition and activity forecasting experiments)

Dataset	Description
*hh122.AD**	The *hh122* dataset with activity labels generated by the Activity Discovery algorithm.
*hh123**	1 month of annotated data.
*hh123.AD**	The *hh123* dataset with activity labels generated by the Activity Discovery algorithm.
*hh125**	2 months of annotated data.
*hh125.AD**	The *hh125* dataset with activity labels generated by the Activity Discovery algorithm.
*hh126**	1 month of annotated data.
*hh126.AD**	The *hh126* dataset with activity labels generated by the Activity Discovery algorithm.
*hh127**	1 month of annotated data.
*hh127.AD**	The *hh127* dataset with activity labels generated by the Activity Discovery algorithm.
*hh128**	2 months of annotated data.
*hh128.AD**	The *hh128* dataset with activity labels generated by the Activity Discovery algorithm.
*hh129**	1 month of annotated data.

Table 7.2: HH datasets utilized in experiments and their descriptions.

(* identifies testbeds only utilized in activity recognition and activity forecasting experiments)

Dataset	Description
*hh129.AD**	The *hh129* dataset with activity labels generated by the Activity Discovery algorithm.

Table 7.2: HH datasets utilized in experiments and their descriptions.

(* identifies testbeds only utilized in activity recognition and activity forecasting experiments)

defined activity labels. The *navan_week.DTW* dataset contains the same sensor data but with pattern-based activity labels as discovered by DTW-based clustering. As we described in Chapter 5, we experimented with different values of the ε parameter and found that a value of 75 yielded optimal results. Thus the dataset is labeled with the discovered patterns using this value. Details of *navan_week* and *navan_week.DTW* can be found in Tables 7.3 and 7.4. Activity recognition results from these two datasets are presented in Tables 7.15 and 7.17. As can be observed from these tables, activity recognition performs similarly for human-defined labels and automatically-discovered labels. This result indicates that automatically-discovered activity classes can be modeled and recognized in a manner very similar to regular activities of daily living (ADLs) classes.

Table 7.1 details additional datasets as well that are used in this chapter. The *navan_2012* dataset contains five months of navan data from the year 2012, annotated with ADL classes that will be used to evaluate activity recognition, activity forecasting, and CARL-based home automation. The *navan_week* dataset is a subset of this dataset. The *navan_2012.AD* dataset contains the sensor data from *navan_2012* but is annotated with AD-based activity labels. The *navan_2014* dataset contains 1.5 months of navan data from the year 2014. This portion of navan data is handled separately because while the residence is the same for the 2012 and 2014 datasets, there are differences in the sensors installed in the space. As a result, *navan_2014* contains sensor data from 2014 with human-defined activity labels, *navan_2014.AD* includes the 2014 sensor data with AD-defined activity labels, and we also include *navan_2014.DTW* as DTW-based cluster discovery of activity labels.

The remaining datasets in Table 7.2 refer to the HH testbeds. For each HH testbed, we include the sensor data with human-defined activity labels (the dataset name for HH testbed xyz is hhxyz) as well as the sensor data with Activity Detection-defined activity labels (notated hhxyz.AD). As stated in Section 3.3, some of the HH testbeds do not have monitored light switch devices. This group of HH testbeds is identified in Table 7.2 with *.

Table 7.3 displays the number of sensor events for each activity class for the *navan_week* dataset. We note that it shares a similar event count distribution with the clusters in the *navan_week.DTW* dataset, shown in Table 7.4. The similarity between the activity labels allows for a straightforward comparison of the two activity recognition confusion matrices, found in Tables 7.15 and 7.17.

Looking at the activity class distributions for *navan_2014*, *navan_2014.AD*, and *navan_2014.DTW*, found in Tables 7.5, 7.6, and 7.7 respectively, we observe a more diverse set of class sizes and distributions than in *navan_week* and *navan_week.DTW*. The higher number of activity classes in *navan_2014.DTW* could potentially benefit the overall fore-

Activity	# Sensor Events
Bathe	1,905
Bed_Toilet_Transition	480
Cook	3,598
Drink	4,730
Eat	846
Enter_Home	146
Leave_Home	232
Other_Activity	82,485
Relax	4,236
Sleep	124,679
Toilet	3,607
Wash_Dishes	2,692
Watch_TV	77,989
Water_Plants	2,408
Work_On_Computer	40,535

Table 7.3: *navan_week* activity classes.

Activity	# Sensor Events
0	107,601
1	31,144
2	122,234
3	481
4	28,513
5	5,282
6	50,390
7	2,534
8	794
9	226
10	842
11	207
12	185
13	8
14	127

Table 7.4: *navan_week.DTW* activity classes.

Activity	# Sensor Events
Bathe	20,801
Bed_Toilet_Transition	6,322
Cook	22,374
Drink	6,776
Eat	16,088
Enter_Home	1,171
Leave_Home	2,307
Other_Activity	706,958
Relax	4,517
Sleep	668,851
Toilet	53,091
Wash_Dishes	204
Watch_TV	372,434
Work_On_Computer	242,126

Table 7.5: *navan_2014* activity classes.

Activity	# Sensor Events
Other_Activity	228,491
Pat_0	1,584,935
Pat_4	64,545
Pat_5	37,459
Pat_7	42,370
Pat_9	84,354
Pat_10	58,477
Pat_12	23,389

Table 7.6: *navan_2014.AD* activity classes.

Activity	# Sensor Events
0	1,056,545
1	131,889
2	8,718
3	602,160
4	6,958
5	885
6	1,463
7	2,810
8	986
9	6,802
10	4,387
11	682
12	44,354
13	5,409
14	135,637
15	35,517
16	3,758
17	529
18	16,562
19	1,013
20	1,058
21	1,264
22	269
23	5,729
24	597
25	469
26	986
27	11,148
28	21,796
29	481
30	229
31	789
32	180
33	9,723
34	2,238

Table 7.7: *navan_2014.DTW* activity classes.

casting performance, which would improve the performance of CARLv2 and CARLv3.

7.2 Activity Recognition

Using datasets summarized in Tables 7.1 and 7.2, we evaluate the ability of the activity recognition algorithm to model and recognize activities as defined by humans or activity discovery algorithms.

7.2.1 Activities of Daily Living

Utilizing a 3-fold partitioning validation, the results from the *navan_2014* dataset with activity recognition can be seen in Table 7.10. Looking at the confusion matrix, it is apparent that Other_Activity was often confused with the other activities. This confusion is because Other_Activity occurs right before and right after the labeled activity classes, and in the same spaces. The accuracy of activity recognition on this dataset is 93.893. This accuracy is relatively high and much greater than random choice, which for 14 activities would yield an accuracy of 7.143. Overall, this is a good foundation on which to build the CARL algorithms.

Activity	# Sensor Events
Bathe	55,649
Bed_Toilet_Transition	8,848
Cook	11,757
Drink	18,144
Eat	3,210
Enter_Home	5,570
Entertain_Guests	2,726
Leave_Home	1,954,226
Other_Activity	1,162,217
Relax	7,565
Sleep	2,141,340
Toilet	134,132
Watch_TV	1,400,127
Water_Plants	21,217
Work_On_Computer	523,189

Table 7.8: *navan_2012* activity classes.

Activity	# Sensor Events
Other_Activity	3,127,576
Pat_0	1,667,417
Pat_1	398,402
Pat_2	824,217
Pat_3	1,079,538
Pat_8	227,780
Pat_11	59,830
Pat_14	65,357

Table 7.9: *navan_2012.AD* activity classes.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	←guessed
4286	0	0	0	0	0	0	121	0	0	0	0	0	13	0 = Bathe
0	2163	0	0	0	0	0	16	0	294	0	0	0	0	1 = Bed_Toilet_Transition
0	0	11962	0	0	0	0	24	0	0	0	0	2	0	2 = Cook
0	0	0	3477	0	0	0	405	0	0	0	0	42	0	3 = Drink
0	0	4	0	6616	0	0	70	0	0	0	0	0	0	4 = Eat
0	0	0	0	0	293	0	351	0	3	0	0	0	0	5 = Enter_Home
0	0	0	0	0	0	501	450	0	0	0	0	0	0	6 = Leave_Home
36	77	197	393	110	10	7	192301	7	336	371	6	898	1397	7 = Other_Activity
0	0	0	0	0	0	0	23	420	2	0	0	0	2	8 = Relax
0	27	0	0	0	0	0	116	0	16867	0	0	0	0	9 = Sleep
0	10	8	0	2	0	0	5195	0	31	8916	0	164	487	10 = Toilet
0	0	0	0	0	0	0	0	0	0	0	113	2	0	11 = Wash_Dishes
0	0	22	85	0	0	0	6479	0	0	27	0	29015	21	12 = Watch_TV
8	0	0	0	0	0	0	2736	1	1	41	0	3	47982	13 = Work_On_Computer

Table 7.10: Results for *navan_2014* activity recognition using 3-fold partitioning, with an accuracy of 93.893.

7.2.2 Activity Detection

Using the *navan_2014.AD* dataset, which had been labeled using the Activity Detection algorithm, we evaluated the ability to perform activity recognition for these labels. Results of activity recognition using 3-fold cross validation are summarized in the confusion matrix found in Table 7.12. This method did not perform as well as the annotated ADLs. The errors in the activity recognition may be reflected in the observed performance of the CARL smart environment automation algorithms.

7.2.3 DBSCAN with DTW

Table 7.14 lists the results from using 3-fold partitioning to test our activity learning random forest, as well as the class breakdowns for each ε value. The "AR Play-full" column of Table 7.14 lists the accuracy of AR when the labels from heartbeats and non-entity sensors are included, allowing for a better indication of how AR would perform over time (giving time correct more weight in the final score). The last two columns display the percentage of the data that was not in a cluster (similar to the Other_Activity label in the annotated data) and the size of the largest cluster. In the source data file, Sleep was the biggest class, making up 35.57% of the data. Taking these into account, we find a "sweet spot" in the ε range between 65 and 110, where there is not too much lost to the Other_Activity, but also has a distribution of events outside of those two classes. They also have minimal loss in accuracy when comparing the AR 3-fold results with the AR

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.96968	0.0001288	0.99987	0.98466	0.98984	0.96968
Bed_Toilet_Transition	0.87465	0.00033181	0.99967	0.93507	0.94993	0.87465
Cook	0.99783	0.0006915	0.99931	0.99857	0.98105	0.99783
Drink	0.88609	0.0013972	0.9986	0.94066	0.87914	0.88609
Eat	0.98894	0.00033004	0.99967	0.99429	0.98335	0.98894
Enter_Home	0.45286	2.8952e-05	0.99997	0.67294	0.967	0.45286
Leave_Home	0.52681	2.0284e-05	0.99998	0.72581	0.98622	0.52681
Other_Activity	0.9804	0.10665	0.89335	0.93586	0.92325	0.9804
Relax	0.9396	2.3148e-05	0.99998	0.96932	0.98131	0.9396
Sleep	0.99159	0.0020271	0.99797	0.99478	0.96196	0.99159
Toilet	0.6019	0.0013254	0.99867	0.77531	0.95307	0.6019
Wash_Dishes	0.98261	1.7345e-05	0.99998	0.99126	0.94958	0.98261
Watch_TV	0.81391	0.0035793	0.99642	0.90055	0.96312	0.81391
Work_On_Computer	0.94505	0.0065025	0.9935	0.96897	0.96152	0.94505

Table 7.11: *navan_2014* activity recognition accuracies.

0	1	2	3	4	5	6	7	←guessed
101311	0	754	41	11848	2597	11421	3217	0 = Other_Activity
7	0	0	0	0	2	4	1	1 = Pat_0
4237	0	4035	0	24125	38	8	7	2 = Pat_10
11402	0	0	116	0	0	2	2	3 = Pat_12
4472	0	1514	0	58409	97	2	16	4 = Pat_4
16263	0	1	0	425	12769	139	5918	5 = Pat_5
8539	0	0	0	16	81	32029	2	6 = Pat_7
13811	0	0	0	266	2634	88	13379	7 = Pat_9

Table 7.12: Results for *navan_2014.AD* activity recognition, with an accuracy of 64.167.

Play-full results. The result and confusion matrix from performing activity recognition on dataset *navan_week* can be found in Table 7.15. After applying DBSCAN to *navan_week*, we ran activity recognition on the resulting dataset with cluster labels and the resulting confusion matrix can be found in Table 7.17.

To test DBSCAN for activity discovery, we used the navan data. Because of the computational expense of the clustering algorithm, we utilized the *navan_2014* dataset instead of the much larger *navan_2012* dataset. The algorithm generated 34 clusters, and the corresponding results for activity recognition are summarized in Table 7.20. The full list of forecasting confusion matrices can be found in Appendix J.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.77225	0.27335	0.72665	0.7491	0.63303	0.77225
Pat_0	0	0	1	0	-	0
Pat_10	0.12435	0.0072354	0.99276	0.35135	0.64007	0.12435
Pat_12	0.010068	0.00012256	0.99988	0.10033	0.73885	0.010068
Pat_4	0.90543	0.13029	0.86971	0.88739	0.61426	0.90543
Pat_5	0.35954	0.017547	0.98245	0.59433	0.7009	0.35954
Pat_7	0.78759	0.038195	0.9618	0.87035	0.73305	0.78759
Pat_9	0.44334	0.029009	0.97099	0.65611	0.59351	0.44334

Table 7.13: *navan_2014.AD* activity recognition accuracies.

ε	Clusters	AR 3-fold	AR Play	AR Play-full	% Other	Domin. Class
ADLs	*ADLs*	*92.52*	*91.10*	*92.82*	*23.53*	*35.57*
1	45	93.41	94.46	57.81	46.64	15.66
2	46	93.51	94.38	58.15	46.53	15.66
3	46	93.56	94.69	58.39	46.24	15.66
4	46	93.23	94.55	58.19	45.80	15.66
5	47	93.02	94.34	58.00	45.68	15.66
6	45	92.88	94.46	58.01	45.52	15.66
7	29	95.23	96.11	76.53	45.02	32.64
8	16	95.92	96.60	78.02	44.07	32.64
10	19	95.25	96.18	77.99	43.59	32.66
12	20	95.38	96.11	77.55	43.27	32.68
15	19	94.96	96.06	77.04	42.43	32.70
18	18	95.04	96.20	77.30	42.09	32.72
20	19	95.00	96.19	77.18	41.53	32.89
25	12	96.28	97.04	79.51	40.52	32.94
30	9	97.12	97.22	78.92	39.44	32.98
35	11	96.78	96.84	79.17	38.57	33.02
40	13	96.82	96.96	79.21	37.30	33.12
45	11	96.96	97.13	79.19	36.78	33.15
50	9	97.74	97.50	79.21	36.04	33.24
55	9	97.76	97.82	79.75	35.81	33.34
60	10	97.73	97.75	80.17	35.55	33.42
65	11	93.85	94.35	88.83	31.26	34.71
70	13	93.95	94.32	88.75	31.04	34.72
75	14	93.89	93.93	88.44	30.69	34.87
80	11	94.07	94.53	88.80	30.42	35.51
85	10	94.19	94.38	88.74	30.22	35.58
90	10	94.15	94.36	88.48	29.99	35.70
95	10	94.09	94.57	88.99	29.83	35.76
100	10	94.11	94.38	88.61	29.59	35.82
110	10	94.10	94.19	88.66	29.02	36.02
120	10	97.69	97.51	79.93	32.13	35.24
130	8	97.70	97.56	80.89	31.66	52.67
140	7	98.08	97.73	80.97	31.42	52.94
150	7	97.95	97.75	80.98	30.82	53.55
160	6	98.10	97.61	80.99	30.46	53.86
170	5	98.11	97.70	81.09	29.92	67.68
180	6	97.93	97.54	80.82	29.32	68.13
190	7	98.19	97.66	81.32	28.48	69.86
200	8	98.07	97.41	81.23	27.84	70.35

Table 7.14: Different cluster results for DBSCAN on a week of navan data.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
262	0	0	0	0	0	0	26	0	0	0	0	0	0	0	0 = Bathe
0	135	0	0	0	0	0	0	0	28	0	0	0	0	0	1 = Bed_Toilet_Transition
0	0	1265	0	0	0	0	1	0	0	0	0	3	0	0	2 = Cook
0	0	0	1894	0	0	0	16	0	0	1	0	272	0	59	3 = Drink
0	0	20	0	6	0	0	4	0	0	0	0	20	0	0	4 = Eat
0	0	0	0	0	0	0	75	0	0	0	10	5	0	0	5 = Enter_Home
0	0	0	0	0	0	54	60	0	0	0	3	4	5	0	6 = Leave_Home
3	0	53	12	0	0	0	9649	0	28	16	1	242	25	128	7 = Other_Activity
0	0	0	10	0	0	0	14	141	1	0	0	0	0	0	8 = Relax
0	4	0	0	0	0	0	82	0	1620	0	0	3	0	0	9 = Sleep
0	0	0	17	0	0	0	400	1	3	274	0	104	0	40	10 = Toilet
0	0	0	0	0	0	0	0	0	0	0	990	0	0	0	11 = Wash_Dishes
0	0	18	63	0	0	12	274	0	0	0	0	8113	0	10	12 = Watch_TV
0	0	0	0	0	0	0	5	0	0	0	0	0	887	7	13 = Water_Plants
0	0	0	30	0	0	0	307	0	0	0	0	11	0	6076	14 = Work_On_Computer

Table 7.15: Results for *navan_week* activity recognition, with an accuracy of 92.52.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.90972	8.9249e-05	0.99991	0.95375	0.98868	0.90972
Bed_Toilet_Transition	0.82822	0.00011856	0.99988	0.91001	0.97122	0.82822
Cook	0.99685	0.0027886	0.99721	0.99703	0.93289	0.99685
Drink	0.84478	0.0041693	0.99583	0.9172	0.93485	0.84478
Eat	0.12	0	1	0.34641	1	0.12
Enter_Home	0	0	1	0	-	0
Leave_Home	0.42857	0.00035528	0.99964	0.65454	0.81818	0.42857
Other_Activity	0.94999	0.053232	0.94677	0.94838	0.88417	0.94999
Relax	0.8494	2.9642e-05	0.99997	0.92161	0.99296	0.8494
Sleep	0.94792	0.0018638	0.99814	0.97271	0.96429	0.94792
Toilet	0.32658	0.00051417	0.99949	0.57132	0.94158	0.32658
Wash_Dishes	1	0.00042538	0.99957	0.99979	0.98606	1
Watch_TV	0.95559	0.026129	0.97387	0.96469	0.92435	0.95559
Water_Plants	0.98665	0.00090901	0.99909	0.99285	0.96728	0.98665
Work_On_Computer	0.94583	0.0088798	0.99112	0.96821	0.96139	0.94583

Table 7.16: *navan_week* activity recognition accuracies.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
15969	233	0	0	0	0	0	268	1	297	47	273	15	0	5	0 = c0
280	3530	0	0	0	0	0	30	0	0	5	3	2	0	0	1 = c1
20	0	29	0	0	0	0	0	0	0	0	0	0	0	0	2 = c10
16	0	0	0	0	0	0	4	0	0	0	0	0	0	0	3 = c11
7	0	0	0	34	0	0	2	0	0	0	6	0	0	0	4 = c12
0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	5 = c13
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6 = c14
27	0	0	0	0	0	0	3949	0	8	0	0	0	0	0	7 = c2
0	0	0	0	0	0	0	0	61	0	0	0	0	0	0	8 = c3
308	27	0	0	0	0	0	7	3	4163	3	14	0	0	0	9 = c4
49	0	0	0	0	0	0	0	0	0	626	0	0	0	0	10 = c5
5	0	0	0	0	0	0	0	0	0	0	3177	0	0	0	11 = c6
53	4	0	0	0	0	0	7	0	0	0	4	260	0	0	12 = c7
0	0	0	0	0	0	0	16	0	0	0	0	0	0	0	13 = c8
11	0	0	0	0	0	0	0	0	0	0	0	0	0	31	14 = c9

Table 7.17: Results for *navan_week.DTW* activity recognition, with an accuracy of 93.885.

The *navan_2014.DTW* dataset has a very low error rate compared to the error rate of the *navan_2014.AD* dataset. With this dataset, class '0' is considered noise and approximately equivalent to Other_Activity. A similar classification error pattern can be seen between '0' and the other classes as was observed between Other_Activity and the other ADL classes in the confusion matrix, found in Table 7.20.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
0	0.93342	0.046862	0.95314	0.94323	0.95303	0.93342
1	0.91688	0.0087848	0.99122	0.95332	0.93042	0.91688
10	0.59184	0	1	0.76931	1	0.59184
11	0	0	1	0	-	0
12	0.69388	0	1	0.83299	1	0.69388
13	0	0	1	0	-	0
14	0	0	1	0	-	0
2	0.99121	0.011231	0.98877	0.98999	0.92159	0.99121
3	1	0.0001182	0.99988	0.99994	0.93846	1
4	0.92	0.010382	0.98962	0.95417	0.93174	0.92
5	0.92741	0.0016553	0.99834	0.96222	0.91924	0.92741
6	0.99843	0.0097656	0.99023	0.99432	0.91372	0.99843
7	0.79268	0.00050634	0.99949	0.8901	0.93863	0.79268
8	0	0	1	0	-	0
9	0.7381	0.00014767	0.99985	0.85906	0.86111	0.7381

Table 7.18: *navan_week.DTW* activity recognition accuracies.

Activity	TPR for True	True % Events
Bathe	0.76991	1.0671%
Bed_Toilet_Transition	0.22059	0.6422%
Cook	0.68889	1.6999%
Drink	0.80456	7.8761%
Eat	0.72727	0.5194%
Enter_Home	0.54032	1.1710%
Leave_Home	0.58915	1.2182%
Other_Activity	0.97027	37.4820%
Relax	0.92727	1.5582%
Sleep	0.99791	40.7590%
Toilet	0.62981	7.6022%
Wash_Dishes	0.79487	0.7366%
Watch_TV	0.99345	25.9330%
Water_Plants	0.77966	1.1144%
Work_On_Computer	0.95170	14.4680%

Table 7.19: TPR for *navan_week* forecasting of activities for the *true case*.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	←guessed
288390	382	30	0	90	23	29	0	7	0	19	0	0	6	18	0	0	0	0	0	0	2	0	1032	0	0	0	0	0	18	0	7	0	6	3	0 = 0
1210	17056	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	1 = 1
5	0	946	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	2 = 10
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	3 = 11
544	6	0	0	6671	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	1	4 = 12
17	0	4	0	0	2204	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5 = 13
109	3	0	0	0	0	2458	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	6 = 14
42	0	0	0	0	0	0	524	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7 = 15
52	0	0	0	0	0	0	0	355	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8 = 16
0	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9 = 17
266	2	0	0	0	0	0	0	0	0	1473	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10 = 18
17	5	0	0	0	0	0	0	0	0	0	140	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11 = 19
20	2	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	12 = 2
78	0	0	0	2	0	0	0	0	0	0	0	0	254	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13 = 20
23	0	0	0	0	0	0	0	0	0	0	0	0	0	185	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	14 = 21
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	15 = 22
9	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	82	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16 = 23
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	69	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17 = 24
0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	18 = 25
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	19 = 26
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	78	0	0	8	0	0	0	0	0	0	0	0	0	0	0	20 = 27
10	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	143	0	14	0	0	0	0	0	0	0	0	0	0	0	21 = 28
2	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	54	0	0	0	0	0	0	0	0	0	0	0	0	22 = 29
240	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16801	0	0	0	0	0	0	0	0	0	0	0	23 = 3
0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24 = 30
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	238	0	0	0	6	0	0	0	0	0	25 = 31
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	56	0	0	0	0	0	0	0	0	26 = 32
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	27 = 33
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	34	0	0	0	0	0	0	28 = 34
100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1307	0	0	0	0	0	29 = 4
10	0	0	0	24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	205	0	0	0	0	30 = 5
12	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	512	0	0	0	31 = 6
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	38	0	0	0	0	0	0	0	0	0	0	0	32 = 7
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	22	0	0	0	0	0	0	0	0	0	216	0	33 = 8
118	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	648	34 = 9

Table 7.20: Results for *navan_2014.DTW* activity recognition, with an accuracy of 98.6.

7.3 Activity Forecasting

Using datasets summarized in Tables 7.1 and 7.2, we evaluate the ability of the activity forecasting algorithm to accurately identify when activities will occur in the next 10 minutes. We look at and compare the performance of human-generated activity labels, labels generated by the activity discovery algorithm, and clusters identified by our DBSCAN-DTW algorithm. The tables presented here are summaries of the resulting performance. A select number of the confusion matrices are located in Appendix D

7.3.1 Activities of Daily Living

Table 7.22 shows the number of datapoints for the *true case* and *false case* for each activity. Table 7.23 shows the true positive rate for classifying the *true case* of each activity, as well as g-mean, specificity, precision, and recall. Bed_Toilet_Transition has a similar class distribution to Eat, but the forecasting TPR value is much lower. This TPR value is because the activity Bed_Toilet_Transition often happens in the middle of the night without much warning that the random forest can identify. The activity Eat is much easier to determine as there are signs, such as the activity Cook or getting food from the kitchen that the random forest can utilize for informing the classification.

Table 7.24 shows the number of datapoints for the *true case* and *false case* for each activity. Table 7.25 shows the true positive rate for classifying the true case of each activity. As with the *navan_week* dataset, the *navan_2014* dataset had issues with the

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
0	0.99424	0.051998	0.948	0.97084	0.99001	0.99424
1	0.93365	0.001437	0.99856	0.96556	0.97313	0.93365
10	0.98851	9.8526e-05	0.9999	0.99419	0.96531	0.98851
11	0	0	1	0	-	0
12	0.92243	0.00034237	0.99966	0.96027	0.98291	0.92243
13	0.99056	8.1438e-05	0.99992	0.99523	0.98746	0.99056
14	0.95605	9.6077e-05	0.9999	0.97773	0.98675	0.95605
15	0.9258	0	1	0.96218	1	0.9258
16	0.87224	2.0252e-05	0.99998	0.93393	0.98066	0.87224
17	0	0	1	0	-	0
18	0.84607	5.5184e-05	0.99994	0.91979	0.98727	0.84607
19	0.8642	0	1	0.92962	1	0.8642
2	0.74627	0	1	0.86387	1	0.74627
20	0.76048	1.7356e-05	0.99998	0.87205	0.97692	0.76048
21	0.88517	5.2048e-05	0.99995	0.94081	0.91133	0.88517
22	0	0	1	0	-	0
23	0.86316	0	1	0.92906	1	0.86316
24	0.94521	0	1	0.97222	1	0.94521
25	0	0	1	0	-	0
26	0	0	1	0	-	0
27	0.85714	0	1	0.92582	1	0.85714
28	0.77297	5.7827e-06	0.99999	0.87919	0.98621	0.77297
29	0.84375	0	1	0.91856	1	0.84375
3	0.98592	0.0035136	0.99649	0.99119	0.93562	0.98592
30	0	0	1	0	-	0
31	0.97541	0	1	0.98763	1	0.97541
32	1	0	1	1	1	1
33	0	0	1	0	-	0
34	0.7907	0	1	0.88921	1	0.7907
4	0.92893	7.254e-05	0.99993	0.96377	0.98123	0.92893
5	0.85774	0	1	0.92614	1	0.85774
6	0.97338	2.8942e-05	0.99997	0.98659	0.98084	0.97338
7	0	0	1	0	-	0
8	0.88163	1.7351e-05	0.99998	0.93894	0.97297	0.88163
9	0.82971	1.1585e-05	0.99999	0.91088	0.99387	0.82971

Table 7.21: *navan_2014.DTW* activity recognition accuracies.

Activity	# True Events	# False Events
Bathe	113	10476
Bed_Toilet_Transition	68	10521
Cook	180	10409
Drink	834	9755
Eat	55	10534
Enter_Home	124	10465
Leave_Home	129	10460
Other_Activity	3969	6620
Relax	165	10424
Sleep	4316	6273
Toilet	805	9784
Wash_Dishes	78	10511
Watch_TV	2746	7843
Water_Plants	118	10471
Work_On_Computer	1532	9057

Table 7.22: *navan_week* forecast classes.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	1	0.23009	0.76991	0.87745	0.99752	1
Bathe-True	0.76991	0	1	0.87745	1	0.76991
Bed_Toilet_Transition-False	1	0.77941	0.22059	0.46967	0.99499	1
Bed_Toilet_Transition-True	0.22059	0	1	0.46967	1	0.22059
Cook-False	1	0.31111	0.68889	0.82999	0.99465	1
Cook-True	0.68889	0	1	0.82999	1	0.68889
Drink-False	0.99877	0.19544	0.80456	0.89642	0.98355	0.99877
Drink-True	0.80456	0.0012301	0.99877	0.89642	0.98243	0.80456
Eat-False	1	0.27273	0.72727	0.8528	0.99858	1
Eat-True	0.72727	0	1	0.8528	1	0.72727
Enter_Home-False	1	0.45968	0.54032	0.73507	0.99458	1
Enter_Home-True	0.54032	0	1	0.73507	1	0.54032
Leave_Home-False	1	0.41085	0.58915	0.76756	0.99496	1
Leave_Home-True	0.58915	0	1	0.76756	1	0.58915
Other_Activity-False	0.9929	0.02973	0.97027	0.98152	0.98236	0.9929
Other_Activity-True	0.97027	0.0070997	0.9929	0.98152	0.98794	0.97027
Relax-False	0.9999	0.072727	0.92727	0.9629	0.99885	0.9999
Relax-True	0.92727	9.5932e-05	0.9999	0.9629	0.99351	0.92727
Sleep-False	0.99362	0.0020853	0.99791	0.99577	0.99856	0.99362
Sleep-True	0.99791	0.0063765	0.99362	0.99577	0.9908	0.99791
Toilet-False	0.9999	0.37019	0.62981	0.79357	0.97044	0.9999
Toilet-True	0.62981	0.00010221	0.9999	0.79357	0.99803	0.62981
Wash_Dishes-False	1	0.20513	0.79487	0.89156	0.99848	1
Wash_Dishes-True	0.79487	0	1	0.89156	1	0.79487
Watch_TV-False	0.99541	0.006555	0.99345	0.99443	0.9977	0.99541
Watch_TV-True	0.99345	0.0045901	0.99541	0.99443	0.98698	0.99345
Water_Plants-False	1	0.22034	0.77966	0.88298	0.99752	1
Water_Plants-True	0.77966	0	1	0.88298	1	0.77966
Work_On_Computer-False	0.99856	0.048303	0.9517	0.97485	0.99188	0.99856
Work_On_Computer-True	0.9517	0.0014354	0.99856	0.97485	0.99116	0.9517

Table 7.23: *navan_week* activity forecasting accuracies.

Bed_Toilet_Transition activity. The poor performance with Eat and Drink indicates that CARL might turn off devices associated with these activities right before they are utilized, or that CARLv3 might not turn on devices for these activities.

7.3.2 Activity Detection

In an interesting change, the AD datasets appear to have a class distribution for forecasting the *true case* in the opposite direction, with many more instances of *true* than of *false*. This class distribution is not true of all AD activity labels though, where many seem to show an equal distribution between the *true* and *false case*. Table 7.29 illustrates the number of datapoints for the *true case* and *false case* for each activity in the *navan_2014.AD* dataset. Table 7.30 shows the true positive rate for classifying the *true case* of each activity in the *navan_2014.AD* dataset. A large number of *true cases* for forecasting in this dataset identifies the distribution of the AD activity labels. Many of the labels are occurring at points throughout the day without large spans of time where the activity label will not be seen for more than 10 minutes.

7.3.3 DBSCAN with DTW

Table 7.31 shows the number of datapoints for the *true case* and *false case* for each activity in the *navan_week.DTW* dataset. Table 7.32 shows the true positive rate for classifying the *true case* of each activity in the *navan_week.DTW* dataset. The distribution of *true cases* to *false cases* for forecasting for the *navan_week.DTW* dataset is much closer

Activity	# True Events	# False Events
Bathe	883	63586
Bed_Toilet_Transition	878	63591
Cook	563	63906
Drink	1048	63421
Eat	599	63870
Enter_Home	609	63860
Leave_Home	653	63816
Other_Activity	31231	33238
Relax	177	64292
Sleep	24718	39751
Toilet	8129	56340
Wash_Dishes	12	64457
Watch_TV	17713	46756
Work_On_Computer	9843	54626

Table 7.24: *navan_2014* forecast classes.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	1	0.23556	0.76444	0.87432	0.99674	1
Bathe-True	0.76444	0	1	0.87432	1	0.76444
Bed_Toilet_Transition-False	1	0.94761	0.052392	0.22889	0.98709	1
Bed_Toilet_Transition-True	0.052392	0	1	0.22889	1	0.052392
Cook-False	0.99991	0.13677	0.86323	0.92906	0.9988	0.99991
Cook-True	0.86323	9.3888e-05	0.99991	0.92906	0.9878	0.86323
Drink-False	0.99994	0.54389	0.45611	0.67534	0.99109	0.99994
Drink-True	0.45611	6.3071e-05	0.99994	0.67534	0.9917	0.45611
Eat-False	1	0.41068	0.58932	0.76767	0.99616	1
Eat-True	0.58932	0	1	0.76767	1	0.58932
Enter_Home-False	1	0.77997	0.22003	0.46908	0.99262	1
Enter_Home-True	0.22003	0	1	0.46908	1	0.22003
Leave_Home-False	1	0.66769	0.33231	0.57647	0.99321	1
Leave_Home-True	0.33231	0	1	0.57647	1	0.33231
Other_Activity-False	0.97136	0.026512	0.97349	0.97242	0.975	0.97136
Other_Activity-True	0.97349	0.028642	0.97136	0.97242	0.96964	0.97349
Relax-False	1	0.096045	0.90395	0.95077	0.99974	1
Relax-True	0.90395	0	1	0.95077	1	0.90395
Sleep-False	0.99904	0.0090622	0.99094	0.99498	0.99439	0.99904
Sleep-True	0.99094	0.00095595	0.99904	0.99498	0.99845	0.99094
Toilet-False	0.99975	0.36401	0.63599	0.79739	0.95009	0.99975
Toilet-True	0.63599	0.00024849	0.99975	0.79739	0.9973	0.63599
Wash_Dishes-False	1	1	0	0	0.99981	1
Wash_Dishes-True	0	0	1	0	-	0
Watch_TV-False	0.9923	0.022808	0.97719	0.98472	0.99137	0.9923
Watch_TV-True	0.97719	0.0076995	0.9923	0.98472	0.97963	0.97719
Work_On_Computer-False	0.998	0.095195	0.90481	0.95026	0.9831	0.998
Work_On_Computer-True	0.90481	0.0019954	0.998	0.95026	0.98791	0.90481

Table 7.25: *navan_2014* activity forecasting accuracies.

Activity	# True Events	# False Events	True Positive Rate
Bathe	3,026	227,369	0.52875
Bed_Toilet_Transition	1,142	229,253	0.031524
Cook	527	229,868	0.3852
Drink	4,081	226,314	0.29062
Eat	172	230,223	0.57558
Enter_Home	3,546	226,849	0.090807
Entertain_Guests	156	230,239	0.73077
Leave_Home	69,356	161,039	0.97605
Other_Activity	61,858	168,537	0.80276
Relax	307	230,088	0.66124
Sleep	74,147	156,248	0.98686
Toilet	18,593	211,802	0.2885
Watch_TV	54,836	175,559	0.9599
Water_Plants	1,136	229,259	0.29577
Work_On_Computer	20,890	209,505	0.78526

Table 7.26: *navan_2012* forecast classes.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	1	0.47125	0.52875	0.72715	0.99377	1
Bathe-True	0.52875	4.3981e-06	1	0.72715	0.99938	0.52875
Bed_Toilet_Transition-False	1	0.96848	0.031524	0.17755	0.9952	1
Bed_Toilet_Transition-True	0.031524	0	1	0.17755	1	0.031524
Cook-False	1	0.6148	0.3852	0.62064	0.99859	1
Cook-True	0.3852	0	1	0.62064	1	0.3852
Drink-False	0.99994	0.70938	0.29062	0.53907	0.98737	0.99994
Drink-True	0.29062	5.7442e-05	0.99994	0.53907	0.98916	0.29062
Eat-False	1	0.42442	0.57558	0.75867	0.99968	1
Eat-True	0.57558	0	1	0.75867	1	0.57558
Enter_Home-False	1	0.90919	0.090807	0.30134	0.98599	1
Enter_Home-True	0.090807	0	1	0.30134	1	0.090807
Entertain_Guests-False	1	0.26923	0.73077	0.85485	0.99982	1
Entertain_Guests-True	0.73077	0	1	0.85485	1	0.73077
Leave_Home-False	0.99696	0.023949	0.97605	0.98645	0.98976	0.99696
Leave_Home-True	0.97605	0.0030365	0.99696	0.98645	0.99283	0.97605
Other_Activity-False	0.98916	0.19724	0.80276	0.8911	0.9318	0.98916
Other_Activity-True	0.80276	0.01084	0.98916	0.8911	0.96451	0.80276
Relax-False	1	0.33876	0.66124	0.81317	0.99955	1
Relax-True	0.66124	0	1	0.81317	1	0.66124
Sleep-False	0.99716	0.013136	0.98686	0.992	0.99379	0.99716
Sleep-True	0.98686	0.0028416	0.99716	0.992	0.99397	0.98686
Toilet-False	0.99994	0.7115	0.2885	0.5371	0.94121	0.99994
Toilet-True	0.2885	6.1378e-05	0.99994	0.5371	0.99758	0.2885
Watch_TV-False	0.99328	0.040101	0.9599	0.97645	0.98755	0.99328
Watch_TV-True	0.9599	0.0067157	0.99328	0.97645	0.97809	0.9599
Water_Plants-False	1	0.70423	0.29577	0.54385	0.99652	1
Water_Plants-True	0.29577	0	1	0.54385	1	0.29577
Work_On_Computer-False	0.99892	0.21474	0.78526	0.88567	0.97901	0.99892
Work_On_Computer-True	0.78526	0.0010787	0.99892	0.88567	0.98641	0.78526

Table 7.27: *navan_2012* activity forecasting accuracies.

Activity	TPR for True	True % Events
Other_Activity	0.99986	98.843%
Pat_0	0.99959	98.877%
Pat_10	0.86151	22.166%
Pat_12	0.79732	26.273%
Pat_4	0.87065	22.245%
Pat_5	0.86367	44.065%
Pat_7	0.82446	25.237%
Pat_9	0.88920	63.361%

Table 7.28: TPR for *navan_2014.AD* forecasting of activities for the *true case*.

Activity	# True Events	# False Events
Other_Activity	63723	746
Pat_0	63745	724
Pat_10	14290	50179
Pat_12	16938	47531
Pat_4	14341	50128
Pat_5	28408	36061
Pat_7	16270	48199
Pat_9	40848	23621

Table 7.29: *navan_2014.AD* forecast classes.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.27748	0.00014124	0.99986	0.52673	0.95833	0.27748
Other_Activity-True	0.99986	0.72252	0.27748	0.52673	0.99161	0.99986
Pat_0-False	0.80801	0.00040788	0.99959	0.89871	0.95745	0.80801
Pat_0-True	0.99959	0.19199	0.80801	0.89871	0.99782	0.99959
Pat_10-False	0.99448	0.13849	0.86151	0.92561	0.96186	0.99448
Pat_10-True	0.86151	0.0055202	0.99448	0.92561	0.97799	0.86151
Pat_12-False	0.9352	0.20268	0.79732	0.86351	0.92831	0.9352
Pat_12-True	0.79732	0.0648	0.9352	0.86351	0.81429	0.79732
Pat_4-False	0.99433	0.12935	0.87065	0.93044	0.96412	0.99433
Pat_4-True	0.87065	0.0056655	0.99433	0.93044	0.97776	0.87065
Pat_5-False	0.96303	0.13633	0.86367	0.912	0.89967	0.96303
Pat_5-True	0.86367	0.036965	0.96303	0.912	0.94847	0.86367
Pat_7-False	0.99515	0.17554	0.82446	0.90579	0.9438	0.99515
Pat_7-True	0.82446	0.0048549	0.99515	0.90579	0.98285	0.82446
Pat_9-False	0.85399	0.1108	0.8892	0.87141	0.81675	0.85399
Pat_9-True	0.8892	0.14601	0.85399	0.87141	0.91328	0.8892

Table 7.30: *navan_2014.AD* activity forecasting accuracies.

to the human generated ADL *navan_week* dataset than the *navan_week.AD* dataset. A large number of activity labels in the *navan_week.DTW* dataset with high true positive rates for the *true case* in forecasting will help the CARL home automation algorithm perform better.

Table 7.34 shows the number of datapoints for the *true case* and *false case* for each activity in the *navan_2014.DTW* dataset. Table 7.35 shows the true positive rate for classifying the *true case* of each activity in the *navan_2014.DTW* dataset. While there are several activity labels with lower true positive rates for the *true case* in forecasting, there are much more with high true positive rates. If the greater performing activity labels are associated with devices, then the high accuracy in forecasting will allow the *navan_2014.DTW* dataset to perform well with the CARL activity-aware automation algorithm.

7.4 CARL

Using datasets summarized in Tables 7.1 and 7.2, we evaluate the ability of the three versions of the CARL algorithm to utilize activity recognition and activity forecasting to perform home automation. We look at and compare the performance of human-generated activity labels, labels generated by the activity discovery algorithm, and clusters identified by our DBSCAN-DTW algorithm.

Activity	# True Events	# False Events
0	5187	5402
1	1662	8927
10	46	10543
11	47	10542
12	34	10555
13	21	10568
14	23	10566
2	4385	6204
3	33	10556
4	1406	9183
5	210	10379
6	1649	8940
7	171	10418
8	56	10533
9	53	10536

Table 7.31: *navan_week.DTW* forecast classes.

Activity	True Positive Rate
0	0.9705
1	0.97413
10	0.91304
11	0.44681
12	0.61765
13	0.38095
14	0.86957
2	0.99886
3	0.93939
4	0.99218
5	0.9619
6	0.99576
7	0.74269
8	0.76786
9	0.71698

Table 7.32: *navan_week.DTW* forecast true positive rate.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
0-False	0.97186	0.029497	0.9705	0.97118	0.97168	0.97186
0-True	0.9705	0.028138	0.97186	0.97118	0.97069	0.9705
1-False	0.99552	0.025872	0.97413	0.98477	0.99518	0.99552
1-True	0.97413	0.0044808	0.99552	0.98477	0.97589	0.97413
10-False	1	0.086957	0.91304	0.95553	0.99962	1
10-True	0.91304	0	1	0.95553	1	0.91304
11-False	1	0.55319	0.44681	0.66844	0.99754	1
11-True	0.44681	0	1	0.66844	1	0.44681
12-False	1	0.38235	0.61765	0.78591	0.99877	1
12-True	0.61765	0	1	0.78591	1	0.61765
13-False	1	0.61905	0.38095	0.61721	0.99877	1
13-True	0.38095	0	1	0.61721	1	0.38095
14-False	1	0.13043	0.86957	0.9325	0.99972	1
14-True	0.86957	0	1	0.9325	1	0.86957
2-False	0.9921	0.0011403	0.99886	0.99548	0.99919	0.9921
2-True	0.99886	0.0078981	0.9921	0.99548	0.98894	0.99886
3-False	0.99991	0.060606	0.93939	0.96918	0.99981	0.99991
3-True	0.93939	9.4733e-05	0.99991	0.96918	0.96875	0.93939
4-False	0.9963	0.0078236	0.99218	0.99423	0.9988	0.9963
4-True	0.99218	0.0037025	0.9963	0.99423	0.97621	0.99218
5-False	0.9999	0.038095	0.9619	0.98072	0.99923	0.9999
5-True	0.9619	9.6348e-05	0.9999	0.98072	0.99507	0.9619
6-False	0.99989	0.004245	0.99576	0.99782	0.99922	0.99989
6-True	0.99576	0.00011186	0.99989	0.99782	0.99939	0.99576
7-False	1	0.25731	0.74269	0.86179	0.99579	1
7-True	0.74269	0	1	0.86179	1	0.74269
8-False	0.99972	0.23214	0.76786	0.87615	0.99877	0.99972
8-True	0.76786	0.00028482	0.99972	0.87615	0.93478	0.76786
9-False	1	0.28302	0.71698	0.84675	0.99858	1
9-True	0.71698	0	1	0.84675	1	0.71698

Table 7.33: *navan_week.DTW* activity forecasting accuracies.

Activity	# True Events	# False Events
0	34169	30300
1	7576	56893
10	247	64222
11	84	64385
12	2350	62119
13	311	64158
14	5256	59213
15	1238	63231
16	198	64271
17	50	64419
18	837	63632
19	58	64411
2	393	64076
20	85	64384
21	79	64390
22	43	64426
23	198	64271
24	29	64440
25	56	64413
26	52	64417
27	430	64039
28	742	63727
29	55	64414
3	23669	40800
30	28	64441
31	45	64424
32	13	64456
33	374	64095
34	93	64376
4	381	64088
5	70	64399
6	96	64373
7	174	64295
8	81	64388
9	510	63959

Table 7.34: *navan_2014.DTW* forecast classes.

Activity	True Positive Rate
0	0.93319
1	0.95987
10	0.82186
11	0.083333
12	0.90638
13	0.81672
14	0.99182
15	0.96931
16	0.82828
17	0.2
18	0.92593
19	0.63793
2	0.91603
20	0.6
21	0.81013
22	0
23	0.98485
24	0.93103
25	0.017857
26	0.46154
27	0.93488
28	0.94609
29	0.61818
3	0.99916
30	0.25
31	0.8
32	0.76923
33	1
34	1
4	0.83465
5	0.47143
6	0.79167
7	0.33908
8	0.59259
9	0.87059

Table 7.35: *navan_2014.DTW* forecast true positive rate.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
0-False	0.96871	0.066815	0.93319	0.95078	0.92783	0.96871
0-True	0.93319	0.031287	0.96871	0.95078	0.97113	0.93319
1-False	0.99439	0.040127	0.95987	0.97698	0.99466	0.99439
1-True	0.95987	0.005607	0.99439	0.97698	0.95798	0.95987
10-False	0.99997	0.17814	0.82186	0.90655	0.99932	0.99997
10-True	0.82186	3.1142e-05	0.99997	0.90655	0.99024	0.82186
11-False	1	0.91667	0.083333	0.28868	0.99881	1
11-True	0.083333	0	1	0.28868	1	0.083333
12-False	0.99947	0.093617	0.90638	0.95179	0.99647	0.99947
12-True	0.90638	0.00053124	0.99947	0.95179	0.98474	0.90638
13-False	1	0.18328	0.81672	0.90373	0.99911	1
13-True	0.81672	0	1	0.90373	1	0.81672
14-False	0.99981	0.0081811	0.99182	0.99581	0.99927	0.99981
14-True	0.99182	0.00018577	0.99981	0.99581	0.99789	0.99182
15-False	1	0.030695	0.96931	0.98453	0.9994	1
15-True	0.96931	0	1	0.98453	1	0.96931
16-False	1	0.17172	0.82828	0.9101	0.99947	1
16-True	0.82828	0	1	0.9101	1	0.82828
17-False	1	0.8	0.2	0.44721	0.99938	1
17-True	0.2	0	1	0.44721	1	0.2
18-False	0.99984	0.074074	0.92593	0.96217	0.99903	0.99984
18-True	0.92593	0.00015715	0.99984	0.96217	0.98726	0.92593
19-False	1	0.36207	0.63793	0.79871	0.99967	1
19-True	0.63793	0	1	0.79871	1	0.63793
2-False	1	0.083969	0.91603	0.95709	0.99949	1
2-True	0.91603	0	1	0.95709	1	0.91603
20-False	1	0.4	0.6	0.7746	0.99947	1
20-True	0.6	0	1	0.7746	1	0.6
21-False	1	0.18987	0.81013	0.90007	0.99977	1
21-True	0.81013	0	1	0.90007	1	0.81013
22-False	1	1	0	0	0.99933	1
22-True	0	0	1	0	-	0
23-False	1	0.015152	0.98485	0.9924	0.99995	1
23-True	0.98485	0	1	0.9924	1	0.98485
24-False	1	0.068966	0.93103	0.9649	0.99997	1
24-True	0.93103	0	1	0.9649	1	0.93103
25-False	1	0.98214	0.017857	0.13363	0.99915	1
25-True	0.017857	0	1	0.13363	1	0.017857
26-False	1	0.53846	0.46154	0.67937	0.99957	1
26-True	0.46154	0	1	0.67937	1	0.46154
27-False	1	0.065116	0.93488	0.96689	0.99956	1
27-True	0.93488	0	1	0.96689	1	0.93488
28-False	1	0.053908	0.94609	0.97267	0.99937	1
28-True	0.94609	0	1	0.97267	1	0.94609
29-False	1	0.38182	0.61818	0.78625	0.99967	1
29-True	0.61818	0	1	0.78625	1	0.61818
3-False	0.98735	0.00084499	0.99916	0.99324	0.9995	0.98735
3-True	0.99916	0.012647	0.98735	0.99324	0.97865	0.99916
30-False	1	0.75	0.25	0.5	0.99967	1
30-True	0.25	0	1	0.5	1	0.25
31-False	1	0.2	0.8	0.89443	0.99986	1
31-True	0.8	0	1	0.89443	1	0.8
32-False	1	0.23077	0.76923	0.87706	0.99995	1
32-True	0.76923	0	1	0.87706	1	0.76923
33-False	1	0	1	1	1	1
33-True	1	0	1	1	1	1
34-False	1	0	1	1	1	1
34-True	1	0	1	1	1	1
4-False	0.99995	0.16535	0.83465	0.91357	0.99902	0.99995
4-True	0.83465	4.6811e-05	0.99995	0.91357	0.99065	0.83465
5-False	1	0.52857	0.47143	0.68661	0.99943	1
5-True	0.47143	0	1	0.68661	1	0.47143
6-False	1	0.20833	0.79167	0.88976	0.99969	1
6-True	0.79167	0	1	0.88976	1	0.79167
7-False	1	0.66092	0.33908	0.58231	0.99821	1
7-True	0.33908	0	1	0.58231	1	0.33908
8-False	1	0.40741	0.59259	0.7698	0.99949	1
8-True	0.59259	0	1	0.7698	1	0.59259
9-False	0.99975	0.12941	0.87059	0.93294	0.99897	0.99975
9-True	0.87059	0.00025016	0.99975	0.93294	0.96522	0.87059

Table 7.36: *navan_2014.DTW* activity forecasting accuracies.

7.4.1 CARLv1

The primary goal of CARLv1 was to determine how much energy savings could be achieved. However, human factors need to be considered as well. As a result, CARLv1 is evaluated on some different performance measures. These measures include:

- *Total time*. Measures the total time that devices are on.

- *Watt-hours*. Measures the watt-hours of power that are used by a particular method (CARLv1 or the baseline method of no automation) combined over all of the devices located in the testbed. The list of navan's devices and their wattages are found in Table 3.1.

- *RMSE*. The root mean square error (RMSE) is computed to indicate the error in CARLv1's automation due to being too aggressive (turning off devices when the resident needed them) or too conservative (not turning off devices when they were not necessary). The too-conservative case occurred twice. In both situations, this was due to the smart home infrastructure not detecting the request to turn off a device. The too-aggressive situation was more common and was typically due to errors in recognizing the current activity. The errors were indicated by button taps by the resident and are therefore measured using this feedback, as shown in Equation 7.1. In this equation, D represents the number of devices, $CARL_Off(i)$ accounts for the number of times that CARLv1 turned off device i and $DoubleTap(i)$ accounts for the number of times that the resident indicated an automation error via a double tap.

$$RMSE = \sqrt{\frac{\sum_{i=0}^{D}(CARL\_Off(i) - DoubleTap(i))^2}{D}} \tag{7.1}$$

- *NRMSE*. To better interpret the RMSE values, we compute a normalized RMSE value. This value is obtained by dividing the RMSE result by the maximum possible error. The resulting value ranges between 0.0 (no error) and 1.0 (maximum possible error).

$$NRMSE = \frac{RMSE}{max_{i \in D}(CARL\_Off(i))} \tag{7.2}$$

The results comparing total time and watt-hours for CARL-based automation and no automation are summarized in Figures 7.1 and 7.2. As the figures indicate, there is a consistent reduction in energy consumption and unnecessary device utilization through activity-aware automation. Most of the energy reduction is due to turning off lamps when they are not needed (e.g., when the resident is not at home) and turning off speakers when the resident is not in the living room listening to music or watching television.

Table 7.37 summarizes the reduction and accuracy results. There is a significant ($p < 0.01$) reduction in both energy consumption and total time using activity-aware automation. This automation does come at the expense of occasional overly-aggressive device control. This is reflective of the almost 3% error reported earlier for recognizing the targeted 17 activities in real time. As activity recognition becomes more robust, this error will be further reduced.

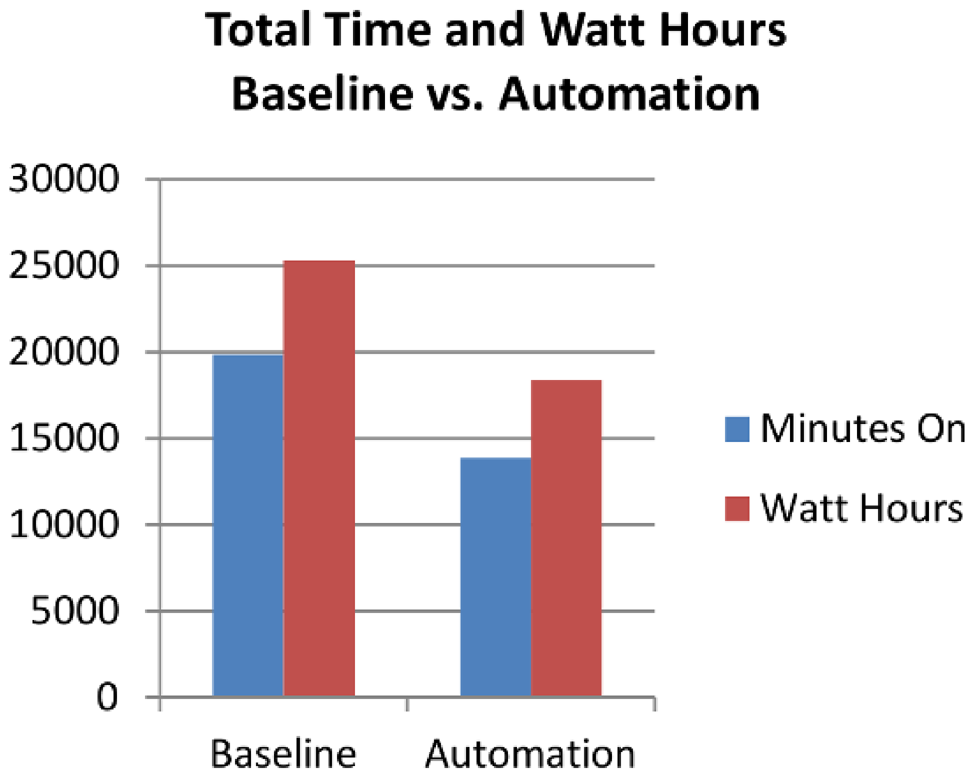


Figure 7.1: Comparison of device total time on and consumption.

	Baseline	CARLv1
Total Time (minutes)	19,826.04	13,867.64
Consumption (watt-hours)	25,297.85	18,352.27
RMSE	0.00	11.15
NRMSE	0.00	0.15

Table 7.37: Reduction and accuracy results for CARLv1.

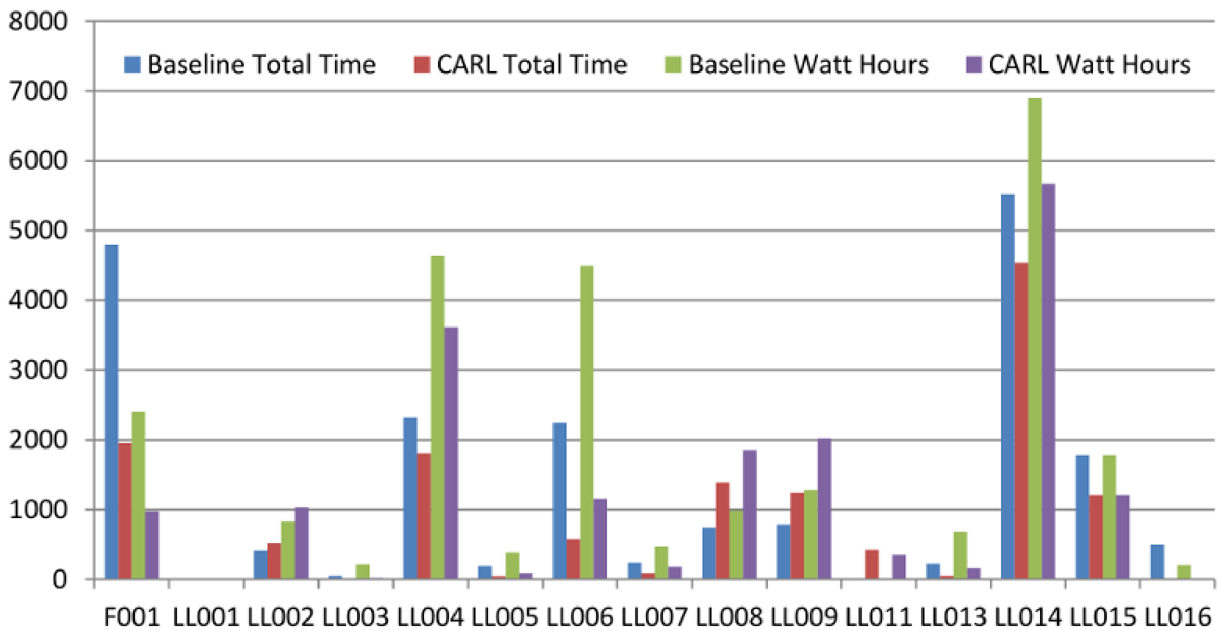


Figure 7.2: Time (in minutes) and energy consumption (in watt-hours), listed for each device, with (CARLv1) and without (baseline) activity-aware home automation.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	←guessed
15211	0	0	0	340	0	0	4331	225	0	248	0	18	428	0 = Bathe
0	2584	0	0	0	0	0	34	0	3704	0	0	0	0	1 = Bed_Toilet_Transition
0	0	17153	0	357	0	0	1731	0	0	288	0	2246	599	2 = Cook
0	0	115	1920	0	0	0	1585	0	61	18	0	2906	171	3 = Drink
0	0	0	0	10808	0	0	3897	0	0	153	0	1047	183	4 = Eat
0	0	0	0	58	22	0	964	0	0	45	0	15	67	5 = Enter_Home
0	0	0	0	0	0	1195	1112	0	0	0	0	0	0	6 = Leave_Home
3097	90	1879	1428	2770	721	61674	562000	181	4298	6935	0	28250	33316	7 = Other_Activity
0	0	0	0	0	0	0	1286	2948	3	0	0	0	280	8 = Relax
0	3713	0	0	77	0	0	4856	92	657036	1766	0	36	1275	9 = Sleep
268	37	350	187	276	0	126	23334	155	1428	17644	0	3715	5571	10 = Toilet
0	0	0	0	0	0	0	0	0	0	0	0	204	0	11 = Wash_Dishes
312	0	2189	3852	19	0	0	104934	0	432	3519	211	252028	4938	12 = Watch_TV
1224	0	905	422	778	0	378	38996	308	940	2887	0	2120	193168	13 = Work_On_Computer

Table 7.38: Results for *navan_2014* CARLv1 activity recognition, with an accuracy of 81.63658632.

0	1	2	3	4	5	6	7	←guessed
147146	0	2323	424	26133	10011	27399	15002	0 = Other_Activity
1212394	0	6841	3153	75933	47533	122551	115888	1 = Pat_0
20722	0	2547	46	23629	3179	3762	4592	2 = Pat_10
21123	0	72	298	721	150	753	272	3 = Pat_12
22069	0	1641	45	27607	4131	3840	5212	4 = Pat_4
18009	0	262	30	4376	6459	2269	6054	5 = Pat_5
17522	0	226	50	2569	1161	19686	1154	6 = Pat_7
44185	0	622	147	6971	6246	4499	21684	7 = Pat_9

Table 7.39: Results for *navan_2014.AD* CARLv1 activity recognition, with an accuracy of 10.61670787.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	←guessed
986663	18052	1420	0	8472	2064	385	0	398	0	1194	221	0	0	26	0	0	0	0	0	105	119	0	34596	0	336	0	0	0	852	105	733	0	12	505	0 = 0
59501	72132	0	0	0	0	0	0	0	0	14	0	0	0	0	0	0	0	0	0	0	0	59	131	0	0	52	0	0	0	0	0	0	0	0	1 = 1
1907	0	1357	0	0	1039	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	84	0	0	0	2 = 10
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	682	0	0	0	0	0	0	0	0	0	0	0	3 = 11
17514	244	0	0	26318	0	0	0	0	0	0	0	0	160	0	0	0	0	0	0	0	0	0	118	0	0	0	0	0	0	0	0	0	0	0	4 = 12
3159	0	4	0	0	2246	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5 = 13
125915	0	0	0	726	0	8996	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6 = 14
34361	0	0	0	0	0	0	1155	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	7 = 15
3095	0	0	0	0	0	0	0	663	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8 = 16
0	529	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9 = 17
7172	158	0	0	0	0	0	0	0	0	9232	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10 = 18
785	12	0	0	0	0	0	0	0	0	0	216	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11 = 19
7890	64	0	0	0	0	0	0	0	0	0	0	218	0	0	0	0	0	0	0	0	0	0	546	0	0	0	0	0	0	0	0	0	0	0	12 = 2
536	0	0	0	89	0	0	0	0	0	0	0	0	433	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13 = 20
156	0	0	0	0	0	0	0	0	0	0	0	0	0	756	0	0	0	0	0	0	0	0	0	0	0	0	0	0	352	0	0	0	0	0	14 = 21
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	269	0	0	0	0	0	0	0	0	0	0	0	15 = 22
5531	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	198	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16 = 23
422	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	175	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17 = 24
0	469	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	18 = 25
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	986	0	0	0	0	0	0	0	0	0	0	0	19 = 26
10647	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	30	0	0	471	0	0	0	0	0	0	0	0	0	0	0	20 = 27
20412	0	0	0	260	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	170	0	954	0	0	0	0	0	0	0	0	0	0	0	21 = 28
335	146	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	22 = 29
36797	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	565360	0	0	0	0	0	0	0	0	0	3	0	23 = 3
28	201	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24 = 30
414	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	241	0	0	0	134	0	0	0	0	0	25 = 31
180	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	26 = 32
9723	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	27 = 33
2152	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	82	0	0	0	0	0	0	28 = 34
2976	0	0	0	0	0	0	0	139	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3841	0	0	0	0	0	29 = 4
352	0	0	0	238	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	295	0	0	0	0	30 = 5
826	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	628	0	0	0	31 = 6
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2786	0	0	0	0	0	0	0	0	0	0	0	32 = 7
71	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	320	0	0	0	0	0	0	0	0	0	595	0	33 = 8
5674	113	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1015	34 = 9

Table 7.40: Results for *navan_2014.DTW* CARLv1 activity recognition, with an accuracy of 79.24795631.

7.4.2 CARLv2

CARLv2's goal is to turn off as many as devices as possible without interfering with resident tasks. Performance can thus be measured regarding the number of times a device is turned off (or the corresponding reduction in energy consumption) and the number of resident disruptions (or the number of times the user double tapped a switch to provide feedback to the system while turning the device back on.

Here, the CARLv2 activity-aware automation architecture is validated using data collected from the navan smart home described in Section 3.2. Much of the system depends on the ability to recognize activities in real time as they occur correctly. First, the accuracy of the activity recognition is evaluated on the navan smart home data. Table 7.41 summarizes the performance of activity recognition using 3-fold partitioning validation. Table 7.41 also provides a confusion matrix that highlights where the errors lie. The performance evaluation is based on two months of smart home data, collected continuously while the resident performed regular routines. As can be seen in Table 7.41, the overall accuracy is high but the larger classes, such as Other_Activity, create a class imbalance that introduces associated errors. CARLv2's automation effectiveness builds on this performance because activity recognition provides the set of current activities, $CurrentActivities$, used in Algorithm 7.

Activity	Bathe	Bed Toilet	Cook	Drink	Eat	Enter Home	Leave Home	Other Activity	Relax	Sleep	Toilet	Wash Dishes	Watch TV	Water Plants	Work_On Computer
Bathe	1201	0	0	0	0	0	3	144	0	0	1059	0	0	0	11
Bed_Toilet_Transition	47	998	0	0	0	0	0	175	0	55	104	0	0	0	4
Cook	0	0	12	63	114	0	25	6358	0	0	0	0	76	0	9
Drink	0	0	35	80	0	0	0	2482	0	41	11	21	406	0	9
Eat	0	3	5	43	379	0	0	2873	0	9	29	0	41	0	0
Enter_Home	0	0	0	0	2	357	2	113	0	0	0	0	1	0	0
Leave_Home	0	0	3	1	11	21	207	336	0	2	0	0	23	0	2
Other_Activity	172	287	1865	2181	1574	93	486	88216	48	863	852	58	5102	0	2686
Relax	0	0	0	0	0	0	0	243	0	58	1	0	6	0	2
Sleep	0	61	0	1	9	0	0	874	4	8400	6	1	4	0	2
Toilet	1159	219	0	17	3	0	0	688	0	1	5667	0	148	0	22
Wash_Dishes	0	0	5	40	0	0	0	406	0	0	0	0	106	0	0
Watch_TV	0	0	74	68	32	0	4	5347	51	1930	70	27	14644	0	8
Water_Plants	0	0	1	84	0	0	0	428	0	0	0	0	0	0	0
Work_On_Computer	2	12	0	12	17	2	1	3206	0	2544	13	0	35	0	23216
Accuracy	0.98	0.99	0.96	0.97	0.98	1	1	0.79	1	0.97	0.98	1	0.93	1	0.96
	-	-	-			Overall Accuracy	0.74		-	-	-	-	-	-	-
	-	-	-			G Mean	0.88		-	-	-	-	-	-	-
	-	-	-			Precision	0.89		-	-	-	-	-	-	-
	-	-	-			Recall	0.8		-	-	-	-	-	-	-

Table 7.41: Activity recognition performance on navan smart home data used in CARLv2.

Performance Metric	Bathe	Bed_ Toilet	Cook	Drink	Eat	Enter_ Home	Leave_ Home	Other_ Activity	Relax	Sleep	Toilet	Wash_ Dishes	Watch_ TV	Water_ Plants	Work Computer
Accuracy	0.93	0.89	0.99	0.89	0.98	0.94	0.96	0.71	1	0.89	0.75	0.99	0.87	1	0.78
G Mean	0.77	0.54	0.73	0.58	0.68	0.51	0.34	0.71	0.87	0.91	0.53	0.36	0.86	0	0.78
Precision (False)	0.99	0.99	1	0.98	1	0.99	0.99	0.82	1	0.99	0.9	1	0.94	1	0.95
Precision (True)	0.11	0.04	0.35	0.09	0.27	0.05	0.04	0.65	0.65	0.79	0.2	0.02	0.71	0	0.39
Recall (False)	0.93	0.9	0.99	0.9	0.99	0.95	0.97	0.59	1	0.83	0.8	0.99	0.87	1	0.78
Recall (True)	0.63	0.32	0.54	0.37	0.47	0.28	0.12	0.85	0.77	0.99	0.35	0.13	0.86	0	0.79

Table 7.42: Activity forecasting performance on navan smart home data.

The next component is CARLv2's activity forecasting. This is a binary classification problem, indicating for each activity whether it will occur in the next ten minutes (class = *true case*) or not (class = *false case*). While activity forecasting, in this case, is expected to outperform activity recognition due to the fewer classes, this is not always the case. Table 7.42 summarizes the 3-fold partitioning validation results of activity forecasting for the navan smart home. As can be seen in Table 7.42, activity forecasting performance varies significantly between particular activities. Activities that occur often have enough training data to learn the activity times adequately. Activities that are highly predictable, such as sleep, also yield substantial predictive accuracy. On the other hands, activities that are less predictable and less frequent have lower accuracy. An additional challenge is the extreme class imbalance in this learning problem. Most activities are not current much more than they are current. For any given activity it is expected that it will be current only $1.0/|A|$ of the time, where A represents the set of activities. Because there are 15 activities, a defined activity will occur on average 6.7% of the time. Machine learning algorithms attempt to optimize classification accuracy. For imbalanced class distributions, this means that most of the forecasts will favor the majority class (the activity will not occur within the next 10 minutes) rather than the minority class (the activity will occur within the next 10 minutes). These influences are reflected in the results shown in Table 7.41.

Finally, CARLv2 is tested as a fully automated home control system in our navan smart apartment. To test CARLv2, the activity recognition algorithm and the activity forecasting algorithm are trained on three months of data with activity labels provided by a human annotator. The automation results are then collected for one week in the apartment. The training data and testing data were separated in time by several months, during which some routine differences would be expected due to concept drift, seasonal changes, and normal behavior variation.

Regarding quantifiable performance evaluation, two measures are used. The first is the number of "double button taps" performed by the resident. These represent false positive cases where CARLv2 turned off a device at a time that was incorrect or inconvenient for the resident, and the resident indicate the mistake by tapping the feedback button twice. The resident was at home almost the entire duration of the test week. However, during the times that he was out of the home, he provided feedback by looking at the automation and sensor data logs to assess whether each automation step was appropriate or was incorrect.

Table 7.43 summarizes the performance of CARLv2 regarding its ability to accurately turn off devices when they are not needed. As the table indicates, not only does performance vary widely from one device to another but it closely mirrors the activity recognition and activity forecasting performance. As an example, Work_On_Computer is an activity with consistent recognition and forecasting performance. Similarly, device LL015 is automated with strong true positive rates (TPR) and false negative rates (FNR). This indicates that as the ability of activity recognition and activity forecasting improves, so will the ability to accurately automate home control. This can be accomplished through additional training data and greater consistency of human activity label annotations.

Finally, Figures 7.3 and 7.4 show the minutes saved and energy reduced through CARLv2 automation. Using activity-aware automation reduces device utilization by 56%

Device	Automated Turn Off	Double Tap On	Manual Off	TPR	FNR
F001	12	2	3	0.83	0.80
LL001	0	0	0	1.00	1.00
LL002	6	0	13	1.00	0.32
LL003	0	0	0	1.00	1.00
LL004	18	3	5	0.83	0.78
LL005	0	0	6	1.00	1.00
LL006	28	17	4	0.39	0.88
LL007	4	1	0	0.75	1.00
LL008	29	10	9	0.66	0.76
LL009	9	6	5	0.33	0.64
LL011	0	0	1	1.00	0.00
LL013	0	0	0	1.00	1.00
LL014	41	31	12	0.24	0.77
LL015	16	3	1	0.81	0.94
LL016	0	0	0	1.00	1.00

Table 7.43: CARLv2 activity occurrence forecasting performance on navan smart home data by device. Device placement is shown in Figure 3.3.

and reduces energy consumption by 50%. Of course, this savings must be balanced with the 21% average positive rate. In some of these cases, the correct automation step was determined but was not executed at an optimal time. To analyze this type of error more carefully, we also compute the normalized root mean squared error (NRMSE) for each CARL-based device automation. The error is calculated as the time between the device automation and when it should have been turned off based on the actual activities that occurred at each time step. Each error value is squared, and the set of errors are normalized to fall within the range of 0-1. The NRMSE over the entire dataset is 0.138577. This indicates that CARLv2 can automate devices based on its awareness of activities that are occurring in the home.

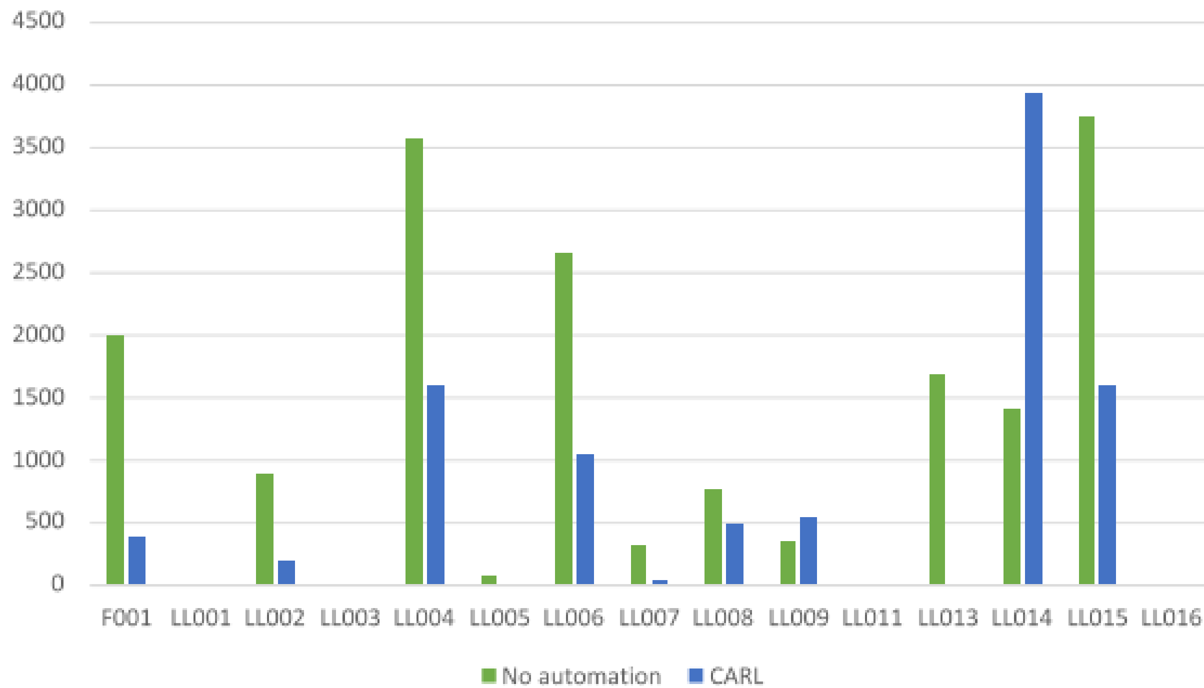


Figure 7.3: Minutes each device is on using the baseline method (no automation) and with CARLv2.

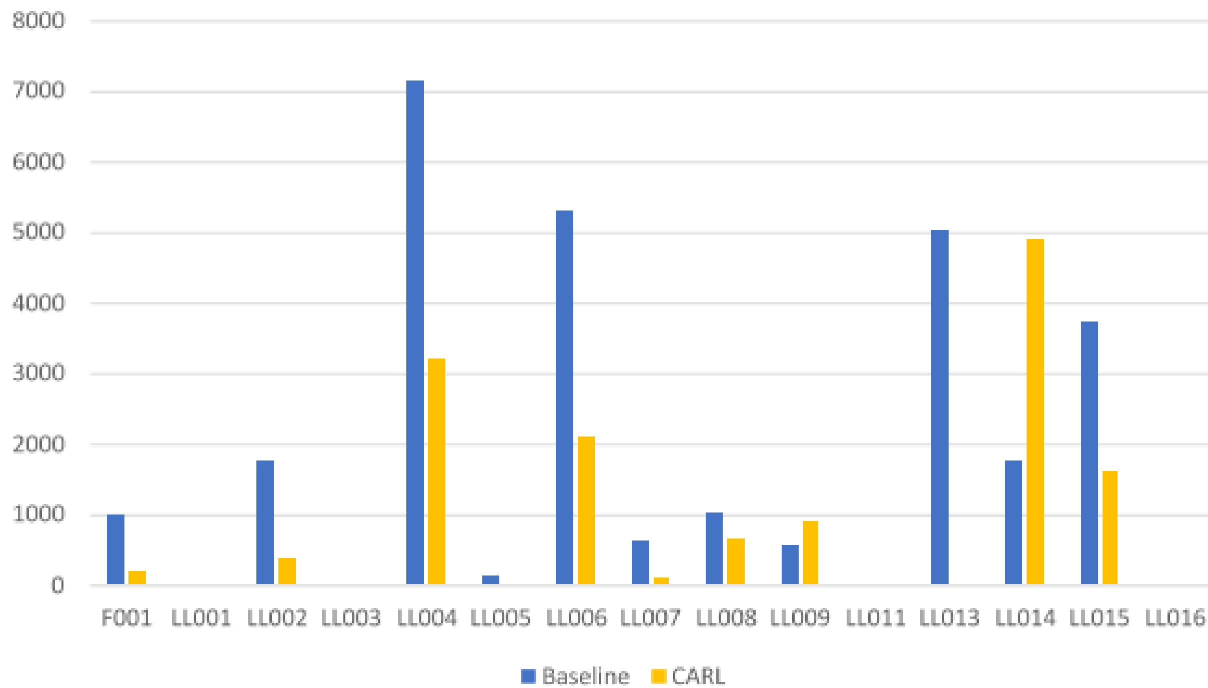


Figure 7.4: Watt-hours consumed using the baseline method (no automation) and with CARLv2.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	←guessed
18093	0	0	0	22	0	0	2309	106	0	110	0	42	119	0 = Bathe
0	4027	0	0	0	0	0	34	0	2261	0	0	0	0	1 = Bed_Toilet_Transition
0	0	19992	0	160	0	0	949	0	0	189	0	854	230	2 = Cook
0	0	21	3571	0	0	0	1153	0	0	0	0	1826	205	3 = Drink
0	0	0	0	13890	0	0	1643	0	0	62	0	418	75	4 = Eat
0	0	0	0	34	76	0	943	0	0	41	0	0	77	5 = Enter_Home
0	0	0	0	0	0	1356	951	0	0	0	0	0	0	6 = Leave_Home
1298	139	1380	1190	1604	662	74129	580171	33	2357	5208	4	16021	22632	7 = Other_Activity
0	0	0	0	0	0	0	920	3488	3	0	0	0	106	8 = Relax
0	2391	0	0	0	0	0	3076	0	662027	1085	0	21	251	9 = Sleep
146	25	237	229	45	0	118	21467	126	851	23999	0	1790	4058	10 = Toilet
0	0	0	0	0	0	0	0	0	0	0	93	111	0	11 = Wash_Dishes
56	0	896	3162	20	0	0	83615	0	15	2096	114	280463	1997	12 = Watch_TV
564	0	399	255	188	0	41	26656	174	214	2087	0	670	210878	13 = Work_On_Computer

Table 7.44: Results for *navan_2014* CARLv2 activity recognition, with an accuracy of 85.79182538.

0	1	2	3	4	5	6	7	←guessed
154383	0	2539	415	23581	9935	24962	12670	0 = Other_Activity
1177057	0	5816	4707	54012	68396	132581	142280	1 = Pat_0
12780	0	6299	0	35573	988	1039	1798	2 = Pat_10
22064	0	16	529	278	60	373	69	3 = Pat_12
11734	0	2579	0	45213	1515	1246	2258	4 = Pat_4
16019	0	181	2	2442	11064	1402	6349	5 = Pat_5
12338	0	192	8	1244	700	27433	455	6 = Pat_7
39635	0	421	58	4306	8056	3041	28837	7 = Pat_9

Table 7.45: Results for *navan_2014.AD* CARLv2 activity recognition, with an accuracy of 12.88923165.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	←guessed
998815	15989	662	0	4567	746	336	0	178	0	573	117	0	35	26	0	0	0	0	0	17	33	0	32606	0	166	0	0	0	489	61	385	0	4	616	0 = 0
50365	81333	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	45	131	0	0	15	0	0	0	0	0	0	0	0	1 = 1
1795	0	2114	0	0	454	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24	0	0	0	2 = 10
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	682	0	0	0	0	0	0	0	0	0	0	0	3 = 11
10296	344	0	0	33543	0	0	0	0	0	0	0	0	53	0	0	0	0	0	0	0	0	0	118	0	0	0	0	0	0	0	0	0	0	0	4 = 12
1241	0	5	0	0	4163	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5 = 13
125810	0	0	0	769	0	9058	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6 = 14
34351	0	0	0	0	0	0	1165	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	7 = 15
2824	0	0	0	0	0	0	0	934	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8 = 16
0	529	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9 = 17
5710	80	0	0	0	0	0	0	0	0	10772	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10 = 18
623	6	0	0	0	0	0	0	0	0	0	384	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11 = 19
7849	105	0	0	0	0	0	0	0	0	0	0	218	0	0	0	0	0	0	0	0	0	0	546	0	0	0	0	0	0	0	0	0	0	0	12 = 2
344	0	0	0	18	0	0	0	0	0	0	0	0	696	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13 = 20
401	0	0	0	0	0	0	0	0	0	0	0	0	0	732	0	0	0	0	0	0	0	0	0	0	0	0	0	0	131	0	0	0	0	0	14 = 21
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	269	0	0	0	0	0	0	0	0	0	0	0	15 = 22
5531	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	198	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16 = 23
422	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	175	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17 = 24
0	469	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	18 = 25
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	986	0	0	0	0	0	0	0	0	0	0	0	19 = 26
10532	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	145	0	0	471	0	0	0	0	0	0	0	0	0	0	0	20 = 27
20417	0	0	0	147	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	278	0	954	0	0	0	0	0	0	0	0	0	0	0	21 = 28
346	121	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	0	0	0	0	0	0	0	0	0	0	0	0	22 = 29
34803	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	567355	0	0	0	0	0	0	0	0	0	2	0	23 = 3
94	135	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24 = 30
221	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	434	0	0	0	134	0	0	0	0	0	25 = 31
113	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	67	0	0	0	0	0	0	0	0	26 = 32
9723	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	27 = 33
2152	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	82	0	0	0	0	0	0	28 = 34
1909	0	0	0	0	0	0	0	97	0	0	0	0	0	26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4926	0	0	0	0	0	29 = 4
141	0	0	0	321	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	423	0	0	0	0	30 = 5
410	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1048	0	0	0	31 = 6
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2785	0	0	0	0	0	0	0	0	0	0	0	32 = 7
76	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	306	0	0	0	0	0	0	0	0	0	604	0	33 = 8
4352	96	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2354	34 = 9

Table 7.46: Results for *navan_2014.DTW* CARLv2 activity recognition, with an accuracy of 81.07882872.

7.4.3 CARLv3

CARLv3's goal is to turn off devices when they are no longer needed and turn on devices that are forecasted to be utilized. This means that the accuracy of the *true case* in forecasting activities has twice the opportunity to impact the performance of CARLv3 (see Section 4.3 for a definition of the *true case*). During the live experiment, we utilized a single decision tree instead of a random forest (see the explanations in Chapter 4) and suffered from the corresponding overfit issues. CARLv3 does not distinguish human-triggered device interaction events from CARL-triggered device control events. As a result, the automation that occurred created a feedback loop where the algorithms started classifying activities where the automation was happening. This feedback loop is what caused the enormous automated ON and OFF values found in Table 7.47. The feedback loop also meant that the automation was occurring while the resident was asleep or out of the apartment and thus was not able to provide feedback on these erroneous interactions.

As we were not able to utilize the same metrics as CARLv1 and CARLv2 where we employed the double tap as a corrective error measure, we will be performing a direct analysis of the performance of CARLv3 on our different activity labeling methods (ADL, AD, and DBSCAN-DTW). Now, in Table 7.47 we have the results from 7 days of the live experiment. We can now compare the use of LL008 in the datasets *navan_2014*, *navan_2014.AD*, and *navan_2014.DTW*, in the Table 7.48. As the table shows, CARLv3 performed much better with the AD and DTW datasets, where it was not excessively turning on LL008, and therefore did not need to turn it back off as much. The ON and

Device	Auto On	Auto Off	Manual On	Manual Off	Double Tap On	Double Tap Off
F001	122	98	7	7	2	24
LL001	35	35	0	2	0	0
LL002	202	148	9	18	0	41
LL003	213	153	0	16	0	46
LL004	111	109	11	8	8	9
LL006	182	162	2	16	3	13
LL007	159	160	0	0	0	3
LL008	86	83	6	8	1	2
LL009	164	163	4	10	0	5
LL011	153	169	0	2	0	0
LL013	157	135	1	14	0	7
LL014	129	156	11	15	28	4
LL015	116	130	7	4	8	5
LL016	109	117	3	5	7	2

Table 7.47: CARLv3 activity occurrence forecasting performance on navan smart home data by device. Device placement is shown in Figure 3.3.

Method	Device	# ON	# OFF	# CARLv3 ON	# CARLv3 OFF
BASELINE	LL008	278	278	0	0
ADL	LL008	90	280	356	165
AD	LL008	77	282	219	13
DTW	LL008	107	281	187	12

Table 7.48: CARLv3 comparison of performance.

OFF columns are where the resident initially turned on and off the device. The BASELINE entry represents how much the light was turned on and off in the original dataset. While the ADL and AD version of CARLv3 managed to reduce the number of times the resident needed to turn on the light, and CARLv3 also turned it on more than was necessary. The DTW dataset appears to be strong at balancing how much to turn on the device and when to turn it back off.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	←guessed
8162	0	69	0	975	0	0	8692	351	0	410	0	867	1275	0 = Bathe
0	792	0	0	0	0	0	9	0	5496	0	0	0	25	1 = Bed_Toilet_Transition
0	0	13640	60	1056	0	0	2924	0	0	347	0	3544	803	2 = Cook
41	0	78	636	0	0	0	3128	0	61	59	0	2466	307	3 = Drink
457	0	0	109	6497	0	0	6186	0	0	396	0	1438	1005	4 = Eat
0	0	0	0	27	0	0	969	0	21	0	0	93	61	5 = Enter_Home
0	0	0	0	0	0	424	1883	0	0	0	0	0	0	6 = Leave_Home
5477	64	4225	1332	3310	62	6632	590032	353	5990	7924	0	36820	44019	7 = Other_Activity
98	0	0	0	375	0	0	3084	637	0	95	0	0	228	8 = Relax
164	5390	0	13	826	0	0	13966	560	642437	2308	0	99	3088	9 = Sleep
979	15	546	224	612	0	189	28550	155	1229	9141	0	5043	6408	10 = Toilet
0	0	0	0	0	0	0	0	0	0	0	0	204	0	11 = Wash_Dishes
509	0	2899	2075	100	0	0	167290	117	2669	4528	210	182654	9383	12 = Watch_TV
1830	0	1256	345	1366	0	397	59389	196	2494	3245	0	3796	167812	13 = Work_On_Computer

Table 7.49: Results for *navan_2014* CARLv3 activity recognition, with an accuracy of 76.43114357.

0	1	2	3	4	5	6	7	←guessed
167949	0	523	64	25705	4020	25337	4831	0 = Other_Activity
1351103	0	1630	396	74152	9659	113843	33413	1 = Pat_0
29520	0	549	4	22843	909	3496	1156	2 = Pat_10
21696	0	10	64	777	57	659	126	3 = Pat_12
31884	0	459	6	25726	1626	3608	1236	4 = Pat_4
25540	0	51	8	4213	3065	2156	2426	5 = Pat_5
19951	0	54	8	2446	841	18747	321	6 = Pat_7
62834	0	125	17	6654	1880	4025	8819	7 = Pat_9

Table 7.50: Results for *navan_2014.AD* CARLv3 activity recognition, with an accuracy of 10.59331194.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	←guessed
983815	15682	1821	0	10260	3170	158	224	285	0	3071	281	24	7	99	0	0	0	0	0	131	0	0	32742	0	555	45	0	0	1789	210	817	0	54	534	0 = 0
90158	41560	0	0	27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13	0	131	0	0	0	0	0	0	0	0	0	0	0	1 = 1
2861	0	714	0	0	636	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	176	0	0	0	2 = 10
65	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	617	0	0	0	0	0	0	0	0	0	0	0	3 = 11
31243	12	0	0	12772	0	0	0	0	0	0	0	0	209	0	0	0	0	0	0	0	0	0	118	0	0	0	0	0	0	0	0	0	0	0	4 = 12
4448	136	0	0	0	825	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5 = 13
133130	1	0	0	0	0	2505	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	6 = 14
35076	0	0	0	0	0	0	441	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7 = 15
3325	0	0	0	0	145	0	0	197	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	91	0	0	0	0	0	8 = 16
202	327	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9 = 17
10833	0	0	0	0	0	0	0	0	0	5729	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10 = 18
865	0	0	0	0	0	0	0	0	0	0	148	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11 = 19
8036	0	0	0	0	0	0	0	0	0	0	0	136	0	0	0	0	0	0	0	0	0	0	546	0	0	0	0	0	0	0	0	0	0	0	12 = 2
862	0	0	0	0	0	0	0	0	0	0	0	0	196	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13 = 20
746	0	0	0	0	0	0	0	0	0	0	0	0	0	202	0	0	0	0	0	0	0	0	0	0	0	0	0	0	316	0	0	0	0	0	14 = 21
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	269	0	0	0	0	0	0	0	0	0	0	0	15 = 22
5571	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	158	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16 = 23
597	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17 = 24
224	245	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	18 = 25
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	986	0	0	0	0	0	0	0	0	0	0	0	19 = 26
10677	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	471	0	0	0	0	0	0	0	0	0	0	0	20 = 27
20772	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	70	0	954	0	0	0	0	0	0	0	0	0	0	0	21 = 28
323	158	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	22 = 29
70384	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	531715	0	0	0	0	0	0	0	0	0	61	0	23 = 3
135	94	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24 = 30
789	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25 = 31
180	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	26 = 32
9723	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	27 = 33
2238	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	28 = 34
5578	52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1328	0	0	0	0	0	29 = 4
675	0	0	0	21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	189	0	0	0	0	30 = 5
1126	0	0	0	0	55	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	282	0	0	0	31 = 6
1308	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1502	0	0	0	0	0	0	0	0	0	0	0	32 = 7
364	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	187	0	0	0	0	0	0	0	0	0	435	0	33 = 8
6459	103	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	240	34 = 9

Table 7.51: Results for *navan_2014.DTW* CARLv3 activity recognition, with an accuracy of 74.58649457.

7.4.4 User Experience

In addition to quantifying the benefit of CARL automation based on energy savings and reduction in necessary resident device control, we also analyze the performance of the system based on usability. In this section, we summarize anecdotal feedback from the smart home resident who experienced home automation. We also analyze quantitative feedback from the resident. Specifically, the resident answered the questions listed in Tables 7.52, 7.53, and 7.54 on a Likert scale from 1 to 7. For transparency, we would like to note that the author was the resident in the live experiments. Here we summarize qualitative and quantitative feedback.

For all three versions of CARL, our experiment resident reported that it was easy to use, clarifying that meant that he did not have to do anything to install or configure the system. There wasn't much to learn other than to perform the double tap when correcting a device that turned off while it was in use. It was easy to use the double tap, but the resident said they would prefer something a little less aggressive controlling the smart environment.

Anecdotal information from the resident indicated that many of the activities were correctly detected, anticipated, and automated. However, the ones that were incorrect were often detrimental to the resident's comfort. The resident also reported that changing between activities made it feel like the devices did not turn off as much, though this was possible because of confusion in the forecasting models. In the questionnaire in Table 7.53, the resident reported that the system had some trouble anticipating upcoming activities.

Question (1=agree, 7=disagree)	1	2	3	4	5	6	7
It was simple to use the system.	X	-	-	-	-	-	-
It was easy to learn to use this system.	X	-	-	-	-	-	-
The system responded well to my current activities.	-	-	X	-	-	-	-
The system anticipated my upcoming activities.	-	-	-	-	-	X	-
It was easy to reverse the automation step.	-	X	-	-	-	-	-
I would like to live in a home automated with this system.	-	-	-	X	-	-	-
I would let an older relative use this system.	-	-	-	-	-	-	X
Comments:							
I'm glad we put in the guard rule so it could not control the bathroom light/fan when the door was shut.							

Table 7.52: CARLv1 questionnaire results

Question (1=agree, 7=disagree)	1	2	3	4	5	6	7
It was simple to use the system.	X	-	-	-	-	-	-
It was easy to learn to use this system.	X	-	-	-	-	-	-
The system responded well to my current activities.	-	X	-	-	-	-	-
The system anticipated my upcoming activities.	-	-	-	-	X	-	-
It was easy to reverse the automation step.	X	-	-	-	-	-	-
I would like to live in a home automated with this system.	-	-	X	-	-	-	-
I would let an older relative use this system.	-	-	-	-	-	-	X
Comments:							
This version of CARL did not turn things off as aggressively as CARLv1. After hearing about the overfitting issue and the new results with switching to a random forest, I wish I still lived in navan so I could try it.							

Table 7.53: CARLv2 questionnaire results

As the quantitative results in Tables 7.52 and 7.53 show, CARLv1 and CARLv2 received "agree" responses for most of the questions. This indicates that the automation was user-friendly for the most part. While all three versions of CARL received a "disagree" on letting an older relative use the system, this was one of the three versions of CARL that the resident would have an older adult use if he had to choose.

The resident had a much more difficult time interacting with CARLv3. The resident ended up removing the light bulbs from his bedroom lamp during the CARLv3 experiment because the system repeatedly identified Sleep as about to occur when the resident was already in bed and trying to go to sleep. The overfit issues and feedback loop caused some annoyances with the resident during the experiment. The resident reported that he stopped trying to correct the system after the second day with the double tap and just worked in the dark, then the light, then the dark again, adjusting his schedule to complete cooking while there was still daylight out. It should be clear in Table 7.54 as to why the resident indicated he would not live in a home with the CARLv3 automation system.

Question (1=agree, 7=disagree)	1	2	3	4	5	6	7
It was simple to use the system.	X	-	-	-	-	-	-
It was easy to learn to use this system.	X	-	-	-	-	-	-
The system responded well to my current activities.	-	-	X	-	-	-	-
The system anticipated my upcoming activities.	-	-	-	X	-	-	-
It was easy to reverse the automation step.	-	-	X	-	-	-	-
I would like to live in a home automated with this system.	-	-	-	-	-	-	X
I would let an older relative use this system.	-	-	-	-	-	-	X
Comments:							
I had lots of hope for this version, but it would start having troubles if I stayed doing one thing too long. If I kept changing what I was doing it would feel like it performed better, but only because I wasn't getting too far along with any particular task. I wish I could have disabled the system when I would leave or go to bed, but it was an experience.							

Table 7.54: CARLv3 questionnaire results

CHAPTER 8. SUMMARY AND CONCLUSION

In this dissertation, we have looked at the current state of home automation and identified areas that could be combined with smart home technologies to provide activity-aware automation. We hypothesized that combining activity recognition, activity forecasting, and smart home technologies could result in an activity-aware smart automation system. With this goal, we built CARL (CASAS Activity-aware Resource Learning) to test the hypothesis.

To create an activity-aware home automation system, we had to introduce and build on several technologies. First, we needed to define a smart home infrastructure that can sense the state of the environment, reason about it in real-time, and take action to meet a specified goal. We accomplished this task by creating the CASAS Smart Home in a Box (SHiB) framework described in Chapter 3. Several of the testbeds that have been set up utilizing this framework are used for experiments throughout this dissertation including navan and a set of HH smart homes.

Second, to make the system activity-aware, we needed to create activity learning algorithms. By labeling smart home sensor events with corresponding activity labels, the home becomes aware of the behaviors that the resident is performing. Activity labels are generated through a variety of activity learning algorithms. One such algorithm is activity recognition, described in Chapter 4. Also discussed in Chapter 4 is activity forecasting, or the ability of an algorithm to predict activities that will occur shortly. Because the activity learning algorithms described in Chapter 4 typically assume that activity classes are predefined by experiments, we introduce an alternative method for activity labeling and learning in Chapter 5. Here we replace human-defined activity categories with automatically-discovered activity categories.

Finally, we created a home automation system that makes automation decisions based on information provided by the SHiB and the activity learning algorithms. This work introduced three novel home automation strategies within the CARL automation system, described in Chapter 6. The first version was designed to turn off devices reactively based on knowledge of current activities. The second version refines turning off of devices to be sensitive not only to ongoing activities (based on activity recognition) but also future activities (based on activity forecasting). The third and most aggressive, version of CARL not only turns off unneeded devices but also turns on devices in anticipation of upcoming activities.

We evaluate each layer of the activity-aware home automation system using data from real smart home testbeds. Overall, we observed that both activity recognition and forecasting performed well on history and live data once the overfit issue was addressed using random forests and sampling strategies. When we replace predefined activity classes with automatically-discovered activities from DBSCAN-DTW clustering, we find that the activity learning algorithms improve performance although they suffer a bit when devices need to be associated with modeled activity classes.

Concerning the overall home automation, CARL's performance does greatly depend on the accuracy of the underlying activity learning algorithms. We observed this in particular with version 3 of CARL which utilized only a decision tree to perform aggressive device automation. However, versions 1 and 2 do yield strong performance both regarding energy savings and reduction of the need for manual control. As expected, the user feedback, both qualitative and quantitative, is consistent with the performance results - versions 1 and 2 of CARL were well received while version 3 was found too disruptive to the resident's lifestyle.

In conclusion, our creation of an actual smart home automation system provides evidence that a smart home can not only be automated but can benefit from activity awareness. The development of these technologies and evaluation on real live testbeds lays a foundation for continued research to make such buildings energy efficient, productive, and enjoyable.

This research explores a relatively new area of research and utilizes many AI and machine learning technologies to implement the ideas. As a result, many avenues can be studied in the future. Here we summarize a few of these directions for future research.

First, we note that the CARL system automates a building based solely on knowledge of user activities. A direction for future research is to learn a resident's automation preferences and incorporate these into the automation strategy. As an example, the double tap feedback that is designed as part of CARL can be combined with reinforcement learning to provide a more adaptive system and converge more quickly on a practical automation strategy. Similarly, a decision-theoretic approach to home automation could be introduced. This formulation will allow us to balance each possible action not only with the probability of its outcome (based on confidence in activity recognition and forecasting) but also with the cost of each possible outcome.

Second, there are many enhancements of activity discovery methods that can be explored and integrated into this research. DTW-based DBSCAN currently operates offline. This needs to perform in real-time. One possible way to do this is to average the cluster centroids incrementally as new data arrives [177]. Some of the discovered patterns should potentially be forgotten over time as well to respond to concept drift that is detected in the activity patterns. Additional device association methods can also be explored to link activity discovery more firmly with automation actions. Using the real-time clustering, our activity-aware automation system could be installed in a home with no manual intervention. This approach might start with a long automation timeout which can be shortened as activity recognition and activity forecasting accuracy improves.

Third, we note that our testbeds facilitated limited automation. Future work can expand this to integrate additional device control. For example, controlling large appliances (e.g., washing machine, dishwasher, water heater) and controlling HVAC systems may result in much more dramatic energy savings for an effective automation scheme.

Finally, there are many aspects of CARL that would benefit from additional, thorough evaluation. It is difficult to perform such evaluation on real testbeds because of the limited number of available testbeds. In earlier work [180] we created a synthetic data generator that utilizes a hidden Markov model to emulate smart home data patterns. Once this type of generative model is refined, it can be used to create arbitrary amounts of smart home data consistent with home and resident habits. This will allow researchers to design and evaluate home automation systems with greater precision.

APPENDIX

A SMART HOME TESTBEDS

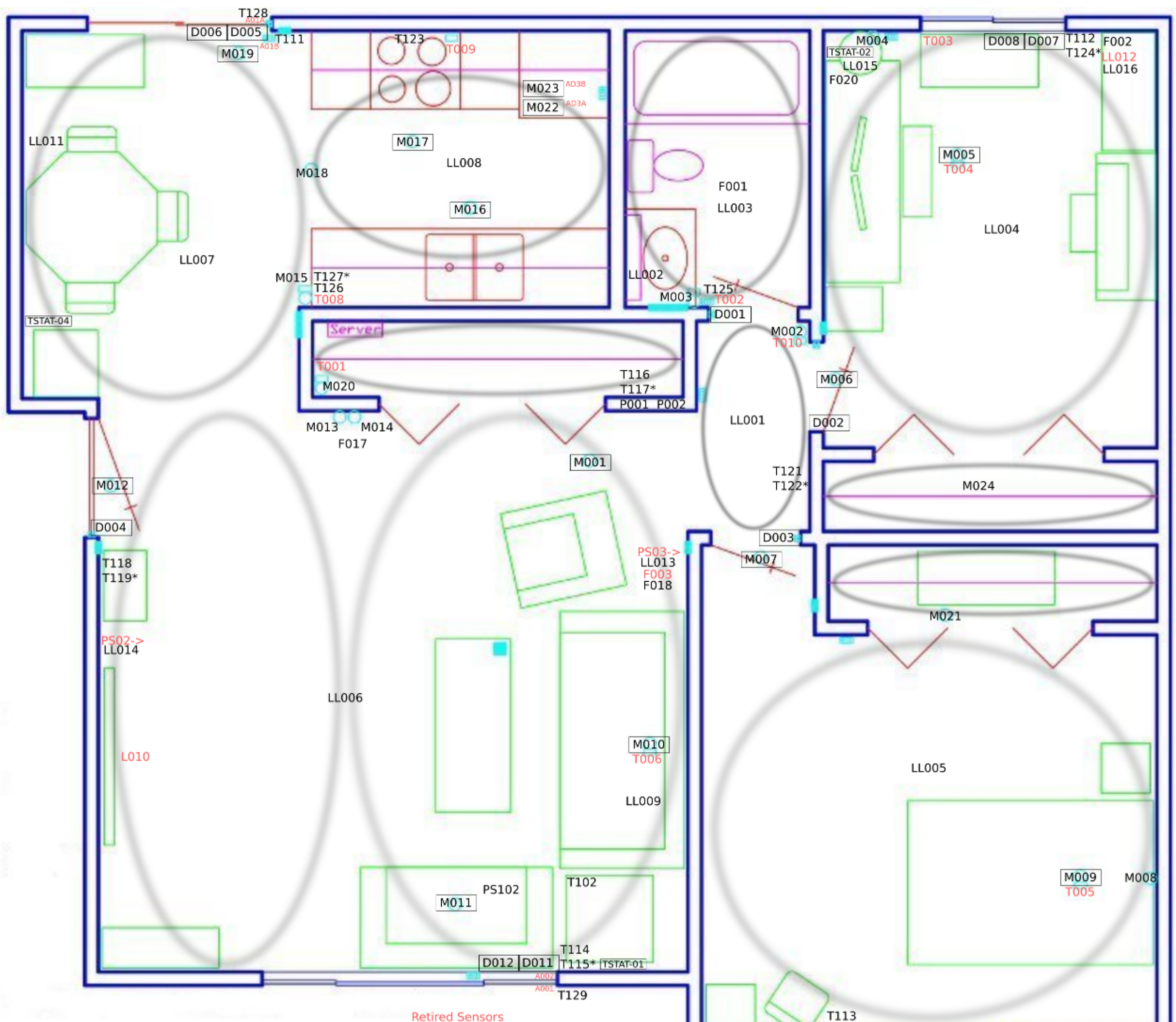


Figure A.1: Floor plan and sensor placement for the testbed navan.

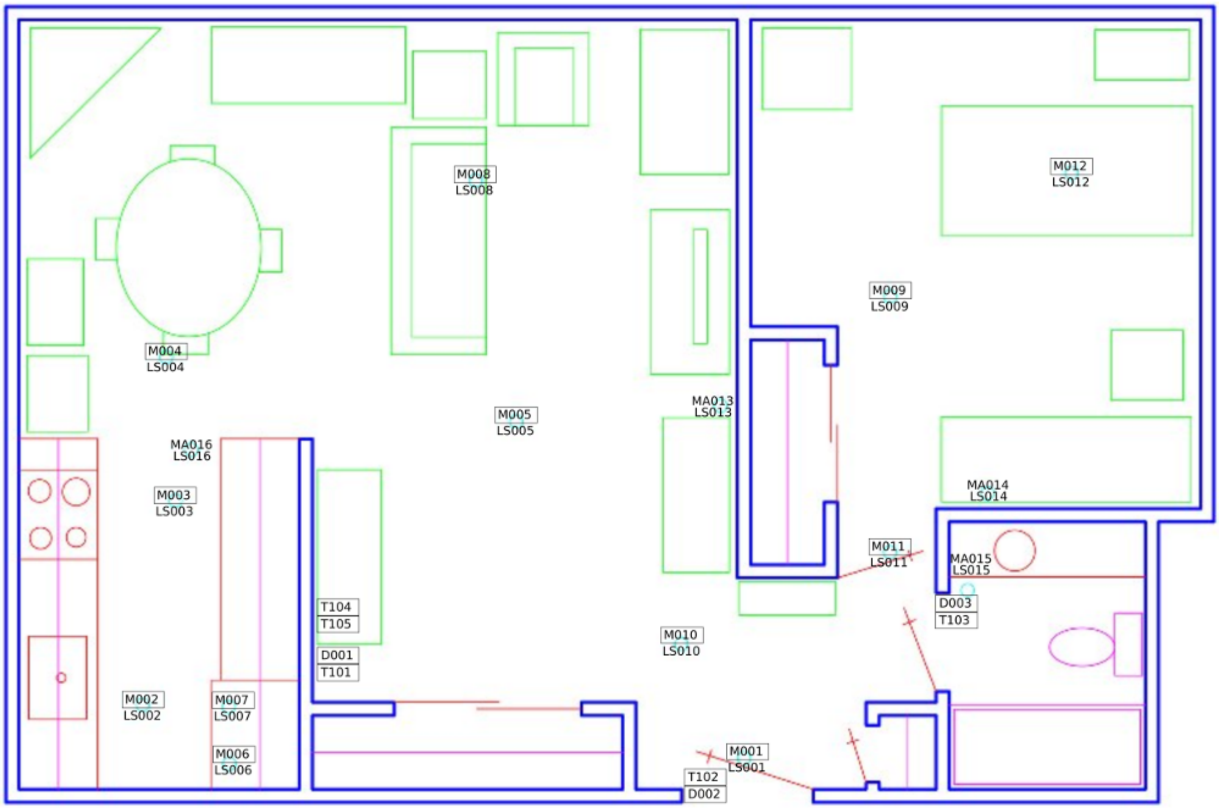


Figure A.2: Floor plan and sensor placement for the testbed hh101.

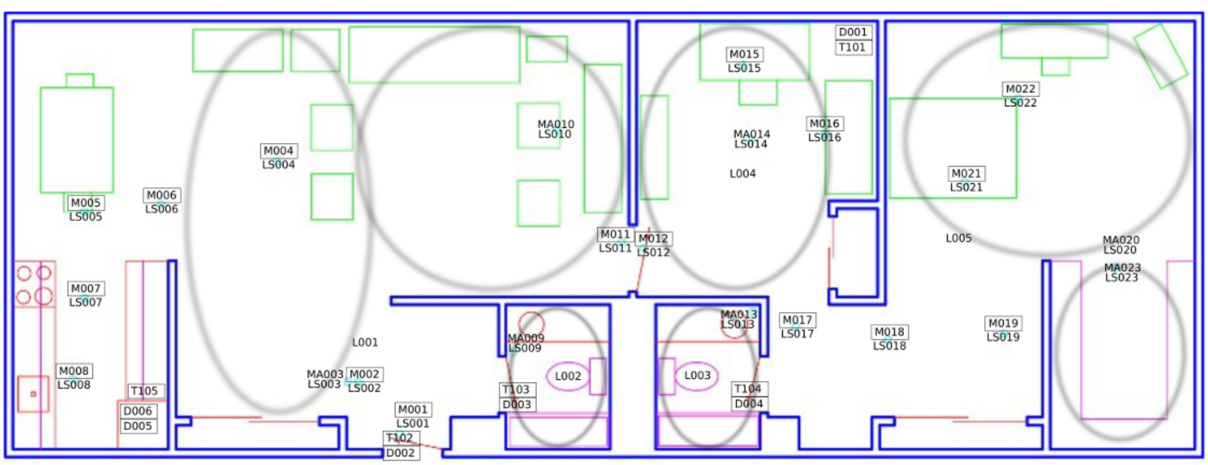


Figure A.3: Floor plan and sensor placement for the testbed hh102.

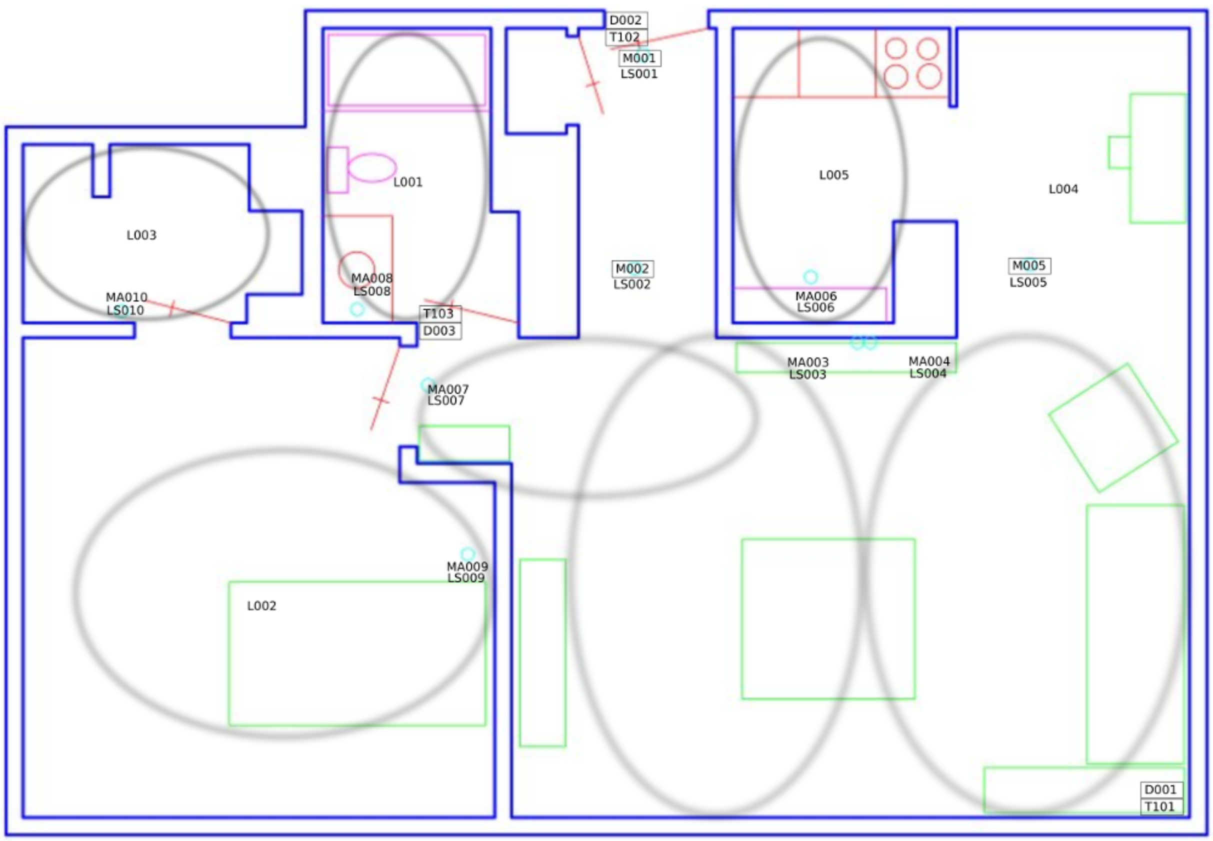


Figure A.4: Floor plan and sensor placement for the testbed hh103.

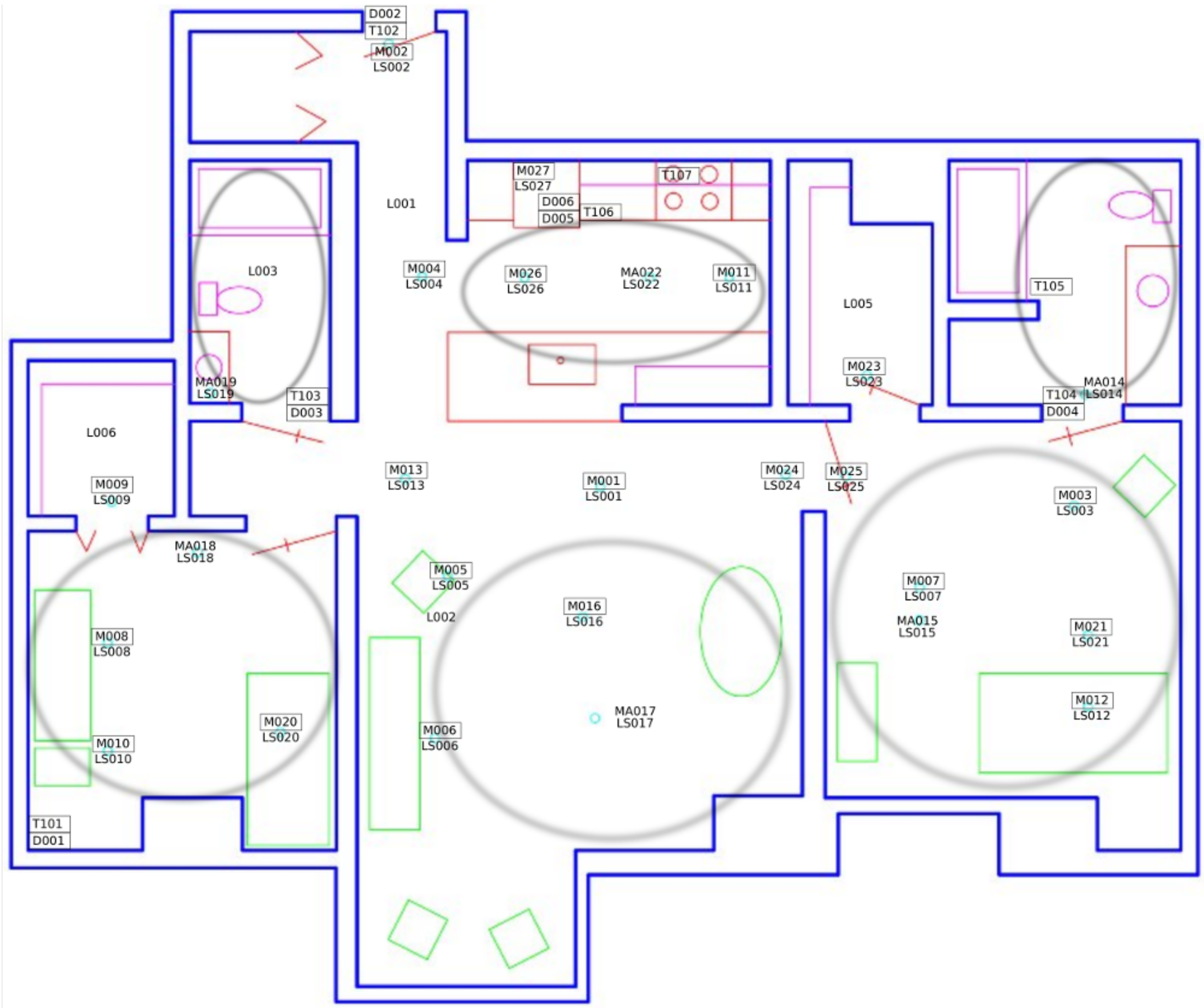


Figure A.5: Floor plan and sensor placement for the testbed hh104.

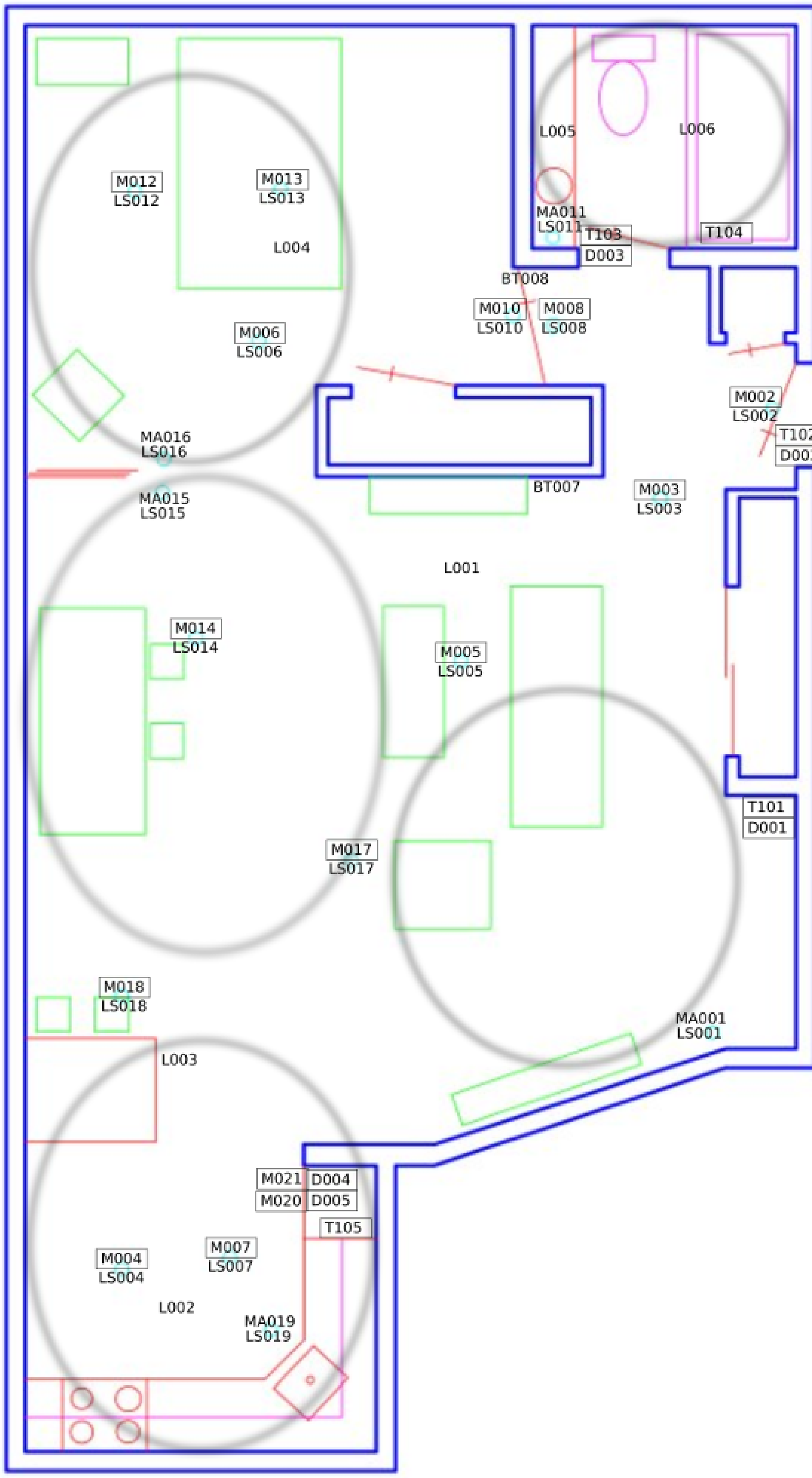


Figure A.6: Floor plan and sensor placement for the testbed hh105.

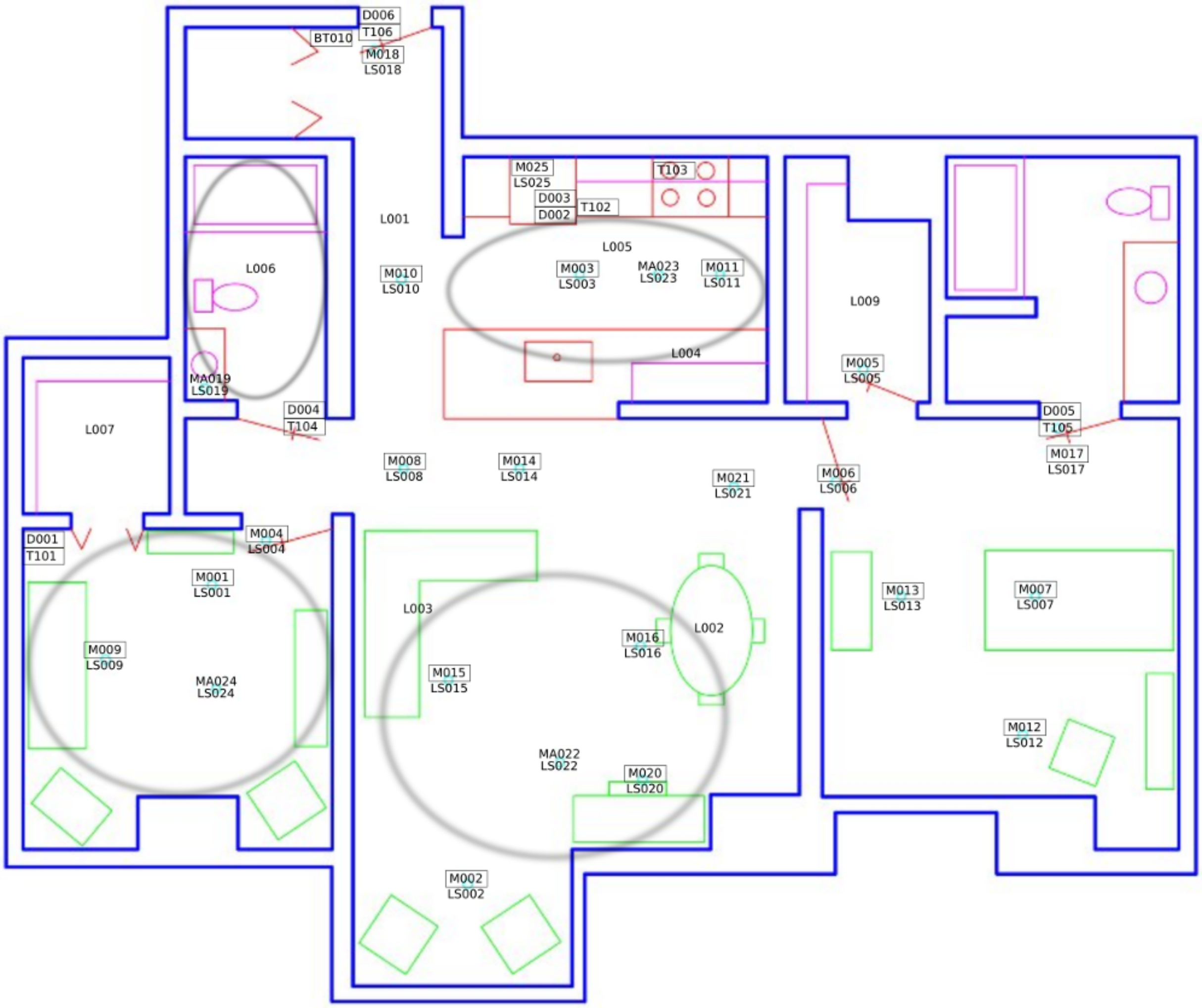


Figure A.7: Floor plan and sensor placement for the testbed hh106.

Figure A.8: Floor plan and sensor placement for the testbed hh107.

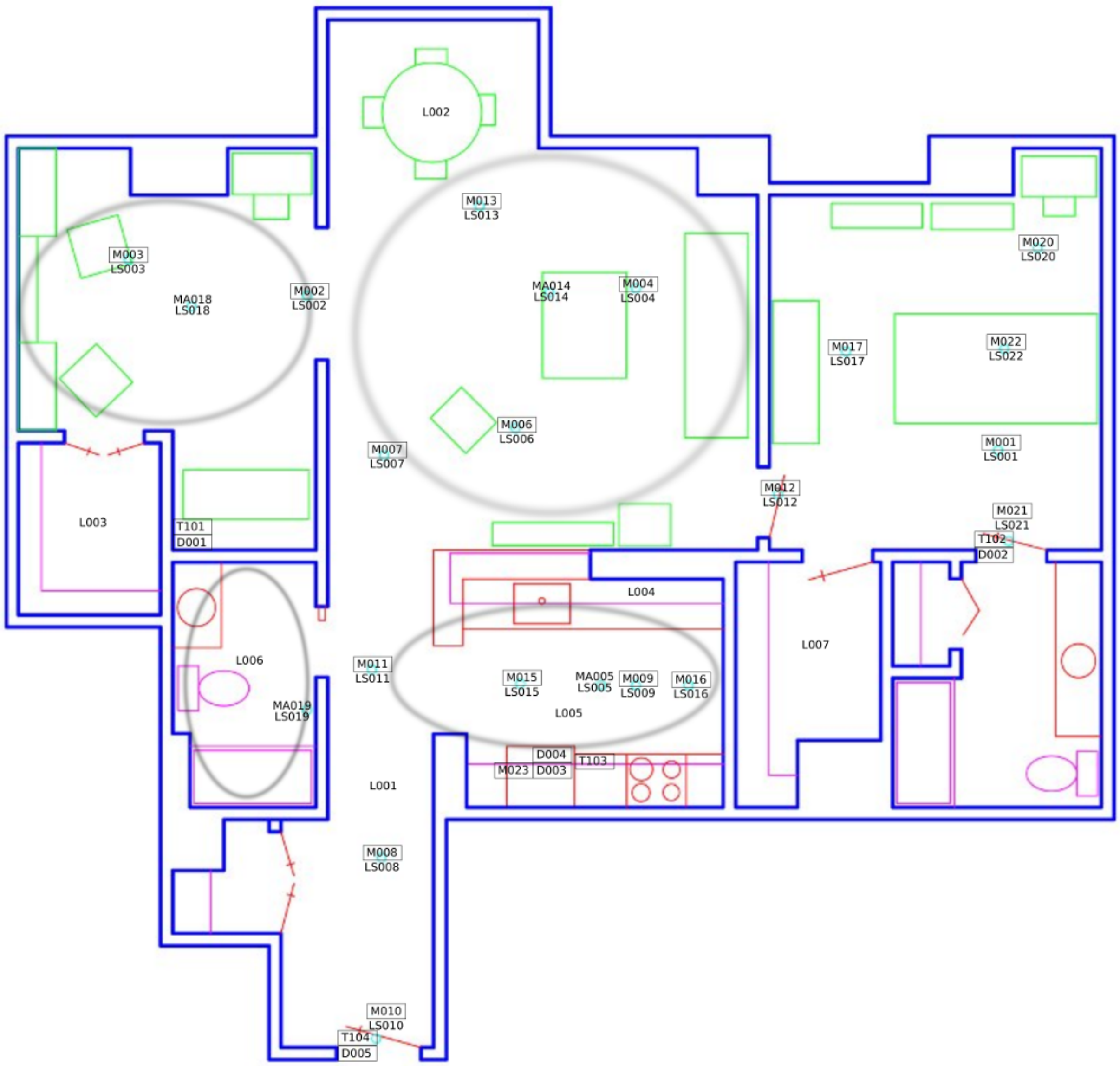


Figure A.9: Floor plan and sensor placement for the testbed hh108.

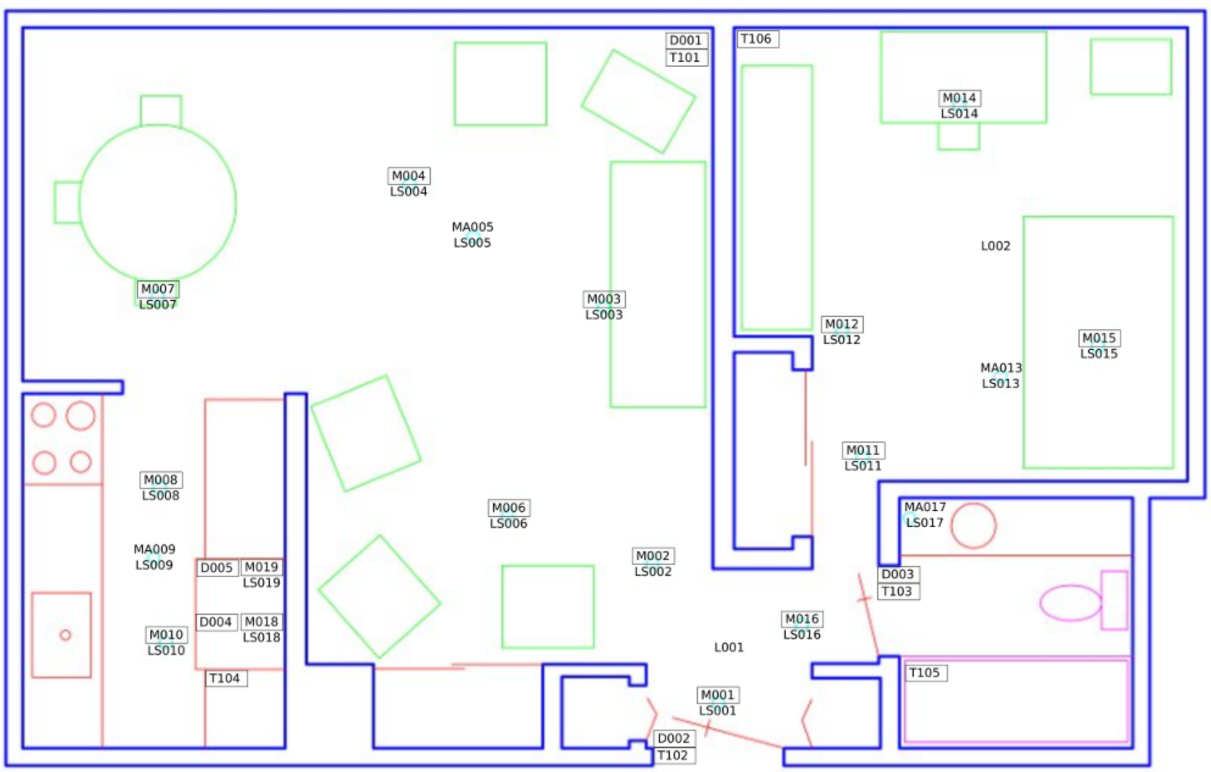


Figure A.10: Floor plan and sensor placement for the testbed hh109.

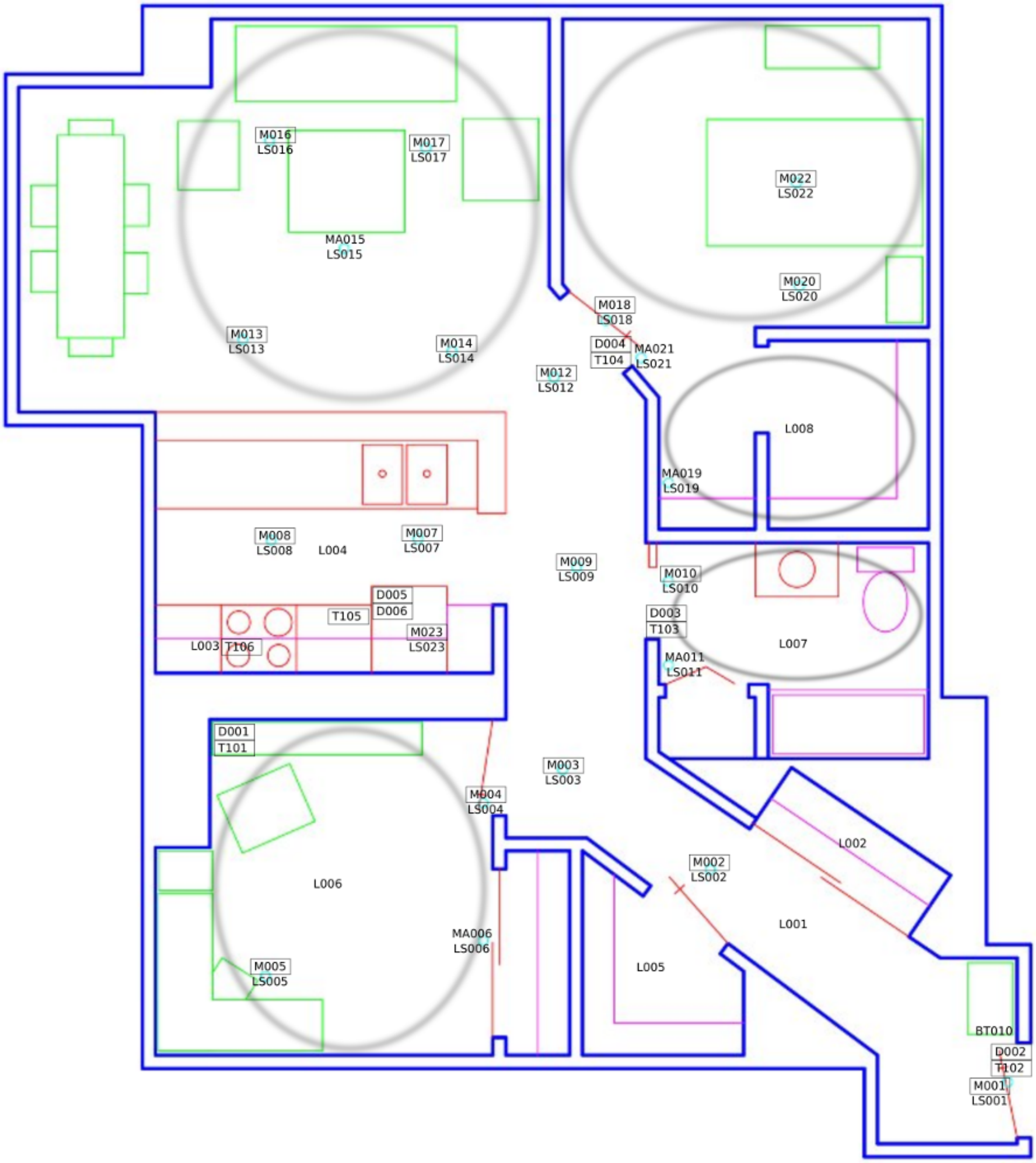


Figure A.11: Floor plan and sensor placement for the testbed hh111.

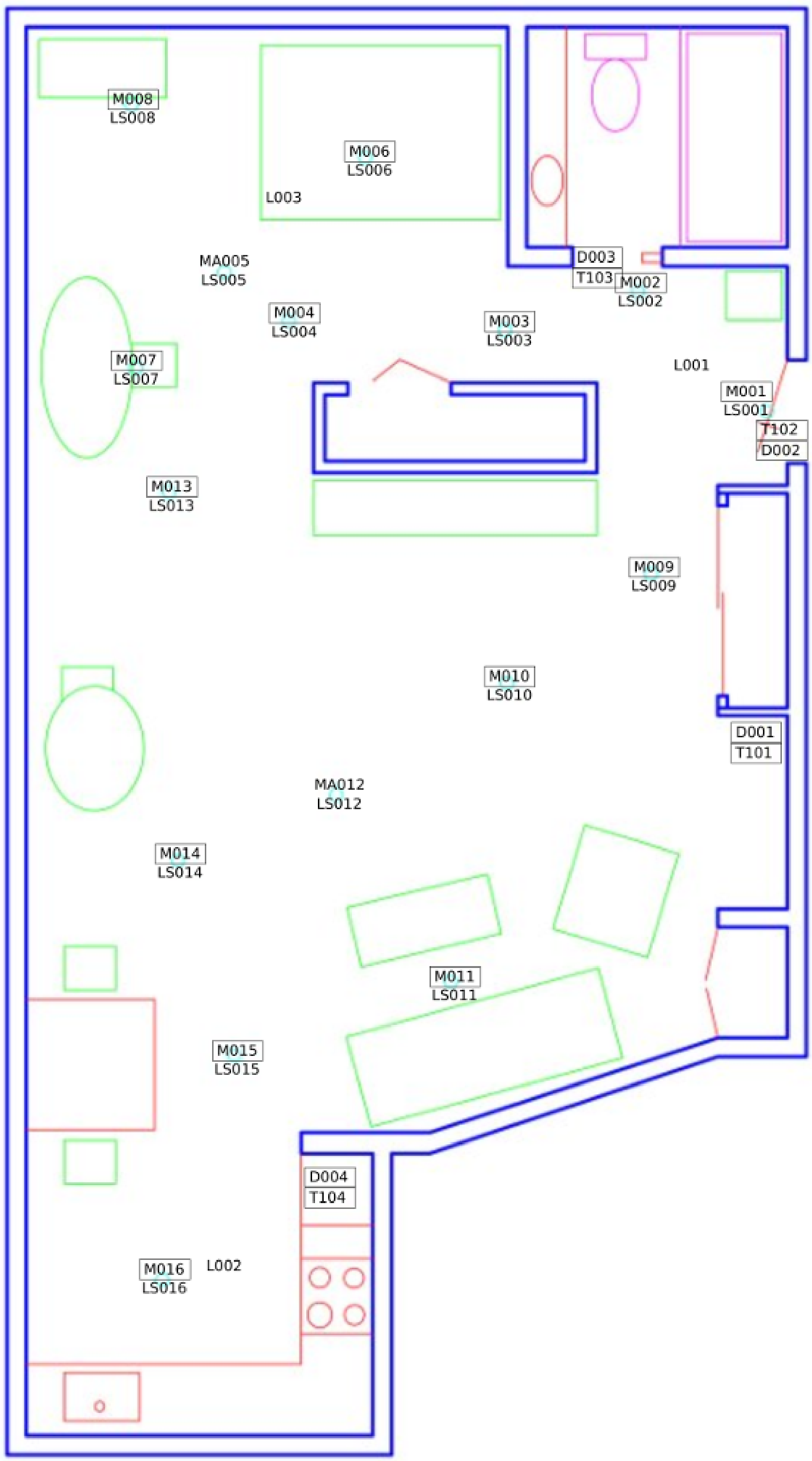


Figure A.12: Floor plan and sensor placement for the testbed hh112.

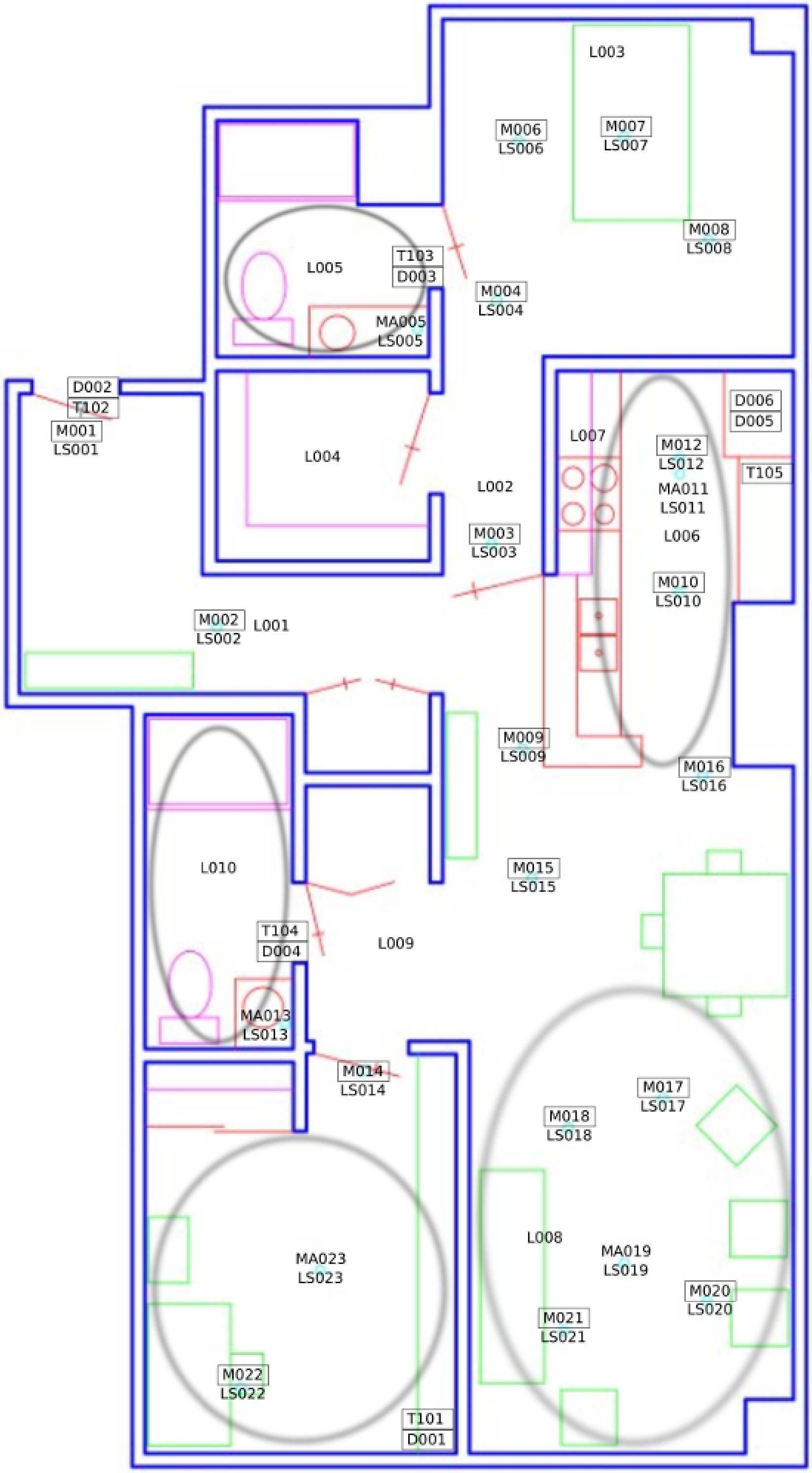


Figure A.13: Floor plan and sensor placement for the testbed hh113.

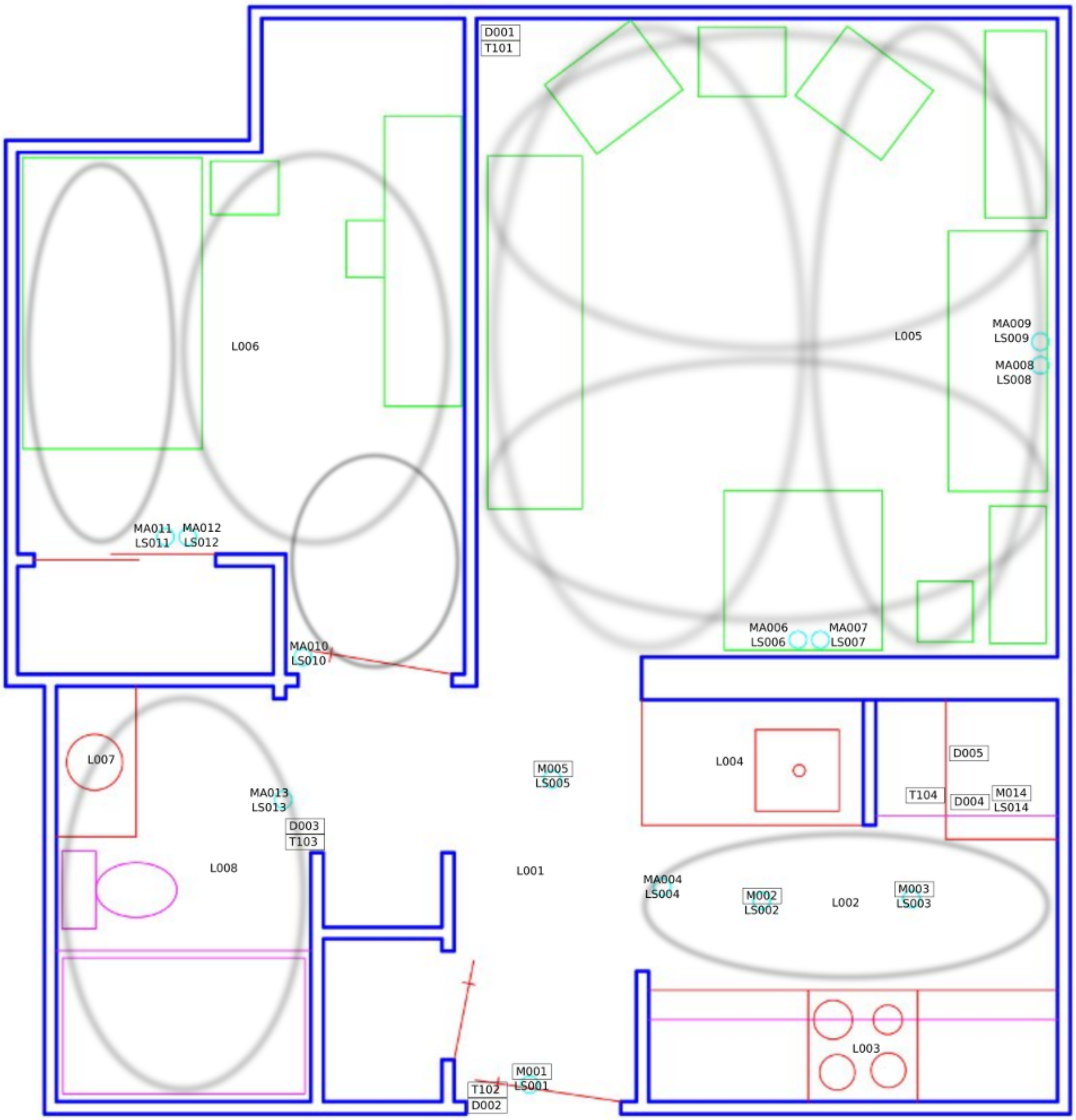


Figure A.14: Floor plan and sensor placement for the testbed hh114.

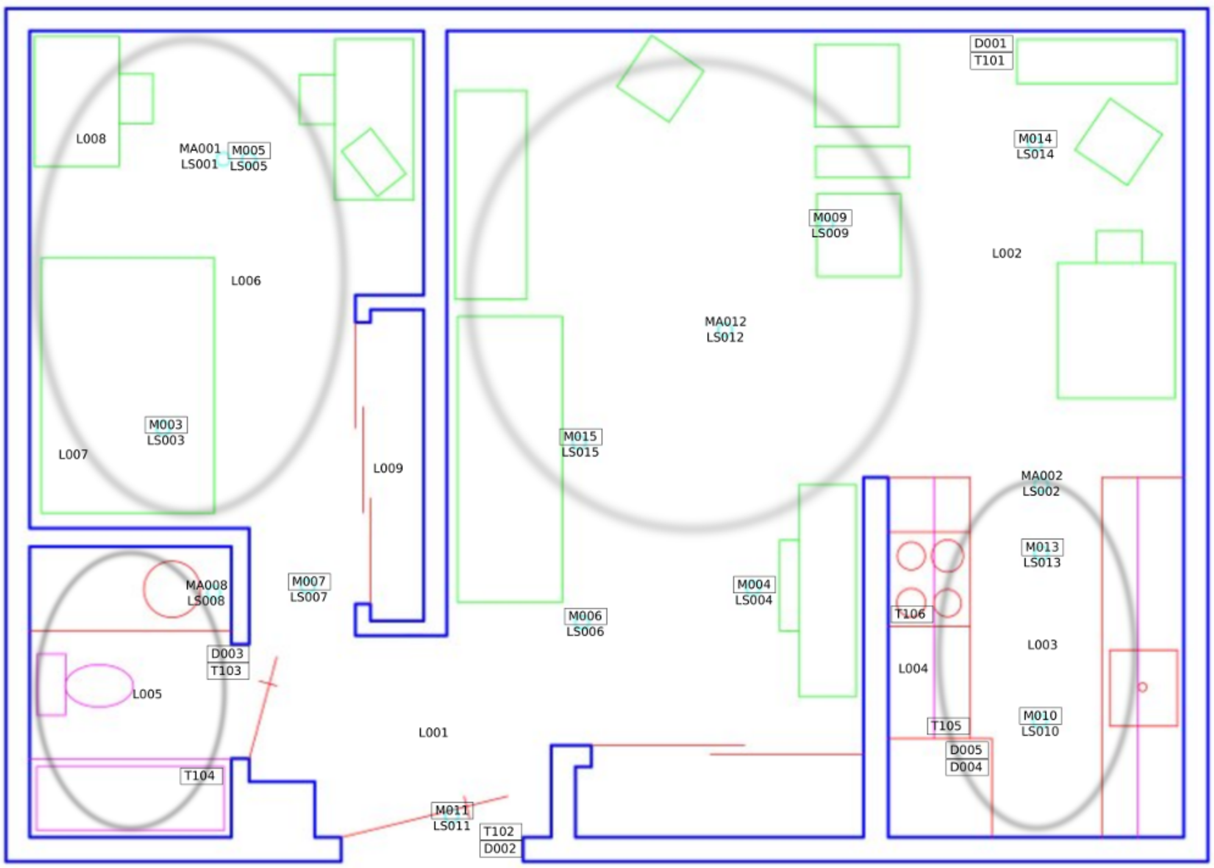


Figure A.15: Floor plan and sensor placement for the testbed hh115.

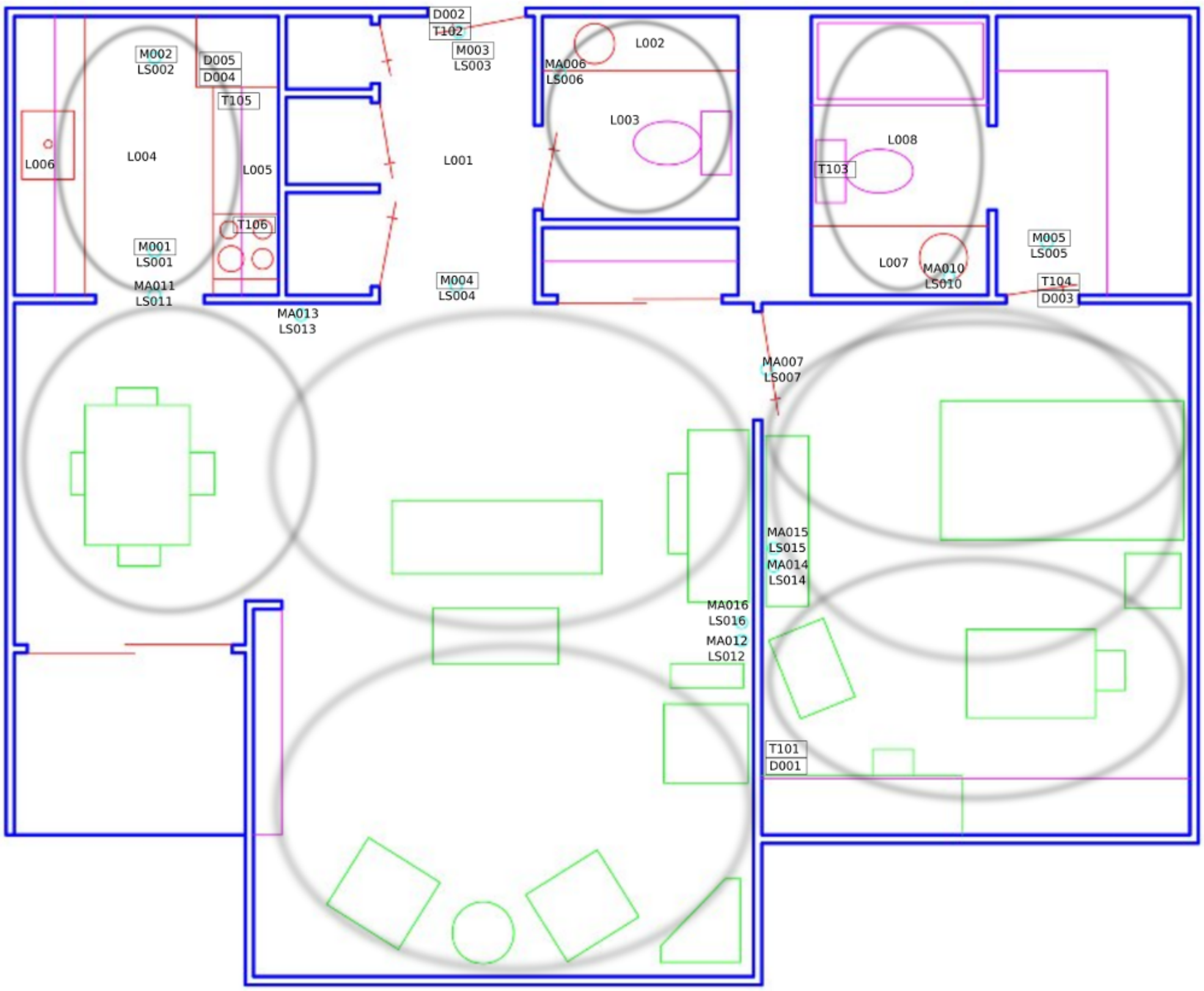


Figure A.16: Floor plan and sensor placement for the testbed hh116.

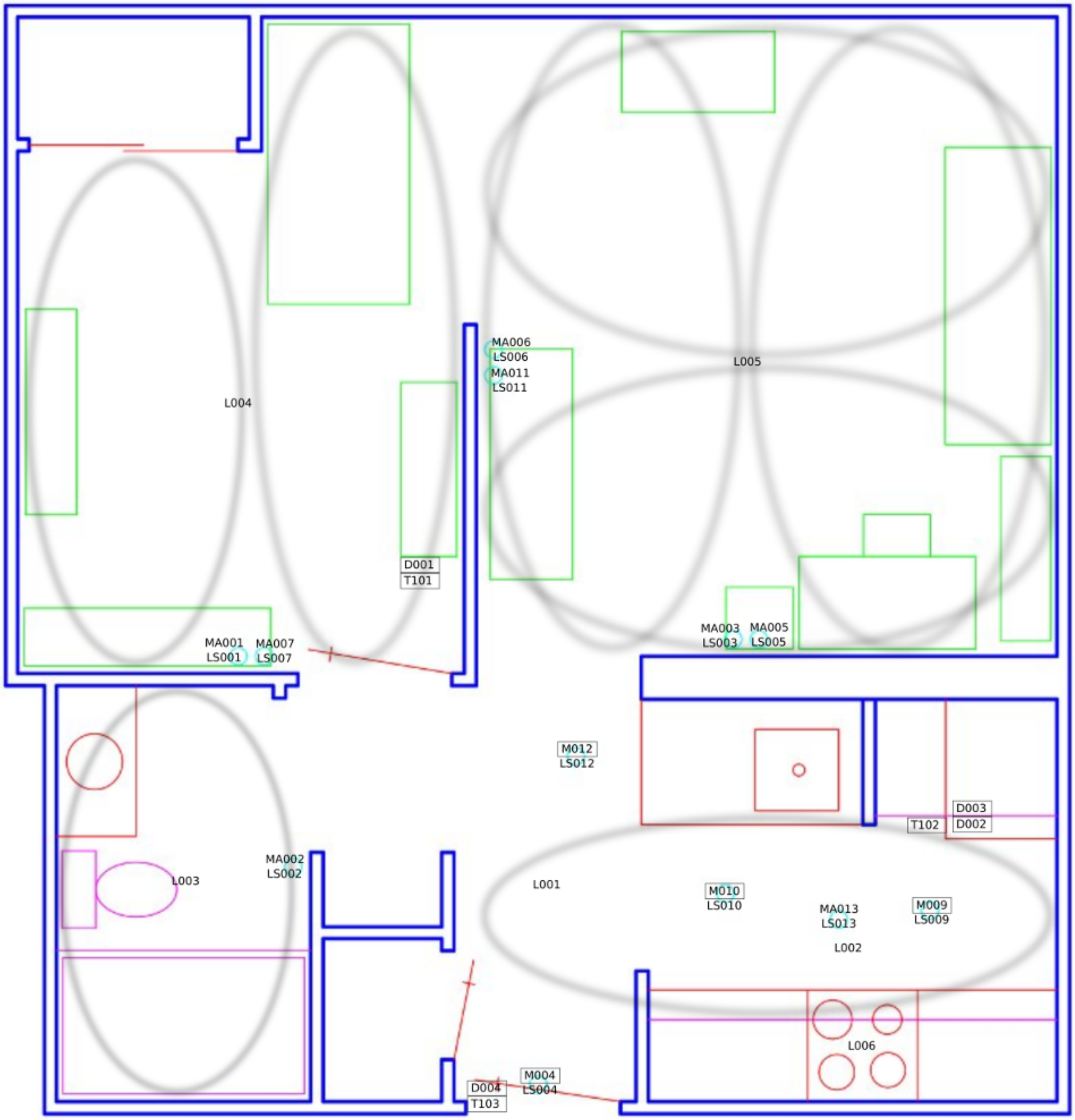


Figure A.17: Floor plan and sensor placement for the testbed hh117.

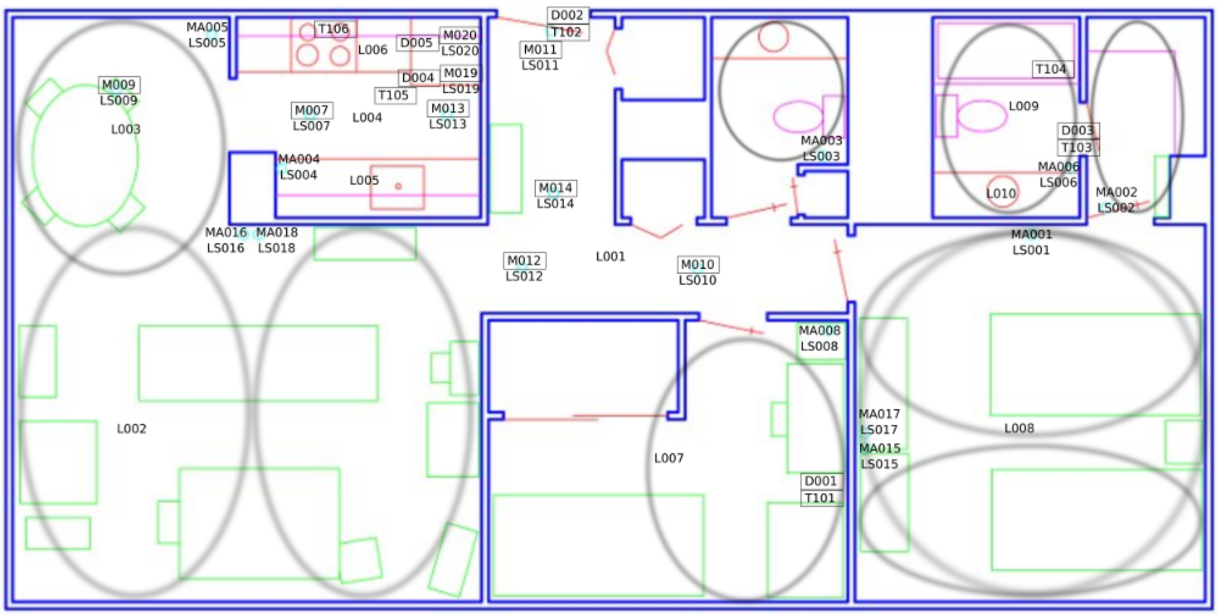


Figure A.18: Floor plan and sensor placement for the testbed hh118.

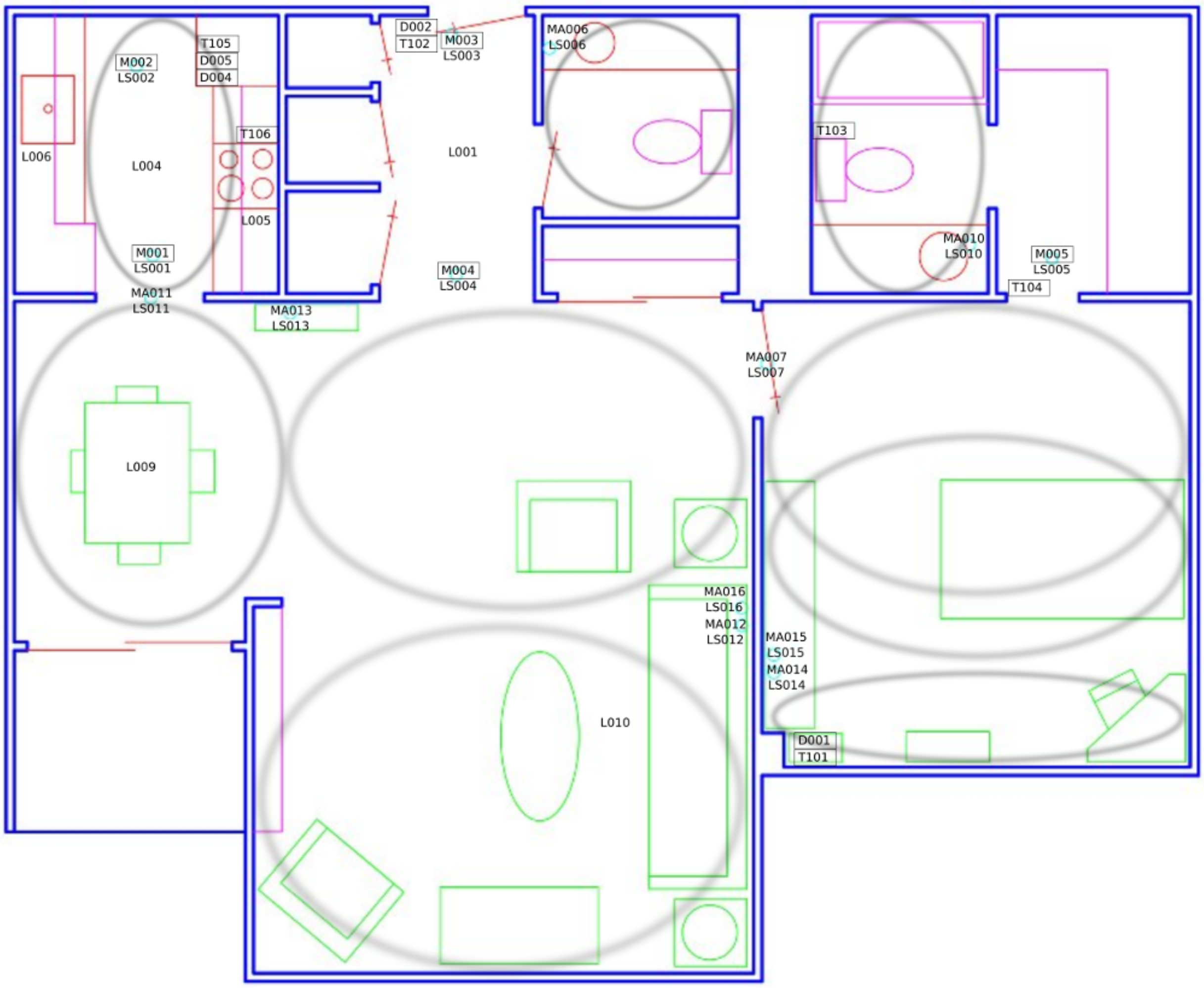


Figure A.19: Floor plan and sensor placement for the testbed hh119.

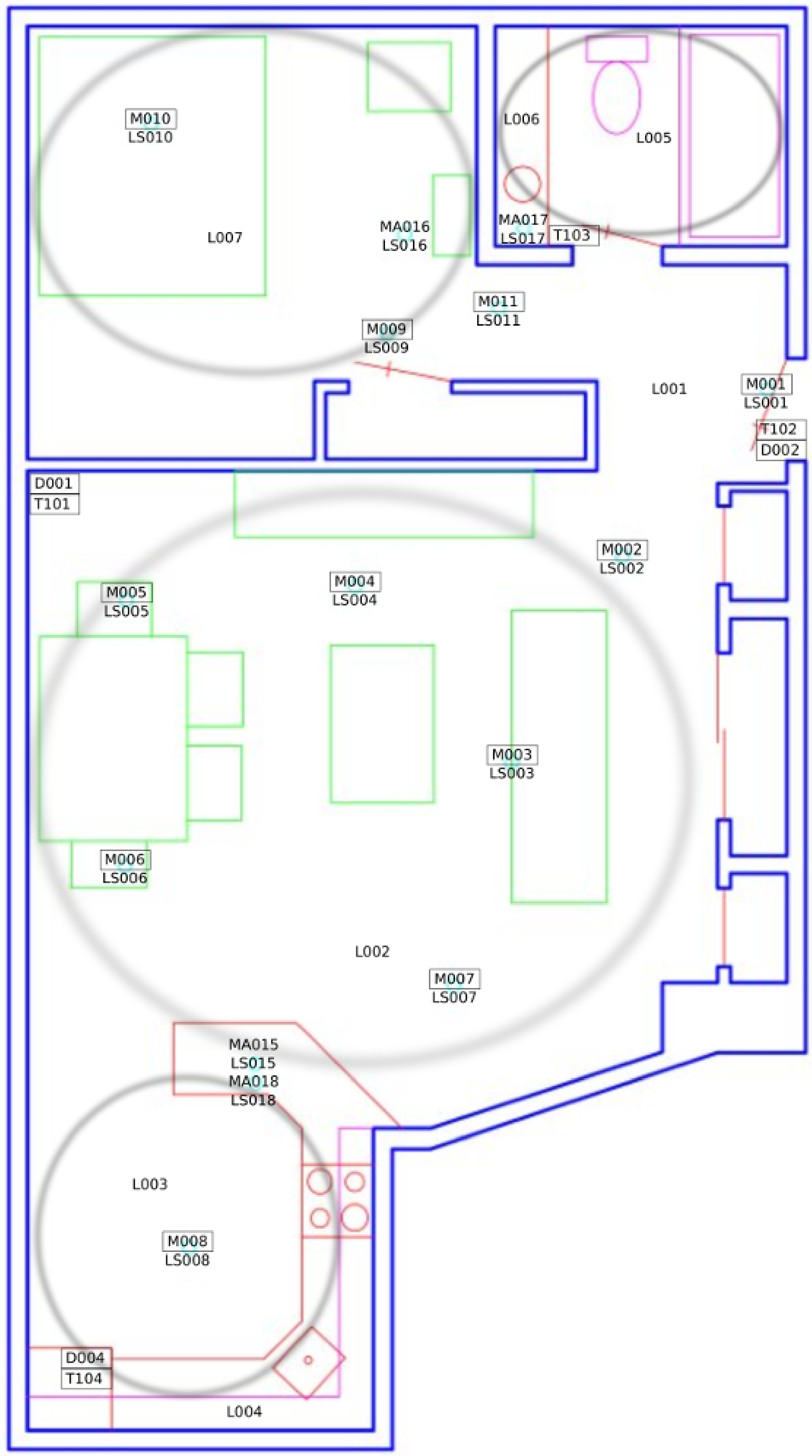


Figure A.20: Floor plan and sensor placement for the testbed hh120.

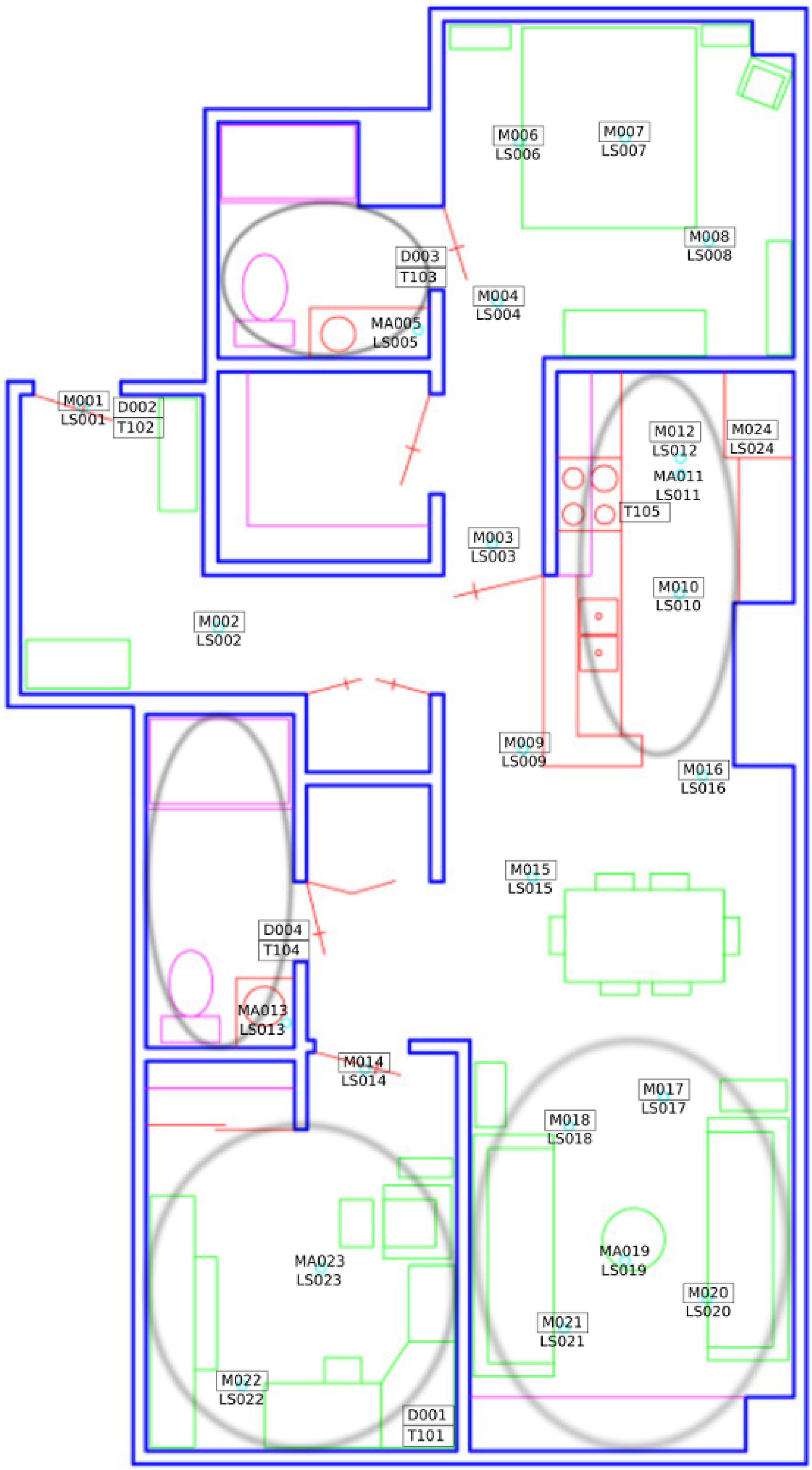


Figure A.21: Floor plan and sensor placement for the testbed hh122.

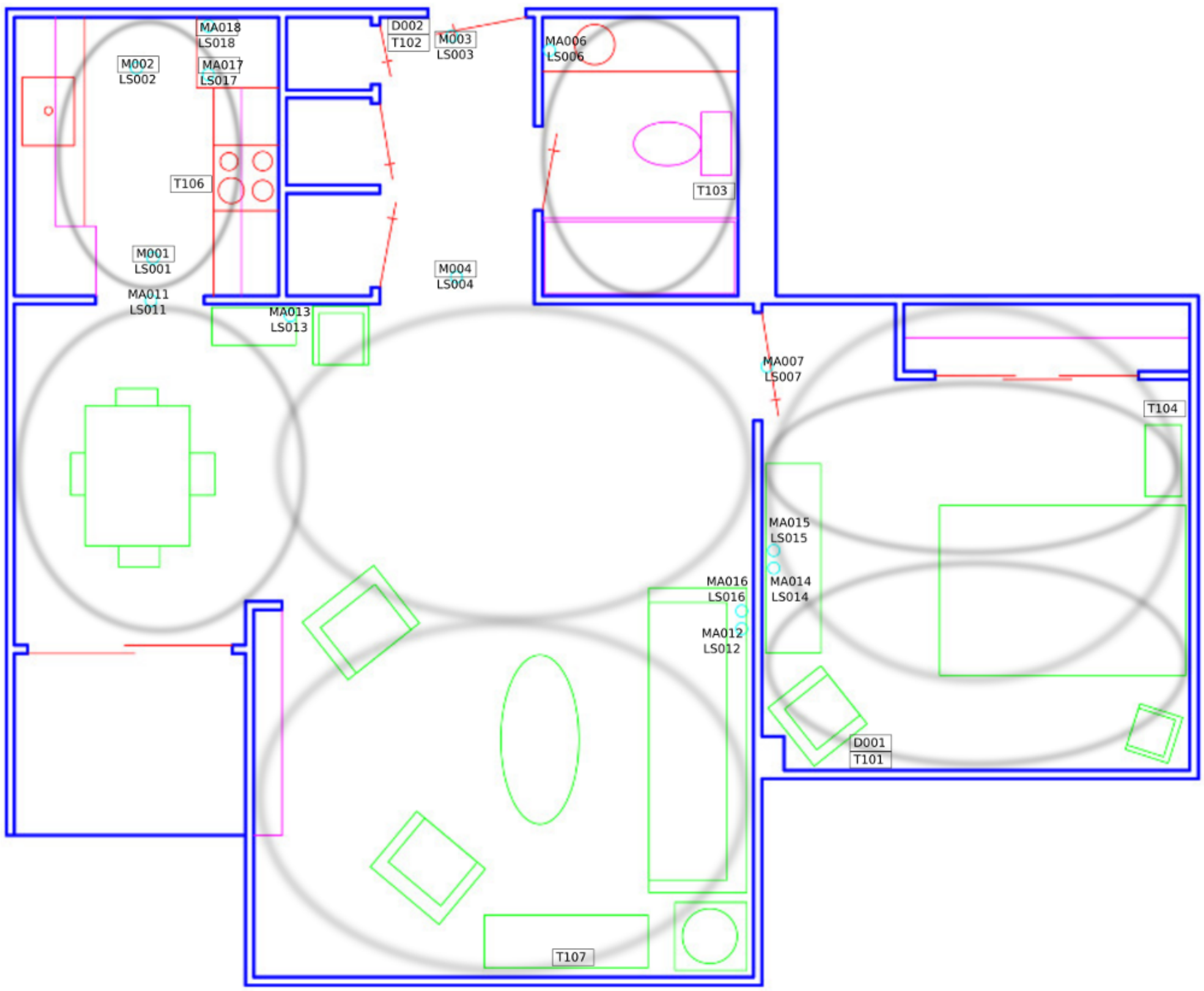


Figure A.22: Floor plan and sensor placement for the testbed hh123.

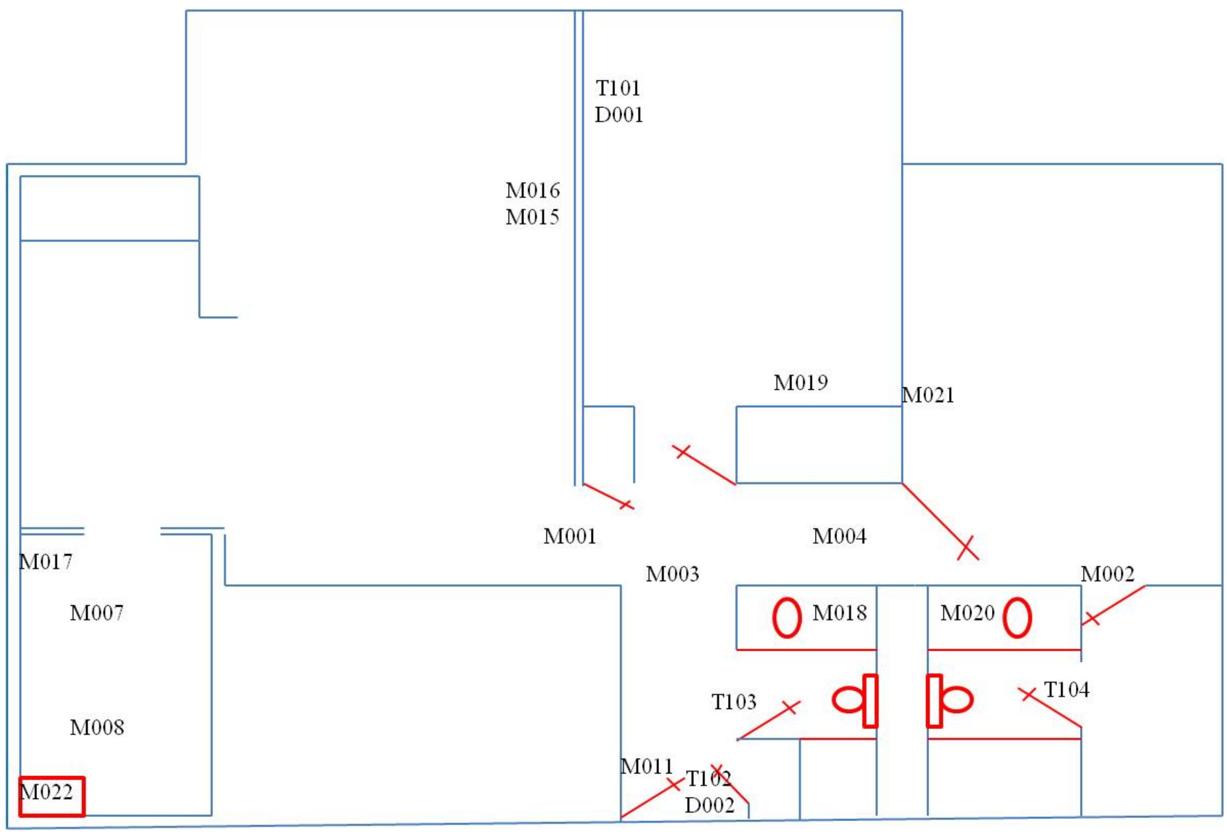


Figure A.23: Floor plan and sensor placement for the testbed hh125.

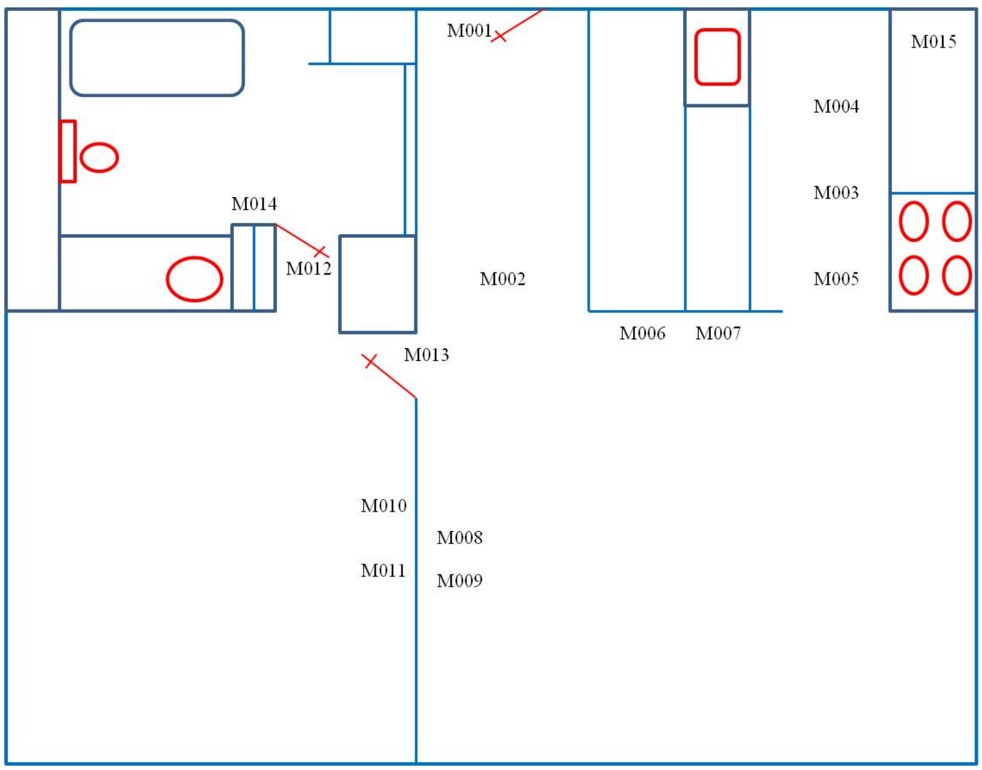


Figure A.24: Floor plan and sensor placement for the testbed hh126.

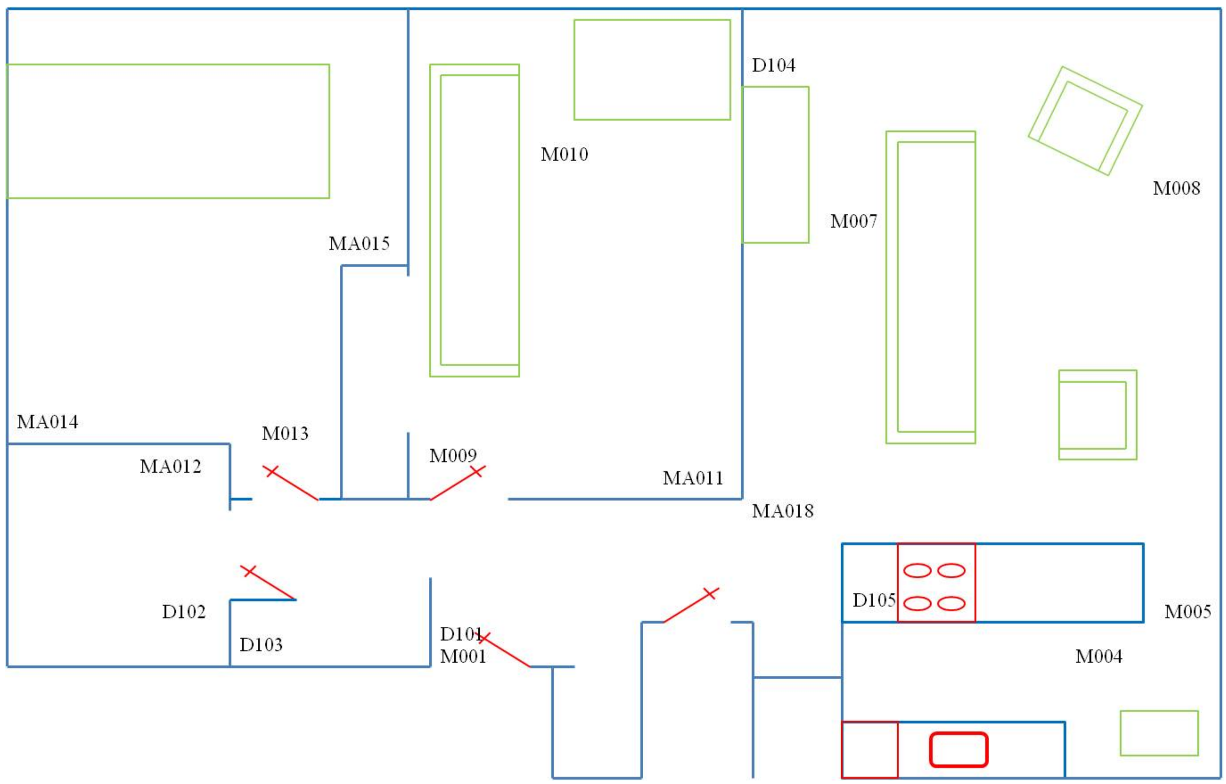


Figure A.25: Floor plan and sensor placement for the testbed hh127.

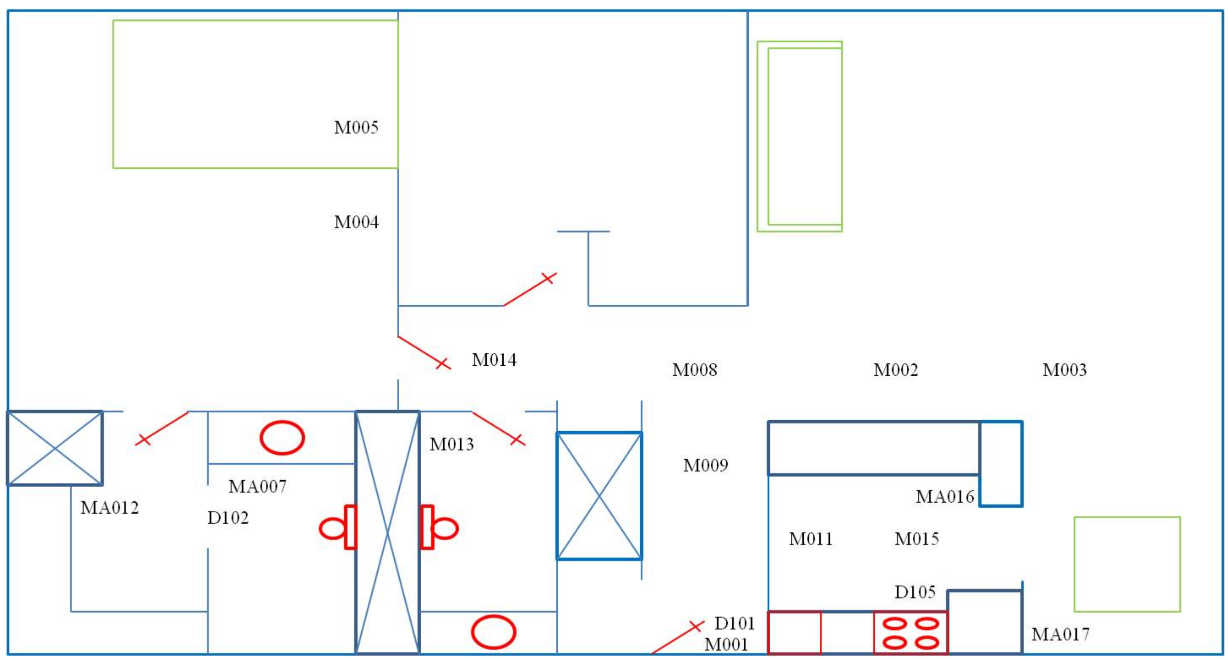


Figure A.26: Floor plan and sensor placement for the testbed hh128.

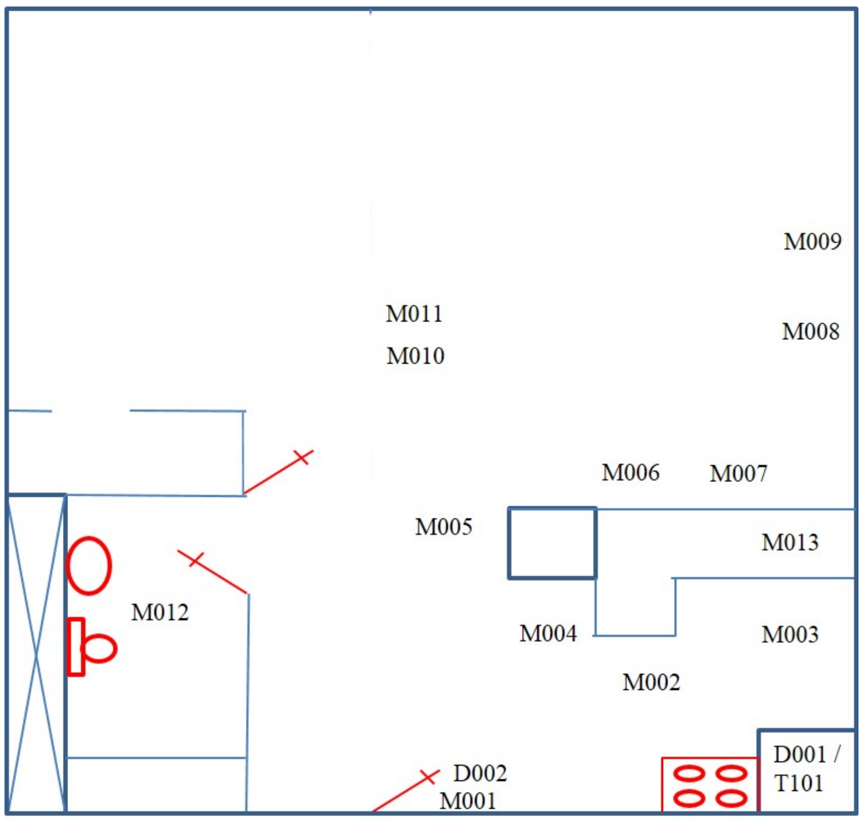


Figure A.27: Floor plan and sensor placement for the testbed hh129.

B ACTIVITY RECOGNITION RESULTS

Here we present some additional results from the activity recognition algorithm.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
8874	0	0	0	0	0	2	0	742	0	0	6	1	0	34	0 = Bathe
0	1984	0	0	0	0	0	0	246	0	465	0	0	0	0	1 = Bed_Toilet_Transition
0	0	4161	0	0	0	0	0	130	0	0	0	9	0	0	2 = Cook
7	0	5	5331	0	0	0	0	1195	3	0	2	1773	0	91	3 = Drink
0	0	26	0	647	0	0	0	54	0	0	0	8	0	0	4 = Eat
0	0	10	0	0	2010	0	0	856	0	27	0	23	0	5	5 = Enter_Home
0	0	0	0	0	0	796	0	49	0	0	0	70	0	0	6 = Entertain_Guests
0	0	1	0	0	8	0	1616	2513	0	0	21	52	84	10	7 = Leave_Home
72	5	121	99	8	112	4	2	347650	0	1002	933	5283	131	2664	8 = Other_Activity
0	0	0	17	0	0	0	0	82	299	38	0	15	0	0	9 = Relax
0	28	0	0	0	0	0	0	1291	0	49546	19	62	0	6	10 = Sleep
0	8	5	18	16	0	10	0	9784	4	63	32114	589	0	682	11 = Toilet
1	0	28	56	0	1	1	0	7057	0	42	72	190170	3	230	12 = Watch_TV
0	0	0	0	0	4	0	0	554	0	0	0	3	6975	22	13 = Water_Plants
0	0	12	18	0	0	0	0	3631	0	3	50	52	1	117157	14 = Work_On_Computer

Table B.1: Results for *navan_2012* activity recognition, with an accuracy of 94.643.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
12501	0	0	33	0	0	0	27	20	5	0	2	16	6	0	0 = Bathe
0	739	0	0	0	0	0	15	0	0	7	0	0	0	0	1 = Bed_Toilet_Transition
0	0	20808	0	9	5	0	99	18	6	0	0	0	8	0	2 = Cook
6	0	0	7798	0	0	0	58	48	2	4	0	4	3	0	3 = Dress
0	0	109	0	3786	0	0	14	0	24	0	5	7	137	0	4 = Eat
0	0	1	0	0	4225	4	158	6	2	0	0	0	10	0	5 = Enter_Home
0	0	0	18	0	62	2145	484	138	45	0	0	16	21	0	6 = Leave_Home
77	46	348	385	81	139	5	41937	745	272	292	227	261	318	3	7 = Other_Activity
1	14	17	57	0	15	1	372	32454	5	12	17	20	30	0	8 = Personal_Hygiene
0	0	10	4	65	107	6	564	114	14344	0	47	46	723	0	9 = Relax
0	10	0	8	0	0	0	36	9	0	7430	0	0	0	0	10 = Sleep
0	0	4	20	0	0	0	75	26	6	0	5039	58	20	0	11 = Take_Medicine
1	0	0	1	10	3	0	71	16	3	0	7	11215	22	2	12 = Wash_Dishes
4	0	2	10	101	40	0	398	154	73	0	27	82	49739	0	13 = Watch_TV
0	0	0	0	0	0	0	8	0	7	0	0	0	0	123	14 = Work

Table B.2: Results for *hh101* activity recognition, with an accuracy of 96.218.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
3124	0	0	16	0	0	0	38	80	0	0	0	0	0	0	0 = Bathe
0	1619	0	0	0	0	0	105	1	0	1	0	0	0	0	1 = Bed_Toilet_Transition
0	0	39324	0	4	28	0	251	0	0	0	0	0	0	28	2 = Cook
5	0	0	7158	0	3	0	75	50	0	0	0	0	0	5	3 = Dress
0	0	352	0	5111	0	0	166	0	39	0	0	19	0	16	4 = Eat
0	0	32	1	0	8795	0	19	5	5	0	0	2	0	169	5 = Enter_Home
0	0	35	0	9	292	488	699	5	41	4	0	10	0	251	6 = Leave_Home
30	315	940	404	158	0	2	67589	1157	448	270	22	487	23	804	7 = Other_Activity
4	0	2	32	0	75	0	841	62851	5	0	2	0	0	81	8 = Personal_Hygiene
0	0	247	0	22	203	0	1447	22	11940	15	0	114	1	140	9 = Relax
0	155	0	4	0	0	0	605	2	6	4531	0	0	0	4	10 = Sleep
0	0	0	6	0	7	0	264	54	0	2	822	0	0	9	11 = Take_Medicine
0	0	0	0	14	14	0	91	0	0	0	0	13047	0	18	12 = Wash_Dishes
0	0	82	0	0	31	0	171	0	117	0	0	6	758	67	13 = Watch_TV
8	0	12	22	5	13	0	220	69	29	0	1	11	4	41484	14 = Work

Table B.3: Results for *hh102* activity recognition, with an accuracy of 95.284.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
2393	12	0	0	0	0	0	2	35	0	0	0	0	0	0	0 = Bathe
0	3238	0	0	0	0	0	0	0	0	12	0	0	0	0	1 = Bed_Toilet_Transition
0	0	29942	0	11	0	0	63	0	0	0	11	0	0	1	2 = Cook
10	0	0	1543	0	0	0	376	83	0	0	2	0	0	0	3 = Dress
0	0	335	0	1861	0	0	101	1	0	0	0	153	0	3	4 = Eat
0	0	0	0	0	768	0	208	0	0	0	0	0	0	0	5 = Enter_Home
0	0	0	2	11	0	447	431	6	4	0	1	0	0	0	6 = Leave_Home
23	153	159	49	20	70	10	29468	144	6	552	1	103	26	7	7 = Other_Activity
1	21	11	0	0	0	0	78	19847	0	9	6	0	0	0	8 = Personal_Hygiene
0	0	0	3	9	0	3	1148	15	1017	0	0	0	35	6	9 = Relax
0	0	0	0	0	0	0	43	0	0	5566	0	0	0	0	10 = Sleep
0	0	58	2	0	0	0	151	348	0	0	1000	3	0	0	11 = Take_Medicine
0	0	13	0	0	0	0	35	0	5	0	0	5228	0	0	12 = Wash_Dishes
0	0	1	2	2	0	0	1338	1	4	0	4	3	1461	2	13 = Watch_TV
0	0	0	0	24	0	0	692	0	18	0	0	36	44	1365	14 = Work

Table B.4: Results for *hh103* activity recognition, with an accuracy of 93.449.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
1963	37	0	6	0	0	0	29	11	0	37	0	0	0	0	0 = Bathe
0	10572	0	0	0	0	0	25	10	0	943	0	0	3	0	1 = Bed_Toilet_Transition
0	0	58191	0	18	25	0	228	46	1	2	5	0	3	32	2 = Cook
12	16	0	4572	0	0	0	174	62	0	5	0	0	17	16	3 = Dress
0	0	181	0	26502	2	0	184	8	0	4	1	24	56	13	4 = Eat
0	0	38	0	18	2539	0	432	7	0	21	0	0	28	87	5 = Enter_Home
0	0	52	8	8	101	185	669	148	27	25	8	34	60	102	6 = Leave_Home
13	699	812	128	605	21	3	60506	858	168	3018	92	301	1079	917	7 = Other_Activity
1	523	26	69	18	42	0	1198	33149	23	186	19	8	382	28	8 = Personal_Hygiene
0	0	2	3	26	10	0	469	142	7559	35	7	10	245	66	9 = Relax
0	944	2	0	0	0	0	374	143	28	35442	22	9	83	40	10 = Sleep
0	9	109	0	54	0	0	327	168	4	17	2416	15	84	13	11 = Take_Medicine
0	0	1	0	50	0	0	185	40	0	1	1	13977	0	9	12 = Wash_Dishes
3	56	8	7	12	35	0	640	142	16	1252	20	20	27931	28	13 = Watch_TV
0	0	35	0	23	31	0	435	36	9	19	2	15	18	37247	14 = Work

Table B.5: Results for *hh104* activity recognition, with an accuracy of 93.631.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
2819	0	0	0	0	3	0	23	3	3	0	0	0	0	0	0 = Bathe
0	1375	0	0	0	0	0	25	0	0	0	0	0	0	0	1 = Bed_Toilet_Transition
0	0	30526	0	7	32	0	88	3	4	0	3	0	0	0	2 = Cook
4	0	9	4485	0	0	0	176	12	0	0	3	2	0	0	3 = Dress
0	0	489	0	2438	7	0	192	11	0	0	0	90	12	12	4 = Eat
0	0	42	0	0	5033	2	209	12	3	1	0	7	0	3	5 = Enter_Home
0	0	38	23	6	194	770	814	102	9	0	0	41	0	2	6 = Leave_Home
26	283	499	208	22	60	1	46772	597	148	157	52	337	86	101	7 = Other_Activity
0	13	5	20	0	27	2	566	18430	1	0	8	5	2	1	8 = Personal_Hygiene
0	0	138	14	0	92	0	1077	36	5149	1	0	53	3	30	9 = Relax
0	165	0	1	0	2	0	255	47	0	877	10	0	0	0	10 = Sleep
0	0	3	8	0	0	0	158	80	0	2	1773	7	0	0	11 = Take_Medicine
0	0	0	4	5	0	0	96	5	0	0	2	11599	4	1	12 = Wash_Dishes
0	0	43	11	7	0	2	569	10	20	0	0	36	1715	31	13 = Watch_TV
0	0	11	7	0	12	0	520	33	14	0	0	31	3	3737	14 = Work

Table B.6: Results for *hh105* activity recognition, with an accuracy of 93.469.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
190	0	0	41	0	3	0	310	7	0	11	0	0	0	10	0 = Bathe
0	6	0	0	0	0	0	2	30	0	437	0	0	0	0	1 = Bed_Toilet_Transition
0	0	27984	0	11	29	0	330	1	0	0	5	0	3	13	2 = Cook
1	0	0	3060	0	0	0	159	18	0	40	0	0	0	0	3 = Dress
0	0	16	0	12906	2	0	337	2	0	0	0	6	0	0	4 = Eat
0	0	14	0	0	5751	0	343	0	6	8	0	5	14	1	5 = Enter_Home
0	0	0	0	9	37	123	977	48	12	0	9	14	4	32	6 = Leave_Home
2	0	778	125	499	56	0	75767	63	218	221	26	352	332	571	7 = Other_Activity
0	0	27	202	19	120	0	4021	3802	34	275	7	21	8	109	8 = Personal_Hygiene
0	0	1	10	13	23	0	986	23	6695	102	6	5	0	9	9 = Relax
0	0	0	4	0	0	0	164	22	0	2111	5	0	0	0	10 = Sleep
0	0	57	16	3	20	0	465	27	3	245	962	11	0	3	11 = Take_Medicine
0	0	0	1	14	0	0	344	0	2	0	0	11364	17	9	12 = Wash_Dishes
0	0	9	0	0	9	0	428	0	0	0	0	0	12010	0	13 = Watch_TV
0	0	2	5	22	1	0	635	5	7	0	9	2	1	25551	14 = Work

Table B.7: Results for *hh106* activity recognition, with an accuracy of 92.536.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
2425	0	14	29	20	1	0	0	69	43	28	1	19	38	52	0 = Bathe
0	0	0	0	0	0	0	0	0	0	1037	0	0	0	0	1 = Bed_Toilet_Transition
0	0	40646	2	570	16	1	5	85	15	0	0	5	442	55	2 = Cook
19	0	71	5971	17	2	1	8	178	82	17	16	57	83	59	3 = Dress
0	0	1018	2	18048	6	0	0	57	42	0	0	516	146	33	4 = Eat
4	0	212	12	35	3173	0	84	74	8	2	0	76	89	32	5 = Enter_Home
15	0	98	74	20	50	697	30	297	136	18	0	131	200	127	6 = Leave_Home
1	0	77	8	24	73	0	2139	41	19	2	0	41	70	11	7 = Other_Activity
11	0	480	134	112	52	9	83	24434	199	116	5	475	543	175	8 = Personal_Hygiene
17	0	172	69	61	20	2	5	291	11254	89	18	144	75	88	9 = Relax
0	0	56	18	21	0	0	4	104	61	15653	26	2	83	0	10 = Sleep
4	0	0	15	0	0	0	0	47	78	2	830	0	36	18	11 = Take_Medicine
0	0	1	14	98	7	0	0	159	52	0	0	22945	211	62	12 = Wash_Dishes
0	0	1372	13	120	28	2	4	143	32	30	1	571	28856	57	13 = Watch_TV
4	0	202	12	32	35	0	12	160	51	0	0	214	150	11374	14 = Work

Table B.8: Results for *hh107* activity recognition, with an accuracy of 92.61.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
87	0	0	31	0	0	0	542	54	2	15	0	0	0	0	0 = Bathe
0	151	0	0	0	0	0	207	0	1	834	0	0	0	0	1 = Bed_Toilet_Transition
0	0	34332	0	4	0	0	844	44	6	0	5	0	1	0	2 = Cook
0	0	0	5014	0	0	0	467	95	6	0	0	0	0	0	3 = Dress
0	0	6	0	9837	16	0	910	14	20	0	9	21	1	8	4 = Eat
0	0	20	0	0	3154	0	635	0	2	19	0	5	0	7	5 = Enter_Home
0	0	5	0	1	8	200	1169	150	5	0	0	3	4	8	6 = Leave_Home
0	0	1240	278	367	49	2	132423	554	429	1026	23	653	198	271	7 = Other_Activity
0	0	46	192	0	7	0	5314	20393	73	284	7	48	11	20	8 = Personal_Hygiene
0	1	34	0	21	8	0	3604	157	11123	207	7	9	9	38	9 = Relax
0	0	0	0	0	0	0	327	15	53	7833	0	0	0	1	10 = Sleep
0	0	48	0	13	0	0	626	11	2	0	1692	23	15	11	11 = Take_Medicine
0	0	0	0	1	0	0	973	26	2	0	4	18831	10	4	12 = Wash_Dishes
0	0	0	0	0	0	0	1092	11	3	0	2	7	7865	19	13 = Watch_TV
0	0	5	0	1	12	0	2490	94	29	0	15	1	4	8581	14 = Work

Table B.9: Results for *hh108* activity recognition, with an accuracy of 90.535.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
5073	0	0	0	0	0	0	55	6	0	0	0	7	0	0	0 = Bathe
0	1699	0	0	0	0	0	86	0	0	4	0	0	0	0	1 = Bed_Toilet_Transition
0	0	71577	0	61	5	0	559	6	7	0	1	0	0	25	2 = Cook
1	0	0	16599	0	0	0	316	15	8	0	6	0	0	3	3 = Dress
0	0	968	0	11629	0	0	371	0	0	0	0	186	0	3	4 = Eat
0	0	0	9	0	5899	3	753	4	0	6	6	2	0	3	5 = Enter_Home
0	0	0	52	0	79	785	2010	77	25	0	30	24	8	24	6 = Leave_Home
49	126	1625	695	283	106	24	161020	718	188	912	134	626	44	375	7 = Other_Activity
0	39	0	32	0	20	1	2152	26879	8	0	6	7	0	8	8 = Personal_Hygiene
0	0	10	0	4	7	0	1754	19	7511	40	16	25	40	27	9 = Relax
0	18	0	66	0	0	0	954	1	5	5904	1	0	0	0	10 = Sleep
0	0	3	26	0	1	0	1298	50	16	1	6030	8	0	27	11 = Take_Medicine
1	0	0	0	17	8	0	200	4	0	0	1	30106	0	0	12 = Wash_Dishes
0	0	5	0	3	0	0	618	25	4	0	4	27	1865	21	13 = Watch_TV
0	0	160	36	17	16	0	2217	5	2	0	6	71	4	24940	14 = Work

Table B.10: Results for *hh109* activity recognition, with an accuracy of 94.521.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
3053	0	0	1	0	0	0	58	29	0	0	5	0	0	0	0 = Bathe
0	1569	0	0	0	0	0	35	0	0	10	0	0	0	0	1 = Bed_Toilet_Transition
0	0	7542	0	7	0	0	317	40	1	0	6	0	32	0	2 = Cook
2	0	0	3476	0	0	0	408	30	0	0	17	0	47	0	3 = Dress
0	0	68	0	4517	0	0	302	10	18	48	0	26	7	115	4 = Eat
2	0	0	0	0	1785	0	355	4	0	9	0	0	0	34	5 = Enter_Home
0	0	0	0	0	6	362	731	246	0	0	13	0	0	81	6 = Leave_Home
92	148	525	166	149	55	5	95959	354	159	718	19	153	223	854	7 = Other_Activity
0	8	33	3	8	11	0	1260	18976	15	1	21	5	11	12	8 = Personal_Hygiene
0	0	9	5	41	0	0	390	63	10762	0	6	0	0	21	9 = Relax
0	117	0	6	0	0	0	194	36	0	10325	19	0	39	16	10 = Sleep
15	0	6	14	0	0	0	391	121	11	1	2316	0	2	19	11 = Take_Medicine
0	0	0	0	19	0	0	373	4	0	14	2	2567	5	7	12 = Wash_Dishes
0	0	60	2	0	0	0	678	49	0	193	0	28	6653	0	13 = Watch_TV
0	0	2	5	8	1	0	874	124	9	0	0	10	11	39278	14 = Work

Table B.11: Results for *hh111* activity recognition, with an accuracy of 94.51.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
488	0	0	10	0	0	0	456	30	0	5	0	0	0	0	0 = Bathe
0	854	0	0	0	0	0	140	0	0	1148	0	0	0	0	1 = Bed_Toilet_Transition
0	0	21196	2	23	2	0	1536	40	1	0	3	0	10	12	2 = Cook
0	0	0	8547	3	0	0	1328	18	1	470	4	0	0	29	3 = Dress
0	0	82	2	9160	0	0	766	0	14	0	0	3	32	98	4 = Eat
0	0	0	0	0	4275	0	498	1	0	20	0	11	0	3	5 = Enter_Home
0	0	0	0	0	22	904	1452	81	9	0	10	0	0	0	6 = Leave_Home
3	0	512	199	347	52	21	198454	209	255	3239	9	193	489	1559	7 = Other_Activity
0	1	28	71	3	29	0	7074	23094	29	206	10	14	3	67	8 = Personal_Hygiene
0	0	10	4	5	7	0	3179	48	9839	1930	0	2	58	50	9 = Relax
0	21	0	19	0	0	0	573	12	3	53072	0	0	0	25	10 = Sleep
0	0	5	24	0	0	0	483	27	0	2	1795	0	0	0	11 = Take_Medicine
0	0	11	0	26	0	0	1420	9	13	0	0	8351	17	3	12 = Wash_Dishes
0	0	4	0	4	2	0	1195	19	44	4	0	18	13120	3	13 = Watch_TV
0	0	0	1	4	7	0	1915	72	12	39	5	9	0	81277	14 = Work

Table B.12: Results for *hh112* activity recognition, with an accuracy of 92.674.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
104131	0	0	0	0	0	0	421	246	22	0	0	0	0	5	0 = Bathe
0	11181	0	0	0	0	0	160	218	0	0	3	0	0	0	1 = Bed_Toilet_Transition
0	0	216531	6	17	0	0	780	4	0	0	0	3	0	1	2 = Cook
11	0	0	17385	0	0	9	3472	689	2200	25	1	2	0	17	3 = Dress
0	0	4364	0	13327	0	0	1366	2	0	0	0	98	0	17	4 = Eat
0	0	34	0	0	16453	52	1968	6	7	1	0	0	0	12	5 = Enter_Home
0	0	8	38	0	162	10420	7116	54	19	2	0	14	0	11	6 = Leave_Home
695	327	6735	355	112	377	44	743243	4877	3752	1204	173	2496	213	5218	7 = Other_Activity
53	69	25	19	0	0	0	3866	487990	54	0	121	60	2	39	8 = Personal_Hygiene
7	8	1	187	0	0	0	4952	228	118619	87	8	1	35	72	9 = Relax
2	28	1	2	0	0	0	942	81	24	54590	0	0	0	0	10 = Sleep
14	13	0	6	0	0	0	1030	9616	15	18	7149	0	0	0	11 = Take_Medicine
0	0	12	11	6	0	0	4247	32	8	0	0	146759	1	48	12 = Wash_Dishes
1	0	0	8	0	0	0	1179	54	0	0	8	0	13062	1228	13 = Watch_TV
2	0	60	4	15	0	0	6688	71	29	2	0	523	64	235234	14 = Work

Table B.13: Results for *hh113* activity recognition, with an accuracy of 96.222.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
782	0	0	0	0	0	0	2	10	2	5	0	0	0	0	0 = Bathe
0	329	0	0	0	0	0	5	0	0	46	0	0	0	0	1 = Bed_Toilet_Transition
0	0	31446	0	0	18	0	118	0	9	0	0	0	0	0	2 = Cook
2	0	0	397	0	0	0	19	0	0	16	0	0	0	0	3 = Dress
0	0	65	0	2004	0	0	156	0	63	0	0	11	0	0	4 = Eat
0	0	17	0	0	8247	0	14	0	17	7	0	0	0	0	5 = Enter_Home
0	0	6	0	0	55	80	291	9	35	8	0	4	0	2	6 = Leave_Home
7	8	235	8	24	0	0	48063	131	298	135	3	96	0	43	7 = Other_Activity
0	0	9	0	0	48	0	579	8400	45	42	1	0	0	9	8 = Personal_Hygiene
0	0	8	0	0	86	0	457	1	14965	9	0	10	0	3	9 = Relax
0	0	4	0	0	17	0	288	13	27	5054	0	0	0	17	10 = Sleep
0	0	0	0	0	0	0	10	0	0	0	414	0	0	0	11 = Take_Medicine
0	0	0	0	0	0	0	17	0	0	0	0	6327	0	0	12 = Wash_Dishes
0	0	0	0	0	2	0	11	0	7	0	0	9	74	0	13 = Watch_TV
0	0	17	0	0	73	0	583	0	34	24	0	0	0	4412	14 = Work

Table B.14: Results for *hh114* activity recognition, with an accuracy of 96.707.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	←guessed
6540	0	10	49	0	16	0	0	45	1047	0	0	18	0	0	31	0 = Bathe
0	25308	0	0	0	0	0	0	109	13	46	1028	0	0	0	0	1 = Bed_Toilet_Transition
0	0	213894	15	0	2	48	0	136	2	2	0	49	43	23	941	2 = Cook
31	200	47	205493	0	134	907	0	414	527	18	48	26	3	174	454	3 = Dress
0	0	319	16	2066	10	11	0	69	3	0	0	1	67	105	188	4 = Eat
2	1	91	132	0	9781	220	0	349	116	237	3	1	7	50	981	5 = Enter_Home
0	0	248	217	0	372	69317	0	80	92	10	0	13	52	159	377	6 = Housekeeping
0	14	15	143	0	171	204	10	1471	107	152	36	22	0	132	521	7 = Leave_Home
99	1642	2927	4890	34	284	531	0	169168	5629	464	5199	1639	1032	2756	13635	8 = Other_Activity
7	1235	69	1114	0	43	484	0	890	178438	12	5	11	7	104	945	9 = Personal_Hygiene
0	4055	181	219	0	19	179	0	557	72	25390	1395	20	52	207	1915	10 = Relax
0	510	0	63	0	2	0	0	175	25	1318	105619	0	0	10	33	11 = Sleep
5	33	83	885	0	190	12	0	943	854	63	0	55247	40	76	3774	12 = Take_Medicine
0	0	9	18	5	103	32	0	168	15	0	0	74	70535	394	886	13 = Wash_Dishes
0	4	622	360	0	41	136	0	877	90	5	12	159	202	133102	5259	14 = Watch_TV
3	2187	3226	1259	8	447	624	0	765	1082	296	260	461	940	1332	228227	15 = Work

Table B.15: Results for *hh115* activity recognition, with an accuracy of 93.728.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
15878	0	0	0	0	0	0	43	5	0	0	0	0	0	1	0 = Bathe
0	13843	0	0	0	0	0	95	0	0	0	0	0	0	0	1 = Bed_Toilet_Transition
0	0	29311	0	1	0	0	215	0	0	0	0	31	0	0	2 = Cook
13	0	0	1515	0	0	0	363	125	0	1	0	0	0	0	3 = Dress
0	0	332	0	977	0	0	489	3	8	0	0	82	6	0	4 = Eat
0	0	3	0	0	671	0	473	0	0	10	0	0	0	0	5 = Enter_Home
0	0	5	0	0	1	166	1136	20	0	0	1	0	0	0	6 = Leave_Home
33	246	535	69	19	17	0	198135	536	23	276	0	594	24	12	7 = Other_Activity
0	15	18	1	0	0	0	702	83006	4	2	0	31	0	0	8 = Personal_Hygiene
0	0	43	0	3	2	0	833	79	1311	0	4	60	0	0	9 = Relax
0	23	0	11	0	0	0	1067	50	0	1935	0	6	0	0	10 = Sleep
0	0	118	2	19	1	0	510	11	22	0	282	169	0	0	11 = Take_Medicine
0	0	0	0	1	0	0	120	1	0	0	0	28709	0	0	12 = Wash_Dishes
0	0	18	0	0	0	0	246	1	12	0	0	10	1344	4	13 = Watch_TV
0	0	18	0	0	0	0	647	12	6	10	0	13	0	804	14 = Work

Table B.16: Results for *hh116* activity recognition, with an accuracy of 97.229.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
526	0	0	0	0	2	0	112	193	0	6	0	6	0	0	0 = Bathe
0	4530	0	0	0	0	0	215	144	0	10	0	0	0	0	1 = Bed_Toilet_Transition
0	0	41759	2	5	21	0	1041	3	0	0	1	0	3	4	2 = Cook
2	0	21	18637	0	0	0	1042	19	3	7	5	9	6	8	3 = Dress
0	0	266	2	14344	0	0	1752	1	0	0	2	33	290	47	4 = Eat
0	0	22	0	0	9753	1	2372	6	0	2	0	6	1	0	5 = Enter_Home
0	0	6	17	4	66	4749	6144	38	17	0	11	65	30	5	6 = Leave_Home
2	123	1323	1315	283	290	16	481658	617	13	826	289	925	969	329	7 = Other_Activity
0	1030	123	96	60	9	0	3913	48945	2	0	4	91	8	12	8 = Personal_Hygiene
0	0	15	15	4	7	3	4151	12	5257	39	10	1	635	54	9 = Relax
0	26	0	94	15	6	0	2823	17	2	7066	6	3	0	0	10 = Sleep
0	1	8	4	7	30	5	1330	25	0	0	9315	95	0	0	11 = Take_Medicine
0	0	2	2	1	12	0	1123	8	0	6	25	37516	7	11	12 = Wash_Dishes
0	0	38	5	24	10	0	6898	6	36	0	2	61	27180	130	13 = Watch_TV
0	0	77	9	18	4	0	4175	6	35	0	6	53	304	17787	14 = Work

Table B.17: Results for *hh117* activity recognition, with an accuracy of 93.666.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	←guessed
174	0	0	0	0	0	0	0	2	42	0	0	0	0	0	0	0 = Bathe
0	929	0	0	0	0	0	0	4	2	0	16	0	0	0	0	1 = Bed_Toilet_Transition
0	0	37536	0	3	43	0	0	111	0	9	0	0	1	8	46	2 = Cook
0	0	0	4465	0	0	11	0	44	0	0	0	0	0	0	2	3 = Dress
0	0	41	0	12479	0	0	0	11	0	0	0	1	2	0	11	4 = Eat
0	0	0	0	0	2828	0	0	0	7	0	1	0	0	0	76	5 = Enter_Home
0	0	0	15	0	0	8727	0	15	2	0	0	0	0	0	3	6 = Housekeeping
0	0	15	0	2	68	0	681	371	23	0	1	0	0	1	178	7 = Leave_Home
4	267	706	69	231	36	178	37	17641	428	146	394	6	337	165	2590	8 = Other_Activity
2	0	27	1	0	19	23	3	655	13736	1	2	0	0	10	208	9 = Personal_Hygiene
0	0	43	0	22	0	0	4	135	0	4248	0	0	23	16	104	10 = Relax
0	48	0	0	0	0	1	0	102	0	0	2497	0	0	0	0	11 = Sleep
0	0	167	21	133	19	2	0	70	174	0	0	171	0	0	0	12 = Take_Medicine
0	0	1	0	31	15	0	0	62	0	19	0	0	9210	30	40	13 = Wash_Dishes
0	0	44	0	14	0	0	0	50	1	15	0	0	10	4791	135	14 = Watch_TV
0	0	61	0	10	36	37	0	332	38	13	0	0	33	10	49727	15 = Work

Table B.18: Results for *hh118* activity recognition, with an accuracy of 94.516.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
1543	108	0	1	0	0	0	0	0	66	0	0	0	0	3	0 = Bathe
6	3838	0	0	0	0	0	0	42	0	0	0	0	0	0	1 = Bed_Toilet_Transition
0	0	11812	0	0	1	0	0	52	0	0	0	0	0	152	2 = Cook
1	36	0	2557	0	0	0	0	145	173	0	0	0	0	73	3 = Dress
0	0	25	0	39	0	0	0	132	11	0	0	0	0	152	4 = Eat
0	0	24	0	0	662	0	0	2	0	0	0	5	0	284	5 = Enter_Home
0	0	0	0	0	14	1633	0	1	0	0	0	0	0	0	6 = Housekeeping
0	0	20	0	0	14	0	395	78	0	0	0	0	0	402	7 = Leave_Home
25	553	360	232	0	2	0	13	11840	609	0	0	1	103	1302	8 = Other_Activity
3	91	1	32	0	2	0	5	66	14728	0	0	0	0	143	9 = Personal_Hygiene
0	0	0	1	0	2	0	0	58	2	16	0	0	0	103	10 = Relax
2	166	0	1	0	0	0	0	239	13	0	0	0	0	3	11 = Sleep
10	0	6	20	0	0	0	0	57	399	0	0	66	0	22	12 = Take_Medicine
0	0	0	0	0	1	0	0	13	0	0	0	0	4588	54	13 = Wash_Dishes
0	13	37	11	0	9	0	0	261	25	0	0	0	10	31919	14 = Work

Table B.19: Results for *hh119* activity recognition, with an accuracy of 92.34.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
5573	0	2	2	0	2	0	53	49	0	0	0	0	2	0	0 = Bathe
0	4110	0	0	0	0	0	40	24	0	21	0	0	0	0	1 = Bed_Toilet_Transition
0	0	7896	0	14	0	0	135	0	0	0	4	0	1	1	2 = Cook
2	0	0	8285	0	0	0	230	17	2	2	1	0	26	0	3 = Dress
0	0	34	0	1979	0	0	74	0	4	0	0	6	59	132	4 = Eat
0	0	0	0	0	2435	0	280	5	0	4	2	0	1	0	5 = Enter_Home
0	0	0	24	0	16	759	1034	77	0	2	14	0	2	24	6 = Leave_Home
21	334	137	295	79	113	6	87338	313	88	1231	104	73	597	662	7 = Other_Activity
0	74	0	33	0	14	0	613	24557	0	0	0	0	21	7	8 = Personal_Hygiene
0	0	0	44	0	0	0	199	0	4474	1	0	0	61	2	9 = Relax
0	47	0	21	0	0	0	747	5	79	11844	0	0	93	9	10 = Sleep
0	0	30	0	2	0	0	888	2	0	3	3391	18	0	55	11 = Take_Medicine
0	0	12	3	17	0	0	100	0	0	0	0	3773	0	16	12 = Wash_Dishes
0	0	0	17	2	0	0	433	36	0	134	4	0	23761	5	13 = Watch_TV
0	0	0	1	0	0	0	475	2	0	0	7	1	0	18396	14 = Work

Table B.20: Results for *hh120* activity recognition, with an accuracy of 95.072.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
2137	0	0	0	0	0	0	8	0	0	0	0	0	0	1	0 = Bathe
0	1480	0	0	0	0	0	90	0	0	63	0	0	0	0	1 = Bed_Toilet_Transition
0	0	16012	0	2	0	0	100	0	0	0	0	0	0	7	2 = Cook
17	0	0	638	0	0	0	284	89	0	0	3	0	0	2	3 = Dress
0	0	244	0	1462	0	0	159	5	0	0	0	15	10	0	4 = Eat
0	0	0	0	0	191	0	276	0	0	0	0	0	0	0	5 = Enter_Home
0	0	0	0	0	0	153	350	39	0	0	0	10	0	18	6 = Leave_Home
35	105	229	5	49	4	1	54024	532	29	423	4	249	222	204	7 = Other_Activity
0	0	25	11	18	1	0	994	14196	2	6	4	20	11	34	8 = Personal_Hygiene
4	0	0	0	4	0	0	243	7	2185	0	0	10	0	16	9 = Relax
0	46	0	0	0	0	0	495	25	10	4061	0	0	0	8	10 = Sleep
0	0	0	0	0	0	0	260	121	0	1	556	0	0	1	11 = Take_Medicine
0	0	0	0	5	0	0	103	2	1	0	0	13352	3	12	12 = Wash_Dishes
0	0	0	0	4	0	0	338	10	0	0	1	21	4848	67	13 = Watch_TV
0	0	0	2	2	0	0	677	45	1	0	0	52	59	6976	14 = Work

Table B.21: Results for *hh122* activity recognition, with an accuracy of 94.101.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
1280	5	0	0	0	0	0	3	0	0	0	0	0	0	0	0 = Bathe
0	684	0	0	0	0	0	2	0	0	0	0	0	0	0	1 = Bed_Toilet_Transition
0	0	17858	0	0	1	0	92	0	0	0	1	0	4	0	2 = Cook
0	0	0	5741	0	0	0	77	0	2	0	0	0	6	0	3 = Dress
0	0	15	0	3357	0	0	70	0	0	2	0	0	30	0	4 = Eat
0	0	0	5	0	1047	0	67	8	0	5	0	0	8	0	5 = Enter_Home
0	0	0	26	9	0	644	350	66	3	0	0	17	8	0	6 = Leave_Home
28	10	503	283	186	27	0	29924	198	34	406	57	324	694	0	7 = Other_Activity
0	0	0	0	0	4	0	76	6675	0	0	0	0	1	0	8 = Personal_Hygiene
0	0	0	10	0	0	0	413	0	2475	6	0	0	34	0	9 = Relax
0	2	0	24	0	0	0	652	0	28	4243	0	0	41	0	10 = Sleep
0	0	82	0	1	0	0	184	0	12	0	919	80	2	0	11 = Take_Medicine
0	0	0	5	4	0	0	85	0	0	0	0	13953	7	0	12 = Wash_Dishes
0	0	7	22	16	0	0	188	0	0	42	0	21	12351	0	13 = Watch_TV
0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	14 = Work

Table B.22: Results for *hh123* activity recognition, with an accuracy of 94.679.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
5424	0	0	0	0	0	0	60	15	0	0	0	0	0	0	0 = Bathe
0	705	0	0	0	0	0	20	29	0	0	0	0	0	0	1 = Bed_Toilet_Transition
0	0	45768	0	4	2	0	252	0	0	0	2	2	4	0	2 = Cook
13	0	0	3419	0	0	0	259	533	2	12	7	4	0	0	3 = Dress
0	0	569	0	2476	1	0	201	0	0	0	0	263	27	0	4 = Eat
0	0	10	0	0	2340	11	586	1	0	2	0	12	3	2	5 = Enter_Home
0	0	17	0	12	11	1455	1485	13	14	0	8	24	4	19	6 = Leave_Home
18	49	1329	100	8	74	14	69594	727	55	267	26	680	88	89	7 = Other_Activity
0	1	12	18	1	0	5	430	30664	0	4	5	8	0	0	8 = Personal_Hygiene
0	0	95	0	32	5	0	1070	39	3263	0	13	157	83	0	9 = Relax
0	2	0	0	0	0	0	164	50	2	1939	2	0	3	0	10 = Sleep
2	10	1	2	0	0	6	225	880	0	8	1457	1	0	0	11 = Take_Medicine
0	0	0	0	1	0	0	328	2	11	0	0	23597	10	0	12 = Wash_Dishes
0	0	126	0	22	10	2	1470	25	49	0	0	271	5114	12	13 = Watch_TV
0	0	5	0	8	18	0	942	6	0	0	0	23	13	4301	14 = Work

Table B.23: Results for *hh125* activity recognition, with an accuracy of 93.189.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
751	0	0	0	0	0	0	21	0	0	0	0	0	0	0	0 = Bathe
0	171	0	0	0	0	0	24	0	0	117	0	0	0	0	1 = Bed_Toilet_Transition
0	0	13472	1	0	1	0	271	2	2	0	1	0	13	0	2 = Cook
45	0	13	1783	0	4	8	215	108	0	14	0	0	8	0	3 = Dress
0	0	186	0	1117	0	0	274	0	0	0	4	18	4	0	4 = Eat
0	0	7	0	0	2286	12	366	0	0	7	0	0	0	0	5 = Enter_Home
0	0	0	1	0	0	2225	641	2	11	0	22	4	10	19	6 = Leave_Home
4	11	626	112	33	110	45	48777	184	28	331	29	151	155	28	7 = Other_Activity
0	0	6	15	4	2	4	621	11440	12	3	0	3	11	3	8 = Personal_Hygiene
0	0	23	5	8	4	28	856	21	4143	28	1	32	17	12	9 = Relax
0	0	0	39	0	0	0	292	0	0	811	4	0	0	0	10 = Sleep
0	0	47	0	1	0	13	226	1	0	0	1099	0	15	0	11 = Take_Medicine
0	0	0	0	0	0	0	163	2	1	0	0	5126	22	1	12 = Wash_Dishes
0	0	56	0	17	8	0	1544	9	29	0	38	41	7707	0	13 = Watch_TV
0	0	0	0	26	5	0	1070	44	21	7	3	2	51	2004	14 = Work

Table B.24: Results for *hh126* activity recognition, with an accuracy of 91.289.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	←guessed
940	0	0	0	0	0	2	0	9	0	0	0	0	0	0 = Bathe
0	0	0	0	0	0	0	7	0	0	7	0	0	0	1 = Bed_Toilet_Transition
0	0	1234	0	23	0	0	12	0	0	9	0	23	0	2 = Cook
2	0	0	656	0	0	32	30	43	0	0	0	13	0	3 = Dress
0	0	18	0	1986	0	38	1	0	13	15	0	31	0	4 = Eat
0	0	0	1	0	0	40	0	0	7	0	0	9	0	5 = Enter_Home
0	0	0	3	0	0	16047	2	0	6	9	0	2	0	6 = Leave_Home
39	0	24	37	21	0	143	6598	83	100	40	9	174	9	7 = Other_Activity
16	0	22	22	0	0	40	46	1110	2	13	1	14	0	8 = Personal_Hygiene
14	0	0	0	6	0	38	2	0	3968	23	14	12	0	9 = Relax
0	0	0	0	0	0	0	0	0	0	22831	0	10	0	10 = Sleep
0	0	0	0	31	0	6	11	0	4	0	394	2	0	11 = Wash_Dishes
0	0	0	22	14	0	83	23	8	21	3	2	4740	0	12 = Watch_TV
0	0	8	0	0	0	7	18	0	0	0	0	2	650	13 = Work

Table B.25: Results for *hh127* activity recognition, with an accuracy of 97.379.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	←guessed
389	0	0	1	0	0	0	16	39	0	0	0	0	0	0	0 = Bathe
0	347	0	0	0	0	0	477	0	0	122	0	0	0	0	1 = Bed_Toilet_Transition
0	0	33164	0	20	1	0	383	74	0	0	3	0	3	0	2 = Cook
1	0	0	7819	0	0	1	1123	310	8	10	0	0	2	0	3 = Dress
0	0	210	0	2460	0	0	826	23	7	0	12	87	0	17	4 = Eat
0	0	0	0	0	2042	7	1124	10	0	3	0	13	0	14	5 = Enter_Home
0	0	0	20	6	0	677	1618	624	22	0	3	5	9	53	6 = Leave_Home
0	4	1709	327	68	98	10	192240	792	38	856	21	723	182	126	7 = Other_Activity
0	4	125	143	0	13	1	3942	90650	17	1	26	10	13	25	8 = Personal_Hygiene
0	0	3	11	3	0	0	1873	223	4209	22	18	44	2	16	9 = Relax
0	4	0	0	0	0	0	501	131	0	5008	0	0	0	0	10 = Sleep
1	0	20	12	13	2	0	880	192	0	0	4486	111	16	28	11 = Take_Medicine
0	0	0	0	1	3	0	529	45	2	0	4	18436	3	0	12 = Wash_Dishes
0	0	0	0	0	1	0	1113	137	0	0	18	24	18148	6	13 = Watch_TV
0	0	9	10	2	5	1	2025	197	32	0	30	32	16	10115	14 = Work

Table B.26: Results for *hh128* activity recognition, with an accuracy of 93.99.

0	1	2	3	4	5	6	7	8	9	10	11	←guessed
1492	0	0	0	0	0	0	0	93	0	0	0	0 = Bed_Toilet_Transition
0	2177	8	0	104	96	39	4	14	0	2	0	1 = Cook
0	0	1827	0	42	1	2	10	10	0	0	0	2 = Eat
0	0	0	47	34	19	1	9	0	0	1	0	3 = Enter_Home
0	0	0	0	29113	9	10	2	31	0	9	0	4 = Leave_Home
0	70	19	14	173	8319	121	27	24	2	11	0	5 = Other_Activity
0	33	0	0	145	28	6192	8	43	29	8	0	6 = Personal_Hygiene
0	6	0	0	150	17	3	7672	50	0	0	0	7 = Relax
27	0	0	0	13	0	3	4	100611	0	0	0	8 = Sleep
0	6	34	0	49	8	16	10	0	223	0	0	9 = Wash_Dishes
0	2	0	0	16	6	9	0	0	0	1282	0	10 = Watch_TV
0	0	0	0	0	4	0	0	0	0	0	0	11 = Work

Table B.27: Results for *hh129* activity recognition, with an accuracy of 98.918.

C ACTIVITY RECOGNITION RESULTS PER ACTIVITY

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.99136	0.00042362	0.99958	0.99546	0.99293	0.99136
Bed_Toilet_Transition	0.97109	0.00031539	0.99968	0.98528	0.91347	0.97109
Cook	0.99308	0.0024337	0.99757	0.99532	0.97695	0.99308
Dress	0.98422	0.0024956	0.9975	0.99084	0.93569	0.98422
Eat	0.92749	0.0012167	0.99878	0.96247	0.93435	0.92749
Enter_Home	0.95892	0.0016995	0.9983	0.97841	0.91928	0.95892
Leave_Home	0.73233	7.2801e-05	0.99993	0.85573	0.9926	0.73233
Other_Activity	0.92913	0.013398	0.9866	0.95743	0.94632	0.92913
Personal_Hygiene	0.98301	0.0068217	0.99318	0.98808	0.96166	0.98301
Relax	0.89482	0.0021773	0.99782	0.94492	0.96958	0.89482
Sleep	0.99159	0.0014637	0.99854	0.99506	0.95933	0.99159
Take_Medicine	0.96018	0.0015267	0.99847	0.97914	0.93819	0.96018
Wash_Dishes	0.98802	0.002413	0.99759	0.99279	0.9565	0.98802
Watch_TV	0.9824	0.0075432	0.99246	0.98742	0.97457	0.9824
Work	0.8913	2.2465e-05	0.99998	0.94408	0.96094	0.8913

Table C.1: *hh101* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.95887	0.00016865	0.99983	0.97914	0.98518	0.95887
Bed_Toilet_Transition	0.93801	0.0016773	0.99832	0.9677	0.77501	0.93801
Cook	0.99215	0.0070243	0.99298	0.99256	0.95851	0.99215
Dress	0.98109	0.0017659	0.99823	0.98962	0.93654	0.98109
Eat	0.89619	0.00076746	0.99923	0.94631	0.96017	0.89619
Enter_Home	0.97419	0.0024404	0.99756	0.98581	0.92961	0.97419
Leave_Home	0.26609	7.1402e-06	0.99999	0.51583	0.99592	0.26609
Other_Activity	0.93035	0.023852	0.97615	0.95297	0.93122	0.93035
Personal_Hygiene	0.98369	0.0066271	0.99337	0.98852	0.97753	0.98369
Relax	0.84376	0.0025767	0.99742	0.91738	0.94537	0.84376
Sleep	0.85378	0.0010556	0.99894	0.92351	0.93946	0.85378
Take_Medicine	0.70619	8.904e-05	0.99991	0.84031	0.97048	0.70619
Wash_Dishes	0.98961	0.0024148	0.99759	0.99359	0.95261	0.98961
Watch_TV	0.61526	9.9748e-05	0.9999	0.78435	0.96438	0.61526
Work	0.99059	0.0066317	0.99337	0.99198	0.96304	0.99059

Table C.2: *hh102* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.97993	0.00030889	0.99969	0.98976	0.98599	0.97993
Bed_Toilet_Transition	0.99631	0.0017023	0.9983	0.9973	0.94568	0.99631
Cook	0.99714	0.006995	0.993	0.99507	0.98109	0.99714
Dress	0.76614	0.00052488	0.99948	0.87506	0.96377	0.76614
Eat	0.75835	0.00069961	0.9993	0.87053	0.96027	0.75835
Enter_Home	0.78689	0.00062758	0.99937	0.88679	0.91647	0.78689
Leave_Home	0.49557	0.00011647	0.99988	0.70392	0.97174	0.49557
Other_Activity	0.95703	0.057095	0.94291	0.94994	0.8633	0.95703
Personal_Hygiene	0.99369	0.0068401	0.99316	0.99343	0.96909	0.99369
Relax	0.45483	0.00033551	0.99966	0.6743	0.9649	0.45483
Sleep	0.99233	0.0053598	0.99464	0.99349	0.90666	0.99233
Take_Medicine	0.6402	0.00022532	0.99977	0.80004	0.97561	0.6402
Wash_Dishes	0.98996	0.002779	0.99722	0.99359	0.94607	0.98996
Watch_TV	0.51845	0.00095718	0.99904	0.71969	0.93295	0.51845
Work	0.62643	0.0001722	0.99983	0.79141	0.98627	0.62643

Table C.3: *hh103* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.94239	8.4641e-05	0.99992	0.97073	0.98544	0.94239
Bed_Toilet_Transition	0.91509	0.0068557	0.99314	0.95332	0.82234	0.91509
Cook	0.99385	0.0044242	0.99558	0.99471	0.97871	0.99385
Dress	0.93804	0.00065032	0.99935	0.96821	0.95389	0.93804
Eat	0.98247	0.0026186	0.99738	0.9899	0.96956	0.98247
Enter_Home	0.80095	0.00078176	0.99922	0.89461	0.90485	0.80095
Leave_Home	0.12964	8.7392e-06	0.99999	0.36006	0.98404	0.12964
Other_Activity	0.87411	0.019489	0.98051	0.92578	0.9185	0.87411
Personal_Hygiene	0.92927	0.0058926	0.99411	0.96114	0.94793	0.92927
Relax	0.88162	0.00082111	0.99918	0.93856	0.96477	0.88162
Sleep	0.95564	0.018091	0.98191	0.96869	0.86429	0.95564
Take_Medicine	0.75124	0.00051832	0.99948	0.86652	0.93174	0.75124
Wash_Dishes	0.97988	0.0013194	0.99868	0.98924	0.96975	0.97988
Watch_TV	0.92579	0.006543	0.99346	0.95903	0.93137	0.92579
Work	0.98355	0.004403	0.9956	0.98955	0.965	0.98355

Table C.4: *hh104* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.98878	0.00020797	0.99979	0.99427	0.98947	0.98878
Bed_Toilet_Transition	0.98214	0.0031639	0.99684	0.98946	0.74891	0.98214
Cook	0.99553	0.010967	0.98903	0.99228	0.95985	0.99553
Dress	0.95609	0.0020784	0.99792	0.97678	0.93809	0.95609
Eat	0.74992	0.00032672	0.99967	0.86584	0.98109	0.74992
Enter_Home	0.94748	0.0030255	0.99697	0.97191	0.92146	0.94748
Leave_Home	0.38519	4.8241e-05	0.99995	0.62062	0.99099	0.38519
Other_Activity	0.94778	0.048774	0.95123	0.9495	0.90749	0.94778
Personal_Hygiene	0.96593	0.0074282	0.99257	0.97916	0.95093	0.96593
Relax	0.78098	0.0014376	0.99856	0.8831	0.96225	0.78098
Sleep	0.64628	0.0011046	0.9989	0.80347	0.84489	0.64628
Take_Medicine	0.87297	0.00053766	0.99946	0.93408	0.95786	0.87297
Wash_Dishes	0.99001	0.0044981	0.9955	0.99275	0.95011	0.99001
Watch_TV	0.70172	0.0007604	0.99924	0.83737	0.93973	0.70172
Work	0.85554	0.0012681	0.99873	0.92437	0.9538	0.85554

Table C.5: *hh105* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.33217	1.4786e-05	0.99999	0.57634	0.98446	0.33217
Bed_Toilet_Transition	0.012632	0	1	0.11239	1	0.012632
Cook	0.98619	0.0051629	0.99484	0.9905	0.96871	0.98619
Dress	0.9335	0.0020181	0.99798	0.9652	0.88337	0.9335
Eat	0.97264	0.003102	0.9969	0.9847	0.95628	0.97264
Enter_Home	0.93634	0.0015203	0.99848	0.96691	0.95042	0.93634
Leave_Home	0.097233	0	1	0.31182	1	0.097233
Other_Activity	0.95895	0.076338	0.92366	0.94114	0.88857	0.95895
Personal_Hygiene	0.43979	0.0012627	0.99874	0.66275	0.93923	0.43979
Relax	0.85037	0.0014417	0.99856	0.92149	0.95958	0.85037
Sleep	0.91544	0.0066563	0.99334	0.9536	0.61188	0.91544
Take_Medicine	0.53091	0.00033225	0.99967	0.72851	0.93489	0.53091
Wash_Dishes	0.96707	0.0021698	0.99783	0.98233	0.96469	0.96707
Watch_TV	0.96419	0.0019841	0.99802	0.98096	0.96941	0.96419
Work	0.97374	0.0042713	0.99573	0.98467	0.97123	0.97374

Table C.6: *hh106* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.88536	0.00037361	0.99963	0.94076	0.97	0.88536
Bed_Toilet_Transition	0	0	1	0	-	0
Cook	0.97142	0.023342	0.97666	0.97403	0.91506	0.97142
Dress	0.90731	0.0020416	0.99796	0.95155	0.93692	0.90731
Eat	0.9084	0.0061542	0.99385	0.95016	0.94108	0.9084
Enter_Home	0.83478	0.0014523	0.99855	0.913	0.91626	0.83478
Leave_Home	0.3682	7.4409e-05	0.99993	0.60677	0.97893	0.3682
Other_Activity	0.85355	0.0011693	0.99883	0.92334	0.90101	0.85355
Personal_Hygiene	0.91076	0.0096516	0.99035	0.94972	0.93477	0.91076
Relax	0.91459	0.0042788	0.99572	0.95429	0.93224	0.91459
Sleep	0.9766	0.0071538	0.99285	0.98469	0.92109	0.9766
Take_Medicine	0.80583	0.00033094	0.99967	0.89753	0.92531	0.80583
Wash_Dishes	0.97435	0.01251	0.98749	0.9809	0.91066	0.97435
Watch_TV	0.92401	0.012575	0.98743	0.95519	0.93018	0.92401
Work	0.92879	0.0040212	0.99598	0.9618	0.93667	0.92879

Table C.7: *hh107* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.11902	0	1	0.34499	1	0.11902
Bed_Toilet_Transition	0.12657	3.4763e-06	1	0.35577	0.99342	0.12657
Cook	0.97434	0.0055358	0.99446	0.98435	0.96071	0.97434
Dress	0.89824	0.0017686	0.99823	0.94692	0.90916	0.89824
Eat	0.9073	0.0014675	0.99853	0.95183	0.96018	0.9073
Enter_Home	0.82093	0.00035086	0.99965	0.90589	0.96927	0.82093
Leave_Home	0.12878	6.9613e-06	0.99999	0.35886	0.9901	0.12878
Other_Activity	0.96299	0.12686	0.87314	0.91696	0.87337	0.96299
Personal_Hygiene	0.77261	0.0046673	0.99533	0.87693	0.94333	0.77261
Relax	0.73091	0.0023133	0.99769	0.85394	0.94616	0.73091
Sleep	0.95188	0.0084988	0.9915	0.97149	0.76659	0.95188
Take_Medicine	0.69316	0.00025138	0.99975	0.83246	0.95918	0.69316
Wash_Dishes	0.94862	0.0028624	0.99714	0.97257	0.96072	0.94862
Watch_TV	0.87399	0.00090403	0.9991	0.93445	0.96883	0.87399
Work	0.76398	0.001394	0.99861	0.87345	0.95685	0.76398

Table C.8: *hh108* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.98677	0.00012936	0.99987	0.9933	0.99005	0.98677
Bed_Toilet_Transition	0.94969	0.00046025	0.99954	0.9743	0.90276	0.94969
Cook	0.99081	0.00847	0.99153	0.99117	0.96273	0.99081
Dress	0.97941	0.0023951	0.9976	0.98846	0.9477	0.97941
Eat	0.88386	0.00099679	0.999	0.93967	0.96795	0.88386
Enter_Home	0.88242	0.00061623	0.99938	0.93908	0.96059	0.88242
Leave_Home	0.25209	7.0657e-05	0.99993	0.50207	0.96556	0.25209
Other_Activity	0.96462	0.057396	0.9426	0.95355	0.92348	0.96462
Personal_Hygiene	0.92203	0.0025119	0.99749	0.95902	0.96656	0.92203
Relax	0.79456	0.00067446	0.99933	0.89108	0.96617	0.79456
Sleep	0.84962	0.0024538	0.99755	0.92062	0.85976	0.84962
Take_Medicine	0.80831	0.00053835	0.99946	0.89882	0.96619	0.80831
Wash_Dishes	0.99239	0.0026635	0.99734	0.99486	0.96838	0.99239
Watch_TV	0.72512	0.00024192	0.99976	0.85143	0.95105	0.72512
Work	0.90777	0.0013874	0.99861	0.95211	0.97973	0.90777

Table C.9: *hh109* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.97044	0.00050884	0.99949	0.98486	0.96492	0.97044
Bed_Toilet_Transition	0.97212	0.0012428	0.99876	0.98535	0.85179	0.97212
Cook	0.94928	0.0032952	0.9967	0.9727	0.91474	0.94928
Dress	0.87337	0.00092956	0.99907	0.93411	0.94508	0.87337
Eat	0.88378	0.0010732	0.99893	0.93959	0.95115	0.88378
Enter_Home	0.81544	0.00033318	0.99967	0.90287	0.96071	0.81544
Leave_Home	0.25156	2.2743e-05	0.99998	0.50156	0.98638	0.25156
Other_Activity	0.96365	0.052305	0.94769	0.95564	0.93779	0.96365
Personal_Hygiene	0.93184	0.0055245	0.99448	0.96265	0.94474	0.93184
Relax	0.95264	0.0010143	0.99899	0.97554	0.98059	0.95264
Sleep	0.96029	0.0047213	0.99528	0.97763	0.91218	0.96029
Take_Medicine	0.79972	0.00049452	0.99951	0.89405	0.95545	0.79972
Wash_Dishes	0.85824	0.001017	0.99898	0.92594	0.9204	0.85824
Watch_TV	0.8682	0.0017648	0.99824	0.93095	0.94637	0.8682
Work	0.97411	0.0064045	0.9936	0.9838	0.97134	0.97411

Table C.10: *hh111* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.49343	6.4133e-06	0.99999	0.70244	0.99389	0.49343
Bed_Toilet_Transition	0.39869	4.7147e-05	0.99995	0.63141	0.97489	0.39869
Cook	0.92863	0.0014621	0.99854	0.96295	0.97016	0.92863
Dress	0.82183	0.00072431	0.99928	0.90622	0.96261	0.82183
Eat	0.90184	0.00090491	0.9991	0.94922	0.95666	0.90184
Enter_Home	0.88914	0.0002608	0.99974	0.94282	0.97247	0.88914
Leave_Home	0.36481	4.5037e-05	0.99995	0.60398	0.9773	0.36481
Other_Activity	0.96552	0.083636	0.91636	0.94062	0.90014	0.96552
Personal_Hygiene	0.75399	0.0012918	0.99871	0.86777	0.97608	0.75399
Relax	0.65021	0.00083988	0.99916	0.80602	0.96272	0.65021
Sleep	0.98785	0.017018	0.98298	0.98541	0.88255	0.98785
Take_Medicine	0.76841	8.7902e-05	0.99991	0.87655	0.97767	0.76841
Wash_Dishes	0.84782	0.00054476	0.99946	0.92052	0.97093	0.84782
Watch_TV	0.91029	0.0013404	0.99866	0.95345	0.95564	0.91029
Work	0.97523	0.0047973	0.9952	0.98517	0.97776	0.97523

Table C.11: *hh112* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.99338	0.00036051	0.99964	0.9965	0.99252	0.99338
Bed_Toilet_Transition	0.96705	0.00019597	0.9998	0.98329	0.96172	0.96705
Cook	0.99627	0.0054432	0.99456	0.99541	0.95065	0.99627
Dress	0.73012	0.0002816	0.99972	0.85435	0.96471	0.73012
Eat	0.69506	6.628e-05	0.99993	0.83367	0.98887	0.69506
Enter_Home	0.88777	0.0002381	0.99976	0.9421	0.96828	0.88777
Leave_Home	0.58395	4.6369e-05	0.99995	0.76415	0.99002	0.58395
Other_Activity	0.96548	0.025248	0.97475	0.9701	0.95113	0.96548
Personal_Hygiene	0.99125	0.009038	0.99096	0.99111	0.96791	0.99125
Relax	0.95503	0.0028405	0.99716	0.97587	0.95086	0.95503
Sleep	0.9806	0.00060136	0.9994	0.98995	0.97606	0.9806
Take_Medicine	0.40026	0.00013867	0.99986	0.63262	0.95793	0.40026
Wash_Dishes	0.97112	0.0015001	0.9985	0.98471	0.97868	0.97112
Watch_TV	0.84054	0.00013896	0.99986	0.91675	0.97645	0.84054
Work	0.96927	0.0032693	0.99673	0.9829	0.97244	0.96927

Table C.12: *hh113* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.97628	6.6838e-05	0.99993	0.98804	0.98862	0.97628
Bed_Toilet_Transition	0.86579	5.9227e-05	0.99994	0.93045	0.97626	0.86579
Cook	0.99541	0.0034757	0.99652	0.99597	0.98865	0.99541
Dress	0.91475	5.925e-05	0.99994	0.9564	0.98025	0.91475
Eat	0.87168	0.00018024	0.99982	0.93356	0.98817	0.87168
Enter_Home	0.99338	0.0023515	0.99765	0.99551	0.96501	0.99338
Leave_Home	0.16327	0	1	0.40406	1	0.16327
Other_Activity	0.97986	0.029513	0.97049	0.97516	0.94962	0.97986
Personal_Hygiene	0.91974	0.0012983	0.9987	0.95841	0.98085	0.91974
Relax	0.96306	0.0044782	0.99552	0.97916	0.96536	0.96306
Sleep	0.93247	0.0022456	0.99775	0.96456	0.94538	0.93247
Take_Medicine	0.97642	2.9623e-05	0.99997	0.98812	0.99043	0.97642
Wash_Dishes	0.99732	0.0010069	0.99899	0.99816	0.97987	0.99732
Watch_TV	0.71845	0	1	0.84761	1	0.71845
Work	0.85787	0.00056787	0.99943	0.92595	0.9835	0.85787

Table C.13: *hh114* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.84322	9.2416e-05	0.99991	0.91823	0.97802	0.84322
Bed_Toilet_Transition	0.95487	0.0062861	0.99371	0.9741	0.7192	0.95487
Cook	0.99414	0.0056729	0.99433	0.99423	0.96461	0.99414
Dress	0.98569	0.0067486	0.99325	0.98946	0.95635	0.98569
Eat	0.72364	2.9457e-05	0.99997	0.85066	0.97776	0.72364
Enter_Home	0.81706	0.0011561	0.99884	0.90339	0.8421	0.81706
Housekeeping	0.97716	0.0022181	0.99778	0.98742	0.9534	0.97716
Leave_Home	0.0033356	0	1	0.057754	1	0.0033356
Other_Activity	0.80583	0.0050761	0.99492	0.8954	0.96	0.80583
Personal_Hygiene	0.97314	0.0068366	0.99316	0.9831	0.94857	0.97314
Relax	0.74108	0.001677	0.99832	0.86014	0.90636	0.74108
Sleep	0.98018	0.0053574	0.99464	0.98738	0.9297	0.98018
Take_Medicine	0.88814	0.0016235	0.99838	0.94165	0.95681	0.88814
Wash_Dishes	0.97641	0.0016021	0.9984	0.98734	0.9665	0.97641
Watch_TV	0.94486	0.0037886	0.99621	0.9702	0.96017	0.94486
Work	0.94654	0.022059	0.97794	0.96211	0.88403	0.94654

Table C.14: *hh115* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.99692	0.00012341	0.99988	0.9984	0.99711	0.99692
Bed_Toilet_Transition	0.99318	0.0007579	0.99924	0.99621	0.9799	0.99318
Cook	0.99164	0.0030354	0.99696	0.9943	0.96415	0.99164
Dress	0.75112	0.00021467	0.99979	0.86658	0.94806	0.75112
Eat	0.51502	0.00011118	0.99989	0.71761	0.95784	0.51502
Enter_Home	0.57995	5.4193e-05	0.99995	0.76152	0.96965	0.57995
Leave_Home	0.12491	0	1	0.35342	1	0.12491
Other_Activity	0.98811	0.036882	0.96312	0.97553	0.96616	0.98811
Personal_Hygiene	0.99077	0.002765	0.99723	0.994	0.98995	0.99077
Relax	0.56146	0.00019414	0.99981	0.74923	0.94589	0.56146
Sleep	0.62581	0.00077548	0.99922	0.79077	0.86616	0.62581
Take_Medicine	0.24868	1.2902e-05	0.99999	0.49867	0.98258	0.24868
Wash_Dishes	0.99577	0.002768	0.99723	0.9965	0.96647	0.99577
Watch_TV	0.82202	7.7515e-05	0.99992	0.90662	0.97817	0.82202
Work	0.53245	4.3911e-05	0.99996	0.72968	0.97929	0.53245

Table C.15: *hh116* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.62249	5.1448e-06	0.99999	0.78898	0.99245	0.62249
Bed_Toilet_Transition	0.92468	0.0015257	0.99847	0.96087	0.79335	0.92468
Cook	0.97479	0.0025847	0.99742	0.98604	0.95646	0.97479
Dress	0.94322	0.0020578	0.99794	0.97019	0.92272	0.94322
Eat	0.85702	0.00055279	0.99945	0.9255	0.97149	0.85702
Enter_Home	0.80186	0.00059648	0.9994	0.8952	0.95524	0.80186
Leave_Home	0.42584	3.2587e-05	0.99997	0.65256	0.99476	0.42584
Other_Activity	0.98503	0.12819	0.87181	0.92669	0.9285	0.98503
Personal_Hygiene	0.9015	0.0015124	0.99849	0.94875	0.97812	0.9015
Relax	0.51524	0.0001406	0.99986	0.71775	0.97987	0.51524
Sleep	0.70253	0.0011663	0.99883	0.83768	0.88747	0.70253
Take_Medicine	0.86091	0.00047036	0.99953	0.92763	0.96269	0.86091
Wash_Dishes	0.96908	0.0018226	0.99818	0.98352	0.96531	0.96908
Watch_TV	0.79035	0.0030285	0.99697	0.88767	0.92345	0.79035
Work	0.79145	0.00079381	0.99921	0.88928	0.96737	0.79145

Table C.16: *hh117* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.79817	3.3431e-05	0.99997	0.89339	0.96667	0.79817
Bed_Toilet_Transition	0.97687	0.0017623	0.99824	0.98749	0.74678	0.97687
Cook	0.99415	0.0077851	0.99221	0.99318	0.9714	0.99415
Dress	0.98739	0.00060512	0.99939	0.99338	0.97681	0.98739
Eat	0.99474	0.0026683	0.99733	0.99603	0.96549	0.99474
Enter_Home	0.97115	0.001335	0.99867	0.98481	0.92298	0.97115
Housekeeping	0.99601	0.0014743	0.99853	0.99726	0.97193	0.99601
Leave_Home	0.50821	0.0002467	0.99975	0.7128	0.93931	0.50821
Other_Activity	0.75924	0.012553	0.98745	0.86586	0.89982	0.75924
Personal_Hygiene	0.93525	0.0043453	0.99565	0.96498	0.95039	0.93525
Relax	0.92448	0.0011593	0.99884	0.96094	0.95439	0.92448
Sleep	0.94298	0.0023384	0.99766	0.96993	0.85778	0.94298
Take_Medicine	0.22589	3.912e-05	0.99996	0.47527	0.96067	0.22589
Wash_Dishes	0.97895	0.0023842	0.99762	0.98824	0.95778	0.97895
Watch_TV	0.94684	0.0013743	0.99863	0.97239	0.9523	0.94684
Work	0.98867	0.026222	0.97378	0.98119	0.93613	0.98867

Table C.17: *hh118* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.89657	0.00051638	0.99948	0.94663	0.97044	0.89657
Bed_Toilet_Transition	0.98765	0.010883	0.98912	0.98838	0.79875	0.98765
Cook	0.98294	0.0058595	0.99414	0.98852	0.9615	0.98294
Dress	0.85662	0.0033201	0.99668	0.924	0.89562	0.85662
Eat	0.10864	0	1	0.3296	1	0.10864
Enter_Home	0.67758	0.00049039	0.99951	0.82295	0.93635	0.67758
Housekeeping	0.9909	0	1	0.99544	1	0.9909
Leave_Home	0.43454	0.00019601	0.9998	0.65913	0.95642	0.43454
Other_Activity	0.78723	0.014749	0.98525	0.88069	0.91175	0.78723
Personal_Hygiene	0.97724	0.016712	0.98329	0.98026	0.91901	0.97724
Relax	0.087912	0	1	0.2965	1	0.087912
Sleep	0	0	1	0	-	0
Take_Medicine	0.11379	6.5104e-05	0.99993	0.33732	0.91667	0.11379
Wash_Dishes	0.9854	0.0012829	0.99872	0.99203	0.97596	0.9854
Work	0.98866	0.044546	0.95545	0.97192	0.92219	0.98866

Table C.18: *hh119* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.98064	0.00010763	0.99989	0.99022	0.99589	0.98064
Bed_Toilet_Transition	0.97974	0.0021144	0.99789	0.98877	0.90033	0.97974
Cook	0.98075	0.0010174	0.99898	0.98982	0.97349	0.98075
Dress	0.96731	0.0020871	0.99791	0.98249	0.94957	0.96731
Eat	0.86495	0.00052512	0.99947	0.92978	0.94553	0.86495
Enter_Home	0.89292	0.00066927	0.99933	0.94463	0.9438	0.89292
Leave_Home	0.38883	2.7595e-05	0.99997	0.62356	0.99216	0.38883
Other_Activity	0.95565	0.041417	0.95858	0.95712	0.94278	0.95565
Personal_Hygiene	0.9699	0.0027311	0.99727	0.98349	0.97887	0.9699
Relax	0.93579	0.00080615	0.99919	0.96697	0.96277	0.93579
Sleep	0.92207	0.0067688	0.99323	0.95699	0.89443	0.92207
Take_Medicine	0.77261	0.00063258	0.99937	0.87871	0.96144	0.77261
Wash_Dishes	0.96225	0.00045484	0.99955	0.98072	0.97468	0.96225
Watch_TV	0.97413	0.0044259	0.99557	0.98479	0.96495	0.97413
Work	0.97426	0.0045536	0.99545	0.9848	0.95272	0.97426

Table C.19: *hh120* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.99581	0.00043822	0.99956	0.99768	0.97446	0.99581
Bed_Toilet_Transition	0.90631	0.0011769	0.99882	0.95144	0.90742	0.90631
Cook	0.99324	0.0043755	0.99562	0.99443	0.96984	0.99324
Dress	0.61762	0.00013964	0.99986	0.78583	0.97256	0.61762
Eat	0.7715	0.00065604	0.99934	0.87806	0.94567	0.7715
Enter_Home	0.40899	3.8619e-05	0.99996	0.63951	0.97449	0.40899
Leave_Home	0.26842	7.73e-06	0.99999	0.51809	0.99351	0.26842
Other_Activity	0.96274	0.059292	0.94071	0.95166	0.92505	0.96274
Personal_Hygiene	0.92651	0.0076343	0.99237	0.95887	0.94194	0.92651
Relax	0.88497	0.00033734	0.99966	0.94057	0.9807	0.88497
Sleep	0.87427	0.0039348	0.99607	0.93318	0.89174	0.87427
Take_Medicine	0.59212	9.3025e-05	0.99991	0.76946	0.97887	0.59212
Wash_Dishes	0.99065	0.0032372	0.99676	0.9937	0.97254	0.99065
Watch_TV	0.91662	0.0024469	0.99755	0.95623	0.94081	0.91662
Work	0.89276	0.0030298	0.99697	0.94343	0.94963	0.89276

Table C.20: *hh122* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.99379	0.00026528	0.99973	0.99676	0.97859	0.99379
Bed_Toilet_Transition	0.99708	0.00016015	0.99984	0.99846	0.97575	0.99708
Cook	0.99454	0.0068294	0.99317	0.99386	0.96713	0.99454
Dress	0.98541	0.0037125	0.99629	0.99083	0.93869	0.98541
Eat	0.96632	0.0020897	0.99791	0.98199	0.93955	0.96632
Enter_Home	0.91842	0.00030276	0.9997	0.9582	0.97034	0.91842
Leave_Home	0.57346	0	1	0.75727	1	0.57346
Other_Activity	0.91584	0.030514	0.96949	0.94228	0.92969	0.91584
Personal_Hygiene	0.98801	0.0027178	0.99728	0.99264	0.96085	0.98801
Relax	0.84241	0.00076036	0.99924	0.91748	0.96907	0.84241
Sleep	0.8503	0.0045264	0.99547	0.92003	0.902	0.8503
Take_Medicine	0.71797	0.00054947	0.99945	0.8471	0.94063	0.71797
Wash_Dishes	0.99281	0.0047639	0.99524	0.99402	0.96929	0.99281
Watch_TV	0.9766	0.0088652	0.99113	0.98384	0.93668	0.9766
Work	0	0	1	0	-	0

Table C.21: *hh123* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.98636	0.00015659	0.99984	0.99308	0.99395	0.98636
Bed_Toilet_Transition	0.93501	0.00028772	0.99971	0.96682	0.91917	0.93501
Cook	0.99422	0.012714	0.98729	0.99075	0.95485	0.99422
Dress	0.80466	0.00056605	0.99943	0.89677	0.96609	0.80466
Eat	0.70003	0.00041371	0.99959	0.8365	0.96568	0.70003
Enter_Home	0.78868	0.00056733	0.99943	0.88782	0.95083	0.78868
Leave_Home	0.47518	0.00017825	0.99982	0.68927	0.97455	0.47518
Other_Activity	0.9518	0.052345	0.94765	0.94973	0.90281	0.9518
Personal_Hygiene	0.98446	0.012534	0.98747	0.98596	0.92966	0.98446
Relax	0.68594	0.00062888	0.99937	0.82795	0.96084	0.68594
Sleep	0.89685	0.0013686	0.99863	0.94638	0.86873	0.89685
Take_Medicine	0.56211	0.00029487	0.99971	0.74963	0.95855	0.56211
Wash_Dishes	0.9853	0.0075145	0.99249	0.98889	0.9423	0.9853
Watch_TV	0.72018	0.0011236	0.99888	0.84816	0.95607	0.72018
Work	0.80907	0.00057839	0.99942	0.89922	0.97242	0.80907

Table C.22: *hh125* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.9728	0.00043766	0.99956	0.98609	0.93875	0.9728
Bed_Toilet_Transition	0.54808	9.7847e-05	0.9999	0.74029	0.93956	0.54808
Cook	0.97886	0.0097404	0.99026	0.98454	0.93322	0.97886
Dress	0.81119	0.0015651	0.99843	0.89996	0.91155	0.81119
Eat	0.69682	0.00080087	0.9992	0.83442	0.9262	0.69682
Enter_Home	0.85362	0.0012176	0.99878	0.92335	0.94463	0.85362
Leave_Home	0.75809	0.0010018	0.999	0.87025	0.95289	0.75809
Other_Activity	0.96352	0.10601	0.89399	0.9281	0.88107	0.96352
Personal_Hygiene	0.94358	0.0037075	0.99629	0.96958	0.96842	0.94358
Relax	0.80012	0.00096696	0.99903	0.89406	0.97551	0.80012
Sleep	0.70768	0.0045436	0.99546	0.83932	0.61533	0.70768
Take_Medicine	0.78388	0.0009162	0.99908	0.88496	0.91507	0.78388
Wash_Dishes	0.96444	0.0023367	0.99766	0.98091	0.95332	0.96444
Watch_TV	0.81564	0.0029627	0.99704	0.90179	0.96181	0.81564
Work	0.61986	0.00057535	0.99942	0.78708	0.96952	0.61986

Table C.23: *hh126* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.98843	0.001148	0.99885	0.99363	0.92977	0.98843
Bed_Toilet_Transition	0	0	1	0	-	0
Cook	0.9485	0.0011708	0.99883	0.97334	0.94487	0.9485
Dress	0.84536	0.0013704	0.99863	0.9188	0.88529	0.84536
Eat	0.94481	0.0015651	0.99843	0.97125	0.95435	0.94481
Enter_Home	0	0	1	0	-	0
Leave_Home	0.99863	0.0091802	0.99082	0.99472	0.97396	0.99863
Other_Activity	0.90669	0.0027376	0.99726	0.9509	0.97748	0.90669
Personal_Hygiene	0.86314	0.0023247	0.99768	0.92797	0.88587	0.86314
Relax	0.97326	0.0026055	0.99739	0.98526	0.96287	0.97326
Sleep	0.99956	0.0029781	0.99702	0.99829	0.99481	0.99956
Wash_Dishes	0.87946	0.00041699	0.99958	0.9376	0.9381	0.87946
Watch_TV	0.9642	0.0050446	0.99496	0.97946	0.94197	0.9642
Work	0.94891	0.00014489	0.99986	0.97405	0.98634	0.94891

Table C.24: *hh127* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe	0.87416	4.8228e-06	1	0.93496	0.99488	0.87416
Bed_Toilet_Transition	0.36681	2.8972e-05	0.99997	0.60564	0.96657	0.36681
Cook	0.98562	0.0054418	0.99456	0.99008	0.94109	0.98562
Dress	0.84311	0.0012911	0.99871	0.91762	0.93719	0.84311
Eat	0.67545	0.00027461	0.99973	0.82175	0.95608	0.67545
Enter_Home	0.63554	0.0002986	0.9997	0.79709	0.94319	0.63554
Leave_Home	0.22292	4.8531e-05	0.99995	0.47213	0.97131	0.22292
Other_Activity	0.97488	0.075385	0.92462	0.94941	0.92126	0.97488
Personal_Hygiene	0.95451	0.0087359	0.99126	0.97271	0.97007	0.95451
Relax	0.6552	0.00030828	0.99969	0.80932	0.97093	0.6552
Sleep	0.88731	0.0024762	0.99752	0.94081	0.83162	0.88731
Take_Medicine	0.77868	0.00032977	0.99967	0.88229	0.97079	0.77868
Wash_Dishes	0.96914	0.0026482	0.99735	0.98315	0.94616	0.96914
Watch_TV	0.9332	0.00062169	0.99938	0.96572	0.98663	0.9332
Work	0.81089	0.00070778	0.99929	0.90017	0.9726	0.81089

Table C.25: *hh128* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bed_Toilet_Transition	0.94132	0.0001697	0.99983	0.97014	0.98223	0.94132
Cook	0.89075	0.00073934	0.99926	0.94345	0.949	0.89075
Eat	0.96564	0.00038413	0.99962	0.98248	0.96769	0.96564
Enter_Home	0.42342	8.7183e-05	0.99991	0.65068	0.77049	0.42342
Leave_Home	0.99791	0.0055201	0.99448	0.99619	0.97567	0.99791
Other_Activity	0.94749	0.0012376	0.99876	0.97279	0.9779	0.94749
Personal_Hygiene	0.95467	0.0013229	0.99868	0.97643	0.96811	0.95467
Relax	0.97139	0.00048431	0.99952	0.98535	0.99045	0.97139
Sleep	0.99953	0.0044141	0.99559	0.99756	0.99737	0.99953
Wash_Dishes	0.64451	0.00019333	0.99981	0.80274	0.87795	0.64451
Watch_TV	0.9749	0.00019451	0.99981	0.98728	0.97639	0.9749
Work	0	0	1	0	-	0

Table C.26: *hh129* activity recognition accuracies.

.

D ACTIVITY FORECASTING RESULTS

Here we present a selection of results from the forecasting experiments.

0	1	←guessed
63586	0	0 = False
208	675	1 = True

Table D.1: Results for *navan_2014* Bathe forecasting, with an accuracy of 99.677.

0	1	←guessed
63591	0	0 = False
832	46	1 = True

Table D.2: Results for *navan_2014* Bed_Toilet_Transition forecasting, with an accuracy of 98.709.

0	1	←guessed
63900	6	0 = False
77	486	1 = True

Table D.3: Results for *navan_2014* Cook forecasting, with an accuracy of 99.871.

0	1	←guessed
63417	4	0 = False
570	478	1 = True

Table D.4: Results for *navan_2014* Drink forecasting, with an accuracy of 99.11.

0	1	←guessed
63870	0	0 = False
246	353	1 = True

Table D.5: Results for *navan_2014* Eat forecasting, with an accuracy of 99.618.

0	1	←guessed
63860	0	0 = False
475	134	1 = True

Table D.6: Results for *navan_2014* Enter_Home forecasting, with an accuracy of 99.263.

0	1	←guessed
63816	0	0 = False
436	217	1 = True

Table D.7: Results for *navan_2014* Leave_Home forecasting, with an accuracy of 99.324.

0	1	←guessed
32286	952	0 = False
828	30403	1 = True

Table D.8: Results for *navan_2014* Other_Activity forecasting, with an accuracy of 97.239.

0	1	←guessed
64292	0	0 = False
17	160	1 = True

Table D.9: Results for *navan_2014* Relax forecasting, with an accuracy of 99.974.

0	1	←guessed
39713	38	0 = False
224	24494	1 = True

Table D.10: Results for *navan_2014* Sleep forecasting, with an accuracy of 99.594.

0	1	←guessed
56326	14	0 = False
2959	5170	1 = True

Table D.11: Results for *navan_2014* Toilet forecasting, with an accuracy of 95.388.

0	1	←guessed
64457	0	0 = False
12	0	1 = True

Table D.12: Results for *navan_2014* Wash_Dishes forecasting, with an accuracy of 99.981.

0	1	←guessed
46396	360	0 = False
404	17309	1 = True

Table D.13: Results for *navan_2014* Watch_TV forecasting, with an accuracy of 98.815.

0	1	←guessed
54517	109	0 = False
937	8906	1 = True

Table D.14: Results for *navan_2014* Work_On_Computer forecasting, with an accuracy of 98.378.

0	1	←guessed
227368	1	0 = False
1426	1600	1 = True

Table D.15: Results for *navan_2012* Bathe forecasting, with an accuracy of 99.381.

0	1	←guessed
229253	0	0 = False
1106	36	1 = True

Table D.16: Results for *navan_2012* Bed_Toilet_Transition forecasting, with an accuracy of 99.52.

0	1	←guessed
229868	0	0 = False
324	203	1 = True

Table D.17: Results for *navan_2012* Cook forecasting, with an accuracy of 99.859.

0	1	←guessed
226301	13	0 = False
2895	1186	1 = True

Table D.18: Results for *navan_2012* Drink forecasting, with an accuracy of 98.738.

0	1	←guessed
230223	0	0 = False
73	99	1 = True

Table D.19: Results for *navan_2012* Eat forecasting, with an accuracy of 99.968.

0	1	←guessed
226849	0	0 = False
3224	322	1 = True

Table D.20: Results for *navan_2012* Enter_Home forecasting, with an accuracy of 98.601.

0	1	←guessed
230239	0	0 = False
42	114	1 = True

Table D.21: Results for *navan_2012* Entertain_Guests forecasting, with an accuracy of 99.982.

0	1	←guessed
160550	489	0 = False
1661	67695	1 = True

Table D.22: Results for *navan_2012* Leave_Home forecasting, with an accuracy of 99.067.

0	1	←guessed
166710	1827	0 = False
12201	49657	1 = True

Table D.23: Results for *navan_2012* Other_Activity forecasting, with an accuracy of 93.911.

0	1	←guessed
230088	0	0 = False
104	203	1 = True

Table D.24: Results for *navan_2012* Relax forecasting, with an accuracy of 99.955.

0	1	←guessed
155804	444	0 = False
974	73173	1 = True

Table D.25: Results for *navan_2012* Sleep forecasting, with an accuracy of 99.385.

0	1	←guessed
211789	13	0 = False
13229	5364	1 = True

Table D.26: Results for *navan_2012* Toilet forecasting, with an accuracy of 94.252.

0	1	←guessed
174380	1179	0 = False
2199	52637	1 = True

Table D.27: Results for *navan_2012* Watch_TV forecasting, with an accuracy of 98.534.

0	1	←guessed
229259	0	0 = False
800	336	1 = True

Table D.28: Results for *navan_2012* Water_Plants forecasting, with an accuracy of 99.653.

0	1	←guessed
209279	226	0 = False
4486	16404	1 = True

Table D.29: Results for *navan_2012* Work_On_Computer forecasting, with an accuracy of 97.955.

.

E ACTIVITY FORECASTING RESULTS PER ACTIVITY

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	0.99989	0.13463	0.86537	0.9302	0.99762	0.99989
Bathe-True	0.86537	0.00010684	0.99989	0.9302	0.99308	0.86537
Bed_Toilet_Transition-False	1	0.84291	0.15709	0.39634	0.99743	1
Bed_Toilet_Transition-True	0.15709	0	1	0.39634	1	0.15709
Cook-False	0.99998	0.34221	0.65779	0.81103	0.99116	0.99998
Cook-True	0.65779	2.3936e-05	0.99998	0.81103	0.99861	0.65779
Dress-False	0.99961	0.36181	0.63819	0.79871	0.99168	0.99961
Dress-True	0.63819	0.00039384	0.99961	0.79871	0.97408	0.63819
Eat-False	0.99959	0.14308	0.85692	0.92551	0.99567	0.99959
Eat-True	0.85692	0.00040864	0.99959	0.92551	0.98456	0.85692
Enter_Home-False	0.99999	0.49123	0.50877	0.71328	0.98676	0.99999
Enter_Home-True	0.50877	1.1983e-05	0.99999	0.71328	0.99914	0.50877
Leave_Home-False	0.99968	0.25573	0.74427	0.86258	0.98772	0.99968
Leave_Home-True	0.74427	0.000318	0.99968	0.86258	0.99128	0.74427
Other_Activity-False	0.9975	0.14348	0.85652	0.92433	0.9587	0.9975
Other_Activity-True	0.85652	0.002501	0.9975	0.92433	0.99034	0.85652
Personal_Hygiene-False	0.9996	0.44003	0.55997	0.74816	0.95991	0.9996
Personal_Hygiene-True	0.55997	0.00039589	0.9996	0.74816	0.9926	0.55997
Sleep-False	0.99628	0.50738	0.49262	0.70056	0.91882	0.99628
Sleep-True	0.49262	0.0037231	0.99628	0.70056	0.95826	0.49262
Take_Medicine-False	0.99994	0.53387	0.46613	0.68271	0.99148	0.99994
Take_Medicine-True	0.46613	5.9259e-05	0.99994	0.68271	0.99216	0.46613
Wash_Dishes-False	0.99999	0.47464	0.52536	0.72481	0.9914	0.99999
Wash_Dishes-True	0.52536	1.1877e-05	0.99999	0.72481	0.99876	0.52536
Watch_TV-False	0.99394	0.029113	0.97089	0.98234	0.98806	0.99394
Watch_TV-True	0.97089	0.0060633	0.99394	0.98234	0.98509	0.97089
Work-False	1	0.25	0.75	0.86603	0.99985	1
Work-True	0.75	0	1	0.86603	1	0.75

Table E.1: *hh101* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	1	0.27194	0.72806	0.85326	0.99787	1
Bathe-True	0.72806	0	1	0.85326	1	0.72806
Bed_Toilet_Transition-False	1	0.93939	0.060606	0.24618	0.99305	1
Bed_Toilet_Transition-True	0.060606	0	1	0.24618	1	0.060606
Cook-False	0.99987	0.27613	0.72387	0.85075	0.98648	0.99987
Cook-True	0.72387	0.00012938	0.99987	0.85075	0.99641	0.72387
Dress-False	0.99982	0.33195	0.66805	0.81727	0.99364	0.99982
Dress-True	0.66805	0.00018275	0.99982	0.81727	0.986	0.66805
Eat-False	0.99974	0.10941	0.89059	0.94359	0.99611	0.99974
Eat-True	0.89059	0.00025532	0.99974	0.94359	0.99202	0.89059
Enter_Home-False	0.99989	0.47538	0.52462	0.72427	0.98927	0.99989
Enter_Home-True	0.52462	0.00011462	0.99989	0.72427	0.99051	0.52462
Leave_Home-False	0.99626	0.071272	0.92873	0.9619	0.98406	0.99626
Leave_Home-True	0.92873	0.0037381	0.99626	0.9619	0.98253	0.92873
Other_Activity-False	0.99067	0.18983	0.81017	0.89589	0.95263	0.99067
Other_Activity-True	0.81017	0.0093293	0.99067	0.89589	0.95751	0.81017
Personal_Hygiene-False	0.99885	0.21452	0.78548	0.88577	0.97562	0.99885
Personal_Hygiene-True	0.78548	0.0011509	0.99885	0.88577	0.98756	0.78548
Relax-False	0.99754	0.025333	0.97467	0.98604	0.99357	0.99754
Relax-True	0.97467	0.0024607	0.99754	0.98604	0.99019	0.97467
Sleep-False	0.98003	0.26136	0.73864	0.85081	0.93231	0.98003
Sleep-True	0.73864	0.019974	0.98003	0.85081	0.90965	0.73864
Take_Medicine-False	1	0.59278	0.40722	0.63814	0.99594	1
Take_Medicine-True	0.40722	0	1	0.63814	1	0.40722
Wash_Dishes-False	0.99998	0.32437	0.67563	0.82196	0.99342	0.99998
Wash_Dishes-True	0.67563	2.287e-05	0.99998	0.82196	0.99834	0.67563
Watch_TV-False	0.99997	0.037255	0.96275	0.98118	0.99913	0.99997
Watch_TV-True	0.96275	3.4405e-05	0.99997	0.98118	0.99847	0.96275
Work-False	0.9998	0.15129	0.84871	0.92116	0.99005	0.9998
Work-True	0.84871	0.00020316	0.9998	0.92116	0.99641	0.84871

Table E.2: *hh102* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	1	0.29844	0.70156	0.83759	0.99768	1
Bathe-True	0.70156	0	1	0.83759	1	0.70156
Bed_Toilet_Transition-False	1	0.8458	0.1542	0.39268	0.98204	1
Bed_Toilet_Transition-True	0.1542	0	1	0.39268	1	0.1542
Cook-False	0.9997	0.28903	0.71097	0.84306	0.98582	0.9997
Cook-True	0.71097	0.00030456	0.9997	0.84306	0.99146	0.71097
Dress-False	1	0.59355	0.40645	0.63753	0.99082	1
Dress-True	0.40645	0	1	0.63753	1	0.40645
Eat-False	0.99746	0.06074	0.93926	0.96792	0.99496	0.99746
Eat-True	0.93926	0.0025403	0.99746	0.96792	0.96852	0.93926
Enter_Home-False	1	0.95122	0.04878	0.22086	0.98065	1
Enter_Home-True	0.04878	0	1	0.22086	1	0.04878
Leave_Home-False	0.99999	0.71697	0.28303	0.532	0.98515	0.99999
Leave_Home-True	0.28303	1.2343e-05	0.99999	0.532	0.99793	0.28303
Other_Activity-False	0.99321	0.11884	0.88116	0.93551	0.93764	0.99321
Other_Activity-True	0.88116	0.0067895	0.99321	0.93551	0.98633	0.88116
Personal_Hygiene-False	0.99885	0.46326	0.53674	0.73221	0.95396	0.99885
Personal_Hygiene-True	0.53674	0.0011478	0.99885	0.73221	0.97986	0.53674
Relax-False	0.99955	0.0915	0.9085	0.95294	0.9905	0.99955
Relax-True	0.9085	0.00045408	0.99955	0.95294	0.99525	0.9085
Sleep-False	0.99716	0.40928	0.59072	0.76749	0.91573	0.99716
Sleep-True	0.59072	0.0028414	0.99716	0.76749	0.979	0.59072
Take_Medicine-False	0.99996	0.65004	0.34996	0.59156	0.99018	0.99996
Take_Medicine-True	0.34996	3.6819e-05	0.99996	0.59156	0.99315	0.34996
Wash_Dishes-False	0.99959	0.34185	0.65815	0.8111	0.99278	0.99959
Wash_Dishes-True	0.65815	0.00040741	0.99959	0.8111	0.97172	0.65815
Watch_TV-False	0.99864	0.14271	0.85729	0.92527	0.98277	0.99864
Watch_TV-True	0.85729	0.0013571	0.99864	0.92527	0.98726	0.85729
Work-False	0.99956	0.12808	0.87192	0.93356	0.99134	0.99956
Work-True	0.87192	0.00043902	0.99956	0.93356	0.99267	0.87192

Table E.3: *hh103* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	1	0.4749	0.5251	0.72464	0.99719	1
Bathe-True	0.5251	0	1	0.72464	1	0.5251
Bed_Toilet_Transition-False	0.99987	0.54052	0.45948	0.67781	0.96416	0.99987
Bed_Toilet_Transition-True	0.45948	0.00013384	0.99987	0.67781	0.99578	0.45948
Cook-False	0.99971	0.17805	0.82195	0.90648	0.98754	0.99971
Cook-True	0.82195	0.0002926	0.99971	0.90648	0.995	0.82195
Dress-False	0.99999	0.42455	0.57545	0.75858	0.99464	0.99999
Dress-True	0.57545	1.1529e-05	0.99999	0.75858	0.99842	0.57545
Eat-False	0.99986	0.26463	0.73537	0.85748	0.98808	0.99986
Eat-True	0.73537	0.00014284	0.99986	0.85748	0.99576	0.73537
Enter_Home-False	0.99995	0.51191	0.48809	0.69862	0.98687	0.99995
Enter_Home-True	0.48809	4.6722e-05	0.99995	0.69862	0.99633	0.48809
Leave_Home-False	0.99832	0.13041	0.86959	0.93173	0.98897	0.99832
Leave_Home-True	0.86959	0.0016805	0.99832	0.93173	0.97786	0.86959
Other_Activity-False	0.99444	0.24203	0.75797	0.86819	0.89807	0.99444
Other_Activity-True	0.75797	0.0055591	0.99444	0.86819	0.98452	0.75797
Personal_Hygiene-False	0.99953	0.40896	0.59104	0.76861	0.95656	0.99953
Personal_Hygiene-True	0.59104	0.00046799	0.99953	0.76861	0.99292	0.59104
Relax-False	0.99953	0.10896	0.89104	0.94372	0.99272	0.99953
Relax-True	0.89104	0.00047386	0.99953	0.94372	0.99215	0.89104
Sleep-False	0.8966	0.047566	0.95243	0.92409	0.97501	0.8966
Sleep-True	0.95243	0.1034	0.8966	0.92409	0.81651	0.95243
Take_Medicine-False	0.99999	0.56815	0.43185	0.65715	0.99092	0.99999
Take_Medicine-True	0.43185	1.1568e-05	0.99999	0.65715	0.99834	0.43185
Wash_Dishes-False	0.99987	0.2942	0.7058	0.84007	0.99254	0.99987
Wash_Dishes-True	0.7058	0.00012843	0.99987	0.84007	0.99293	0.7058
Watch_TV-False	0.99553	0.093587	0.90641	0.94993	0.9808	0.99553
Watch_TV-True	0.90641	0.0044707	0.99553	0.94993	0.97687	0.90641
Work-False	0.99848	0.11768	0.88232	0.93861	0.98249	0.99848
Work-True	0.88232	0.0015204	0.99848	0.93861	0.98874	0.88232

Table E.4: *hh104* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	1	0.29004	0.70996	0.84259	0.99847	1
Bathe-True	0.70996	0	1	0.84259	1	0.70996
Bed_Toilet_Transition-False	1	0.85878	0.14122	0.37579	0.99403	1
Bed_Toilet_Transition-True	0.14122	0	1	0.37579	1	0.14122
Cook-False	0.99981	0.25756	0.74244	0.86157	0.98928	0.99981
Cook-True	0.74244	0.00019021	0.99981	0.86157	0.99394	0.74244
Dress-False	0.99999	0.38415	0.61585	0.78476	0.99493	0.99999
Dress-True	0.61585	1.156e-05	0.99999	0.78476	0.99859	0.61585
Eat-False	0.99992	0.18528	0.81472	0.90258	0.99558	0.99992
Eat-True	0.81472	8.1773e-05	0.99992	0.90258	0.99583	0.81472
Enter_Home-False	1	0.64748	0.35252	0.59373	0.98238	1
Enter_Home-True	0.35252	0	1	0.59373	1	0.35252
Leave_Home-False	0.9991	0.070213	0.92979	0.96382	0.99345	0.9991
Leave_Home-True	0.92979	0.0008985	0.9991	0.96382	0.98981	0.92979
Other_Activity-False	0.9916	0.068171	0.93183	0.96125	0.96794	0.9916
Other_Activity-True	0.93183	0.0084021	0.9916	0.96125	0.98163	0.93183
Personal_Hygiene-False	0.99973	0.32912	0.67088	0.81896	0.9815	0.99973
Personal_Hygiene-True	0.67088	0.00026535	0.99973	0.81896	0.99314	0.67088
Relax-False	0.99928	0.048631	0.95137	0.97503	0.99567	0.99928
Relax-True	0.95137	0.00072088	0.99928	0.97503	0.9916	0.95137
Sleep-False	0.99931	0.46292	0.53708	0.73261	0.95604	0.99931
Sleep-True	0.53708	0.00068975	0.99931	0.73261	0.98723	0.53708
Take_Medicine-False	1	0.56563	0.43438	0.65907	0.99586	1
Take_Medicine-True	0.43438	0	1	0.65907	1	0.43438
Wash_Dishes-False	0.99998	0.25216	0.74784	0.86477	0.99527	0.99998
Wash_Dishes-True	0.74784	2.3247e-05	0.99998	0.86477	0.99835	0.74784
Watch_TV-False	0.99837	0.052524	0.94748	0.97259	0.99818	0.99837
Watch_TV-True	0.94748	0.0016289	0.99837	0.97259	0.95267	0.94748
Work-False	0.99988	0.11283	0.88717	0.94184	0.99588	0.99988
Work-True	0.88717	0.00011827	0.99988	0.94184	0.99638	0.88717

Table E.5: *hh105* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	0.99998	0.20833	0.79167	0.88975	0.99722	0.99998
Bathe-True	0.79167	2.2721e-05	0.99998	0.88975	0.99786	0.79167
Bed_Toilet_Transition-False	1	0.98989	0.010114	0.10057	0.99122	1
Bed_Toilet_Transition-True	0.010114	0	1	0.10057	1	0.010114
Cook-False	0.99991	0.29199	0.70801	0.8414	0.99	0.99991
Cook-True	0.70801	9.2788e-05	0.99991	0.8414	0.99623	0.70801
Dress-False	0.99991	0.34572	0.65428	0.80884	0.99473	0.99991
Dress-True	0.65428	9.1058e-05	0.99991	0.80884	0.99099	0.65428
Eat-False	0.99951	0.08791	0.91209	0.9548	0.99444	0.99951
Eat-True	0.91209	0.00048888	0.99951	0.9548	0.99164	0.91209
Enter_Home-False	1	0.66766	0.33234	0.57649	0.97966	1
Enter_Home-True	0.33234	0	1	0.57649	1	0.33234
Leave_Home-False	0.99865	0.072985	0.92701	0.96217	0.99019	0.99865
Leave_Home-True	0.92701	0.0013494	0.99865	0.96217	0.98937	0.92701
Other_Activity-False	0.98368	0.078934	0.92107	0.95186	0.93344	0.98368
Other_Activity-True	0.92107	0.016325	0.98368	0.95186	0.98045	0.92107
Personal_Hygiene-False	0.99905	0.24655	0.75345	0.8676	0.96789	0.99905
Personal_Hygiene-True	0.75345	0.00095382	0.99905	0.8676	0.99067	0.75345
Relax-False	0.9998	0.20249	0.79751	0.89294	0.98956	0.9998
Relax-True	0.79751	0.0002005	0.9998	0.89294	0.9952	0.79751
Sleep-False	0.98375	0.53952	0.46048	0.67305	0.91253	0.98375
Sleep-True	0.46048	0.016252	0.98375	0.67305	0.83199	0.46048
Take_Medicine-False	1	0.78561	0.21439	0.46302	0.98734	1
Take_Medicine-True	0.21439	0	1	0.46302	1	0.21439
Wash_Dishes-False	0.99962	0.21271	0.78729	0.88713	0.99538	0.99962
Wash_Dishes-True	0.78729	0.00037802	0.99962	0.88713	0.97846	0.78729
Watch_TV-False	0.99975	0.044838	0.95516	0.9772	0.99811	0.99975
Watch_TV-True	0.95516	0.00024536	0.99975	0.9772	0.99395	0.95516
Work-False	0.99938	0.085809	0.91419	0.95584	0.99248	0.99938
Work-True	0.91419	0.00062222	0.99938	0.95584	0.99235	0.91419

Table E.6: *hh106* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	0.99982	0.20084	0.79916	0.89388	0.99451	0.99982
Bathe-True	0.79916	0.00018412	0.99982	0.89388	0.99169	0.79916
Bed_Toilet_Transition-False	1	0.98083	0.019172	0.13846	0.94953	1
Bed_Toilet_Transition-True	0.019172	0	1	0.13846	1	0.019172
Cook-False	0.99933	0.050103	0.9499	0.9743	0.99459	0.99933
Cook-True	0.9499	0.00067042	0.99933	0.9743	0.99354	0.9499
Dress-False	0.99953	0.23105	0.76895	0.87669	0.98969	0.99953
Dress-True	0.76895	0.00046819	0.99953	0.87669	0.98668	0.76895
Eat-False	0.99935	0.059429	0.94057	0.96952	0.99572	0.99935
Eat-True	0.94057	0.00064854	0.99935	0.96952	0.99056	0.94057
Enter_Home-False	0.99995	0.34259	0.65741	0.81079	0.98376	0.99995
Enter_Home-True	0.65741	4.6957e-05	0.99995	0.81079	0.99852	0.65741
Leave_Home-False	0.99934	0.10596	0.89404	0.94523	0.97185	0.99934
Leave_Home-True	0.89404	0.00065592	0.99934	0.94523	0.99732	0.89404
Other_Activity-False	0.99917	0.095732	0.90427	0.95053	0.98777	0.99917
Other_Activity-True	0.90427	0.00083468	0.99917	0.95053	0.99291	0.90427
Personal_Hygiene-False	0.99767	0.098871	0.90113	0.94817	0.98218	0.99767
Personal_Hygiene-True	0.90113	0.002332	0.99767	0.94817	0.98606	0.90113
Relax-False	0.99941	0.086435	0.91357	0.95552	0.99118	0.99941
Relax-True	0.91357	0.0005929	0.99941	0.95552	0.99373	0.91357
Sleep-False	0.89061	0.0048191	0.99518	0.94145	0.99815	0.89061
Sleep-True	0.99518	0.10939	0.89061	0.94145	0.75755	0.99518
Take_Medicine-False	0.99986	0.23282	0.76718	0.87583	0.99724	0.99986
Take_Medicine-True	0.76718	0.00013599	0.99986	0.87583	0.98529	0.76718
Wash_Dishes-False	0.99944	0.082137	0.91786	0.95779	0.99354	0.99944
Wash_Dishes-True	0.91786	0.00055597	0.99944	0.95779	0.99241	0.91786
Watch_TV-False	0.99748	0.025209	0.97479	0.98607	0.9944	0.99748
Watch_TV-True	0.97479	0.0025197	0.99748	0.98607	0.98853	0.97479
Work-False	0.99954	0.11108	0.88892	0.94261	0.99117	0.99954
Work-True	0.88892	0.0004597	0.99954	0.94261	0.99359	0.88892

Table E.7: *hh107* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	0.99993	0.14826	0.85174	0.92286	0.99668	0.99993
Bathe-True	0.85174	6.9858e-05	0.99993	0.92286	0.99636	0.85174
Bed_Toilet_Transition-False	1	0.95856	0.041436	0.20356	0.98814	1
Bed_Toilet_Transition-True	0.041436	0	1	0.20356	1	0.041436
Cook-False	0.99981	0.26342	0.73658	0.85816	0.98947	0.99981
Cook-True	0.73658	0.00018955	0.99981	0.85816	0.99367	0.73658
Dress-False	0.99994	0.38783	0.61217	0.78239	0.99079	0.99994
Dress-True	0.61217	5.83e-05	0.99994	0.78239	0.99604	0.61217
Eat-False	0.99952	0.11131	0.88869	0.94248	0.99478	0.99952
Eat-True	0.88869	0.00047696	0.99952	0.94248	0.98874	0.88869
Enter_Home-False	0.99996	0.72957	0.27043	0.52002	0.97516	0.99996
Enter_Home-True	0.27043	3.5354e-05	0.99996	0.52002	0.99627	0.27043
Leave_Home-False	0.99896	0.10093	0.89907	0.9477	0.986	0.99896
Leave_Home-True	0.89907	0.001039	0.99896	0.9477	0.99184	0.89907
Other_Activity-False	0.94977	0.060057	0.93994	0.94484	0.9464	0.94977
Other_Activity-True	0.93994	0.050233	0.94977	0.94484	0.9437	0.93994
Personal_Hygiene-False	0.99834	0.21031	0.78969	0.8879	0.9659	0.99834
Personal_Hygiene-True	0.78969	0.0016619	0.99834	0.8879	0.9876	0.78969
Relax-False	0.99908	0.1388	0.8612	0.92758	0.98096	0.99908
Relax-True	0.8612	0.00092143	0.99908	0.92758	0.9924	0.8612
Sleep-False	0.90268	0.013164	0.98684	0.94382	0.99518	0.90268
Sleep-True	0.98684	0.097316	0.90268	0.94382	0.77088	0.98684
Take_Medicine-False	1	0.47586	0.52414	0.72398	0.99458	1
Take_Medicine-True	0.52414	0	1	0.72398	1	0.52414
Wash_Dishes-False	0.99991	0.22527	0.77473	0.88015	0.99212	0.99991
Wash_Dishes-True	0.77473	9.4311e-05	0.99991	0.88015	0.99656	0.77473
Watch_TV-False	0.99958	0.085444	0.91456	0.95612	0.99557	0.99958
Watch_TV-True	0.91456	0.00041928	0.99958	0.95612	0.99126	0.91456
Work-False	0.99968	0.082217	0.91778	0.95786	0.99347	0.99968
Work-True	0.91778	0.00031971	0.99968	0.95786	0.99566	0.91778

Table E.8: *hh108* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	0.99998	0.15429	0.84571	0.91961	0.99878	0.99998
Bathe-True	0.84571	2.2953e-05	0.99998	0.91961	0.99657	0.84571
Bed_Toilet_Transition-False	1	0.96846	0.03154	0.17759	0.98811	1
Bed_Toilet_Transition-True	0.03154	0	1	0.17759	1	0.03154
Cook-False	0.99933	0.14653	0.85347	0.92353	0.98995	0.99933
Cook-True	0.85347	0.00066962	0.99933	0.92353	0.98879	0.85347
Dress-False	0.99968	0.28883	0.71117	0.84317	0.9917	0.99968
Dress-True	0.71117	0.00031635	0.99968	0.84317	0.98487	0.71117
Eat-False	0.9993	0.065563	0.93444	0.96632	0.99624	0.9993
Eat-True	0.93444	0.0006984	0.9993	0.96632	0.98717	0.93444
Enter_Home-False	0.99994	0.49163	0.50837	0.71298	0.97461	0.99994
Enter_Home-True	0.50837	5.9951e-05	0.99994	0.71298	0.99778	0.50837
Leave_Home-False	0.99998	0.4095	0.5905	0.76843	0.97709	0.99998
Leave_Home-True	0.5905	2.4078e-05	0.99998	0.76843	0.99929	0.5905
Other_Activity-False	0.98006	0.04543	0.95457	0.96723	0.949	0.98006
Other_Activity-True	0.95457	0.01994	0.98006	0.96723	0.9823	0.95457
Personal_Hygiene-False	0.99916	0.27037	0.72962	0.85382	0.9736	0.99916
Personal_Hygiene-True	0.72962	0.00083938	0.99916	0.85382	0.98865	0.72962
Relax-False	0.99971	0.07497	0.92503	0.96164	0.99124	0.99971
Relax-True	0.92503	0.00029275	0.99971	0.96164	0.99732	0.92503
Sleep-False	0.99579	0.66012	0.33988	0.58176	0.88525	0.99579
Sleep-True	0.33988	0.0042065	0.99579	0.58176	0.94047	0.33988
Take_Medicine-False	0.99998	0.62417	0.37583	0.61304	0.98157	0.99998
Take_Medicine-True	0.37583	2.3459e-05	0.99998	0.61304	0.99793	0.37583
Wash_Dishes-False	0.99975	0.097867	0.90213	0.94969	0.99661	0.99975
Wash_Dishes-True	0.90213	0.00024744	0.99975	0.94969	0.99218	0.90213
Watch_TV-False	0.99992	0.083272	0.91673	0.95742	0.99733	0.99992
Watch_TV-True	0.91673	8.2273e-05	0.99992	0.95742	0.99722	0.91673
Work-False	0.99973	0.18764	0.81236	0.90119	0.98332	0.99973
Work-True	0.81236	0.00027315	0.99973	0.90119	0.99629	0.81236

Table E.9: *hh109* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	1	0.24264	0.75736	0.87027	0.99764	1
Bathe-True	0.75736	0	1	0.87027	1	0.75736
Bed_Toilet_Transition-False	1	0.82164	0.17836	0.42233	0.99359	1
Bed_Toilet_Transition-True	0.17836	0	1	0.42233	1	0.17836
Cook-False	0.99992	0.33333	0.66667	0.81646	0.99252	0.99992
Cook-True	0.66667	8.1525e-05	0.99992	0.81646	0.99462	0.66667
Dress-False	0.99998	0.4	0.6	0.77459	0.99249	0.99998
Dress-True	0.6	2.3209e-05	0.99998	0.77459	0.99796	0.6
Eat-False	0.99992	0.1757	0.8243	0.90787	0.99513	0.99992
Eat-True	0.8243	8.1943e-05	0.99992	0.90787	0.99644	0.8243
Enter_Home-False	0.99998	0.7251	0.2749	0.52431	0.98508	0.99998
Enter_Home-True	0.2749	2.3254e-05	0.99998	0.52431	0.99597	0.2749
Leave_Home-False	0.99998	0.59768	0.40232	0.63428	0.98636	0.99998
Leave_Home-True	0.40232	2.3305e-05	0.99998	0.63428	0.9975	0.40232
Other_Activity-False	0.98925	0.066761	0.93324	0.96084	0.93109	0.98925
Other_Activity-True	0.93324	0.010745	0.98925	0.96084	0.98961	0.93324
Personal_Hygiene-False	0.9996	0.44556	0.55444	0.74445	0.97186	0.9996
Personal_Hygiene-True	0.55444	0.00040025	0.9996	0.74445	0.98901	0.55444
Relax-False	0.99981	0.071545	0.92846	0.96347	0.99632	0.99981
Relax-True	0.92846	0.00019162	0.99981	0.96347	0.99601	0.92846
Sleep-False	0.99646	0.45074	0.54926	0.73981	0.92853	0.99646
Sleep-True	0.54926	0.003545	0.99646	0.73981	0.96346	0.54926
Take_Medicine-False	1	0.58537	0.41463	0.64392	0.99341	1
Take_Medicine-True	0.41463	0	1	0.64392	1	0.41463
Wash_Dishes-False	1	0.58705	0.41295	0.64261	0.99232	1
Wash_Dishes-True	0.41295	0	1	0.64261	1	0.41295
Watch_TV-False	0.99889	0.083655	0.91634	0.95673	0.99478	0.99889
Watch_TV-True	0.91634	0.0011134	0.99889	0.95673	0.98097	0.91634
Work-False	0.99809	0.053783	0.94622	0.97181	0.98898	0.99809
Work-True	0.94622	0.0019103	0.99809	0.97181	0.99033	0.94622

Table E.10: *hh111* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	1	0.34916	0.65084	0.80675	0.99758	1
Bathe-True	0.65084	0	1	0.80675	1	0.65084
Bed_Toilet_Transition-False	1	0.98666	0.013341	0.1155	0.98906	1
Bed_Toilet_Transition-True	0.013341	0	1	0.1155	1	0.013341
Cook-False	0.99983	0.27137	0.72863	0.85353	0.98966	0.99983
Cook-True	0.72863	0.00016694	0.99983	0.85353	0.99409	0.72863
Dress-False	0.99999	0.58721	0.41279	0.64248	0.99019	0.99999
Dress-True	0.41279	1.3077e-05	0.99999	0.64248	0.99813	0.41279
Eat-False	0.99997	0.17901	0.82099	0.90607	0.99582	0.99997
Eat-True	0.82099	2.6324e-05	0.99997	0.90607	0.99863	0.82099
Enter_Home-False	0.99997	0.76233	0.23767	0.4875	0.98473	0.99997
Enter_Home-True	0.23767	2.6244e-05	0.99997	0.4875	0.9946	0.23767
Leave_Home-False	0.99982	0.23066	0.76934	0.87704	0.98764	0.99982
Leave_Home-True	0.76934	0.00018303	0.99982	0.87704	0.99563	0.76934
Other_Activity-False	0.98864	0.08306	0.91694	0.95211	0.935	0.98864
Other_Activity-True	0.91694	0.011363	0.98864	0.95211	0.98524	0.91694
Personal_Hygiene-False	0.99942	0.3537	0.6463	0.8037	0.97279	0.99942
Personal_Hygiene-True	0.6463	0.00057588	0.99942	0.8037	0.98885	0.6463
Relax-False	0.99936	0.14068	0.85932	0.9267	0.98553	0.99936
Relax-True	0.85932	0.00063909	0.99936	0.9267	0.99292	0.85932
Sleep-False	0.85292	0.010904	0.9891	0.91849	0.99628	0.85292
Sleep-True	0.9891	0.14708	0.85292	0.91849	0.66238	0.9891
Take_Medicine-False	1	0.54171	0.45829	0.67697	0.99669	1
Take_Medicine-True	0.45829	0	1	0.67697	1	0.45829
Wash_Dishes-False	0.99997	0.39878	0.60122	0.77537	0.99234	0.99997
Wash_Dishes-True	0.60122	2.6218e-05	0.99997	0.77537	0.99775	0.60122
Watch_TV-False	0.99965	0.14142	0.85858	0.92643	0.99456	0.99965
Watch_TV-True	0.85858	0.00034728	0.99965	0.92643	0.98964	0.85858
Work-False	0.9989	0.093029	0.90697	0.95183	0.98846	0.9989
Work-True	0.90697	0.0010999	0.9989	0.95183	0.99042	0.90697

Table E.11: *hh112* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	0.99992	0.049659	0.95034	0.97481	0.99845	0.99992
Bathe-True	0.95034	8.4358e-05	0.99992	0.97481	0.99717	0.95034
Bed_Toilet_Transition-False	0.99999	0.57871	0.42129	0.64906	0.99752	0.99999
Bed_Toilet_Transition-True	0.42129	1.0953e-05	0.99999	0.64906	0.99398	0.42129
Cook-False	0.99908	0.11894	0.88106	0.93822	0.99623	0.99908
Cook-True	0.88106	0.00091711	0.99908	0.93822	0.96829	0.88106
Dress-False	0.99948	0.24846	0.75154	0.86669	0.99206	0.99948
Dress-True	0.75154	0.00051784	0.99948	0.86669	0.97905	0.75154
Eat-False	0.99948	0.04037	0.95963	0.97935	0.99909	0.99948
Eat-True	0.95963	0.0005158	0.99948	0.97935	0.97675	0.95963
Enter_Home-False	0.99999	0.76424	0.23576	0.48555	0.98074	0.99999
Enter_Home-True	0.23576	1.2585e-05	0.99999	0.48555	0.99793	0.23576
Leave_Home-False	0.9999	0.51225	0.48775	0.69835	0.98664	0.9999
Leave_Home-True	0.48775	0.00010495	0.9999	0.69835	0.99193	0.48775
Other_Activity-False	0.95644	0.047668	0.95233	0.95438	0.96039	0.95644
Other_Activity-True	0.95233	0.043558	0.95644	0.95438	0.94762	0.95233
Personal_Hygiene-False	0.99751	0.21867	0.78133	0.88282	0.96926	0.99751
Personal_Hygiene-True	0.78133	0.0024921	0.99751	0.88282	0.97843	0.78133
Relax-False	0.99874	0.12957	0.87043	0.93238	0.99099	0.99874
Relax-True	0.87043	0.0012648	0.99874	0.93238	0.97969	0.87043
Sleep-False	0.98934	0.61421	0.38579	0.6178	0.87906	0.98934
Sleep-True	0.38579	0.010664	0.98934	0.6178	0.8891	0.38579
Take_Medicine-False	0.99866	0.34389	0.65611	0.80946	0.99542	0.99866
Take_Medicine-True	0.65611	0.0013442	0.99866	0.80946	0.86695	0.65611
Wash_Dishes-False	0.99967	0.20847	0.79153	0.88953	0.99149	0.99967
Wash_Dishes-True	0.79153	0.00033497	0.99967	0.88953	0.98982	0.79153
Watch_TV-False	0.99993	0.13188	0.86812	0.9317	0.99795	0.99993
Watch_TV-True	0.86812	7.3379e-05	0.99993	0.9317	0.9946	0.86812
Work-False	0.9989	0.14319	0.85681	0.92513	0.98782	0.9989
Work-True	0.85681	0.0010971	0.9989	0.92513	0.98534	0.85681

Table E.12: *hh113* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	1	0.36364	0.63636	0.79772	0.99863	1
Bathe-True	0.63636	0	1	0.79772	1	0.63636
Bed_Toilet_Transition-False	1	0.80702	0.19298	0.4393	0.9979	1
Bed_Toilet_Transition-True	0.19298	0	1	0.4393	1	0.19298
Cook-False	0.99995	0.22894	0.77106	0.87808	0.98767	0.99995
Cook-True	0.77106	4.8109e-05	0.99995	0.87808	0.99886	0.77106
Dress-False	1	0.42308	0.57692	0.75955	0.99849	1
Dress-True	0.57692	0	1	0.75955	1	0.57692
Eat-False	0.99995	0.091058	0.90894	0.95336	0.9974	0.99995
Eat-True	0.90894	4.6926e-05	0.99995	0.95336	0.9982	0.90894
Enter_Home-False	1	0.25565	0.74435	0.86276	0.99316	1
Enter_Home-True	0.74435	0	1	0.86276	1	0.74435
Leave_Home-False	0.99688	0.043426	0.95657	0.97652	0.9944	0.99688
Leave_Home-True	0.95657	0.003117	0.99688	0.97652	0.97542	0.95657
Other_Activity-False	0.99627	0.12983	0.87017	0.93109	0.96976	0.99627
Other_Activity-True	0.87017	0.0037316	0.99627	0.93109	0.9824	0.87017
Personal_Hygiene-False	0.99971	0.32759	0.67241	0.81989	0.97731	0.99971
Personal_Hygiene-True	0.67241	0.00029312	0.99971	0.81989	0.99388	0.67241
Relax-False	0.99161	0.01887	0.98113	0.98636	0.99389	0.99161
Relax-True	0.98113	0.0083902	0.99161	0.98636	0.97421	0.98113
Sleep-False	0.99374	0.16622	0.83378	0.91025	0.94736	0.99374
Sleep-True	0.83378	0.0062599	0.99374	0.91025	0.9779	0.83378
Take_Medicine-False	1	0.71429	0.28571	0.53452	0.99943	1
Take_Medicine-True	0.28571	0	1	0.53452	1	0.28571
Wash_Dishes-False	0.99998	0.145	0.855	0.92465	0.99799	0.99998
Wash_Dishes-True	0.855	2.3127e-05	0.99998	0.92465	0.99805	0.855
Watch_TV-False	1	0.023904	0.9761	0.98798	0.99986	1
Watch_TV-True	0.9761	0	1	0.98798	1	0.9761
Work-False	0.99889	0.035984	0.96402	0.9813	0.99603	0.99889
Work-True	0.96402	0.0011146	0.99889	0.9813	0.98965	0.96402

Table E.13: *hh114* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	1	0.31949	0.68051	0.82493	0.99712	1
Bathe-True	0.68051	4.521e-06	1	0.82493	0.99927	0.68051
Bed_Toilet_Transition-False	1	0.98057	0.019433	0.1394	0.98202	1
Bed_Toilet_Transition-True	0.019433	2.2821e-06	1	0.1394	0.99375	0.019433
Cook-False	0.99978	0.35888	0.64112	0.80061	0.98373	0.99978
Cook-True	0.64112	0.00022263	0.99978	0.80061	0.99252	0.64112
Dress-False	0.99969	0.38151	0.61849	0.78632	0.96984	0.99969
Dress-True	0.61849	0.00031012	0.99969	0.78632	0.99388	0.61849
Eat-False	0.99995	0.1734	0.8266	0.90915	0.99827	0.99995
Eat-True	0.8266	4.7517e-05	0.99995	0.90915	0.9943	0.8266
Enter_Home-False	0.99995	0.82105	0.17895	0.42301	0.96999	0.99995
Enter_Home-True	0.17895	4.6493e-05	0.99995	0.42301	0.99315	0.17895
Housekeeping-False	0.99997	0.29646	0.70354	0.83876	0.99524	0.99997
Housekeeping-True	0.70354	3.4146e-05	0.99997	0.83876	0.997	0.70354
Leave_Home-False	0.98797	0.092615	0.90739	0.94682	0.97099	0.98797
Leave_Home-True	0.90739	0.012033	0.98797	0.94682	0.96006	0.90739
Other_Activity-False	0.97615	0.24508	0.75492	0.85844	0.85926	0.97615
Other_Activity-True	0.75492	0.023854	0.97615	0.85844	0.9538	0.75492
Personal_Hygiene-False	0.99841	0.37468	0.62532	0.79014	0.95071	0.99841
Personal_Hygiene-True	0.62532	0.0015936	0.99841	0.79014	0.98189	0.62532
Relax-False	0.99952	0.47185	0.52815	0.72657	0.97625	0.99952
Relax-True	0.52815	0.00047586	0.99952	0.72657	0.98282	0.52815
Sleep-False	0.86944	0.0058919	0.99411	0.92968	0.99762	0.86944
Sleep-True	0.99411	0.13056	0.86944	0.92968	0.72798	0.99411
Take_Medicine-False	0.99991	0.58865	0.41135	0.64134	0.97609	0.99991
Take_Medicine-True	0.41135	9.334e-05	0.99991	0.64134	0.99458	0.41135
Wash_Dishes-False	0.99994	0.41539	0.58461	0.76458	0.99102	0.99994
Wash_Dishes-True	0.58461	5.7228e-05	0.99994	0.76458	0.99553	0.58461
Watch_TV-False	0.99624	0.077811	0.92219	0.9585	0.98634	0.99624
Watch_TV-True	0.92219	0.0037609	0.99624	0.9585	0.97751	0.92219
Work-False	0.99721	0.22062	0.77938	0.88159	0.95866	0.99721
Work-True	0.77938	0.002792	0.99721	0.88159	0.98195	0.77938

Table E.14: *hh115* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	0.99997	0.15566	0.84434	0.91886	0.99773	0.99997
Bathe-True	0.84434	3.4434e-05	0.99997	0.91886	0.99721	0.84434
Bed_Toilet_Transition-False	0.99965	0.4137	0.5863	0.76557	0.99163	0.99965
Bed_Toilet_Transition-True	0.5863	0.00034631	0.99965	0.76557	0.97186	0.5863
Cook-False	0.99988	0.28976	0.71024	0.84271	0.98979	0.99988
Cook-True	0.71024	0.00011716	0.99988	0.84271	0.99539	0.71024
Dress-False	0.99999	0.57556	0.42444	0.65149	0.99298	0.99999
Dress-True	0.42444	1.1452e-05	0.99999	0.65149	0.99781	0.42444
Eat-False	0.99932	0.075906	0.92409	0.96097	0.99605	0.99932
Eat-True	0.92409	0.00067851	0.99932	0.96097	0.98613	0.92409
Enter_Home-False	1	0.89358	0.10642	0.32622	0.98201	1
Enter_Home-True	0.10642	0	1	0.32622	1	0.10642
Leave_Home-False	0.99994	0.5352	0.4648	0.68175	0.98862	0.99994
Leave_Home-True	0.4648	5.7781e-05	0.99994	0.68175	0.99425	0.4648
Other_Activity-False	0.98461	0.066004	0.934	0.95897	0.94601	0.98461
Other_Activity-True	0.934	0.015394	0.98461	0.95897	0.98101	0.934
Personal_Hygiene-False	0.99907	0.22779	0.77221	0.87834	0.97445	0.99907
Personal_Hygiene-True	0.77221	0.00093345	0.99907	0.87834	0.9896	0.77221
Relax-False	0.99773	0.055617	0.94438	0.97069	0.99437	0.99773
Relax-True	0.94438	0.0022679	0.99773	0.97069	0.97689	0.94438
Sleep-False	0.99549	0.35563	0.64437	0.80091	0.93493	0.99549
Sleep-True	0.64437	0.0045147	0.99549	0.80091	0.96529	0.64437
Take_Medicine-False	1	0.72306	0.27694	0.52625	0.99078	1
Take_Medicine-True	0.27694	0	1	0.52625	1	0.27694
Wash_Dishes-False	0.99983	0.21465	0.78535	0.88613	0.98961	0.99983
Wash_Dishes-True	0.78535	0.00016613	0.99983	0.88613	0.99569	0.78535
Watch_TV-False	0.99948	0.11779	0.88221	0.93902	0.99836	0.99948
Watch_TV-True	0.88221	0.00051617	0.99948	0.93902	0.95968	0.88221
Work-False	0.99913	0.10103	0.89897	0.94773	0.99611	0.99913
Work-True	0.89897	0.00086948	0.99913	0.94773	0.97556	0.89897

Table E.15: *hh116* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	1	0.38558	0.61442	0.78385	0.99932	1
Bathe-True	0.61442	2.0129e-06	1	0.78385	0.99814	0.61442
Bed_Toilet_Transition-False	1	0.86335	0.13665	0.36966	0.99305	1
Bed_Toilet_Transition-True	0.13665	0	1	0.36966	1	0.13665
Cook-False	0.99999	0.60213	0.39787	0.63077	0.99429	0.99999
Cook-True	0.39787	1.42e-05	0.99999	0.63077	0.99627	0.39787
Dress-False	0.99992	0.50078	0.49922	0.70653	0.99353	0.99992
Dress-True	0.49922	7.9383e-05	0.99992	0.70653	0.98792	0.49922
Eat-False	0.99954	0.19808	0.80192	0.8953	0.99583	0.99954
Eat-True	0.80192	0.00046165	0.99954	0.8953	0.97347	0.80192
Enter_Home-False	0.99995	0.53566	0.46434	0.68141	0.98864	0.99995
Enter_Home-True	0.46434	4.5153e-05	0.99995	0.68141	0.99549	0.46434
Leave_Home-False	0.99997	0.65842	0.34158	0.58444	0.98599	0.99997
Leave_Home-True	0.34158	3.2843e-05	0.99997	0.58444	0.99556	0.34158
Other_Activity-False	0.97613	0.094252	0.90575	0.94028	0.93806	0.97613
Other_Activity-True	0.90575	0.023867	0.97613	0.94028	0.9629	0.90575
Personal_Hygiene-False	0.9997	0.49931	0.50069	0.70749	0.97406	0.9997
Personal_Hygiene-True	0.50069	0.00030266	0.9997	0.70749	0.98879	0.50069
Relax-False	0.99873	0.08307	0.91693	0.95696	0.99456	0.99873
Relax-True	0.91693	0.0012656	0.99873	0.95696	0.97943	0.91693
Sleep-False	0.98084	0.1174	0.8826	0.93042	0.98066	0.98084
Sleep-True	0.8826	0.019164	0.98084	0.93042	0.88358	0.8826
Take_Medicine-False	0.99999	0.69287	0.30713	0.5542	0.99519	0.99999
Take_Medicine-True	0.30713	6.0701e-06	0.99999	0.5542	0.99718	0.30713
Wash_Dishes-False	0.99997	0.59347	0.40653	0.63759	0.99431	0.99997
Wash_Dishes-True	0.40653	2.6373e-05	0.99997	0.63759	0.99331	0.40653
Watch_TV-False	0.99584	0.043068	0.95693	0.97619	0.99469	0.99584
Watch_TV-True	0.95693	0.0041624	0.99584	0.97619	0.96595	0.95693
Work-False	0.99898	0.11596	0.88404	0.93976	0.99559	0.99898
Work-True	0.88404	0.0010159	0.99898	0.93976	0.97078	0.88404

Table E.16: *hh117* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	1	0.24409	0.75591	0.86943	0.99929	1
Bathe-True	0.75591	0	1	0.86943	1	0.75591
Bed_Toilet_Transition-False	1	1	0	0	0.99103	1
Bed_Toilet_Transition-True	0	0	1	0	-	0
Cook-False	0.99942	0.20295	0.79705	0.89252	0.98746	0.99942
Cook-True	0.79705	0.00058234	0.99942	0.89252	0.98845	0.79705
Dress-False	0.99993	0.26891	0.73109	0.85501	0.99631	0.99993
Dress-True	0.73109	6.9452e-05	0.99993	0.85501	0.99315	0.73109
Eat-False	0.99964	0.070362	0.92964	0.964	0.99603	0.99964
Eat-True	0.92964	0.00036193	0.99964	0.964	0.99317	0.92964
Enter_Home-False	1	0.73263	0.26737	0.51708	0.98256	1
Enter_Home-True	0.26737	0	1	0.51708	1	0.26737
Housekeeping-False	0.99995	0.18355	0.81645	0.90355	0.99711	0.99995
Housekeeping-True	0.81645	4.6394e-05	0.99995	0.90355	0.99642	0.81645
Leave_Home-False	0.99662	0.015745	0.98426	0.99042	0.99441	0.99662
Leave_Home-True	0.98426	0.0033752	0.99662	0.99042	0.99046	0.98426
Other_Activity-False	0.99175	0.11142	0.88858	0.93875	0.96282	0.99175
Other_Activity-True	0.88858	0.0082543	0.99175	0.93875	0.97368	0.88858
Personal_Hygiene-False	0.9996	0.4207	0.5793	0.76097	0.96414	0.9996
Personal_Hygiene-True	0.5793	0.00039767	0.9996	0.76097	0.99229	0.5793
Relax-False	0.99912	0.071895	0.9281	0.96296	0.99686	0.99912
Relax-True	0.9281	0.00088192	0.99912	0.96296	0.97875	0.9281
Sleep-False	0.83272	0.0065166	0.99348	0.90956	0.99765	0.83272
Sleep-True	0.99348	0.16728	0.83272	0.90956	0.64118	0.99348
Take_Medicine-False	0.99984	0.33419	0.66581	0.81591	0.99397	0.99984
Take_Medicine-True	0.66581	0.00016276	0.99984	0.81591	0.98672	0.66581
Wash_Dishes-False	0.99988	0.2496	0.7504	0.8662	0.99269	0.99988
Wash_Dishes-True	0.7504	0.00011755	0.99988	0.8662	0.99471	0.7504
Watch_TV-False	0.99966	0.041808	0.95819	0.97871	0.99794	0.99966
Watch_TV-True	0.95819	0.00033547	0.99966	0.97871	0.99295	0.95819
Work-False	0.9977	0.066578	0.93342	0.96503	0.98304	0.9977
Work-True	0.93342	0.0022993	0.9977	0.96503	0.99056	0.93342

Table E.17: *hh118* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	1	0.43132	0.56868	0.75411	0.9924	1
Bathe-True	0.56868	0	1	0.75411	1	0.56868
Bed_Toilet_Transition-False	1	0.98257	0.017431	0.13203	0.976	1
Bed_Toilet_Transition-True	0.017431	0	1	0.13203	1	0.017431
Cook-False	0.99965	0.25323	0.74677	0.864	0.98677	0.99965
Cook-True	0.74677	0.00035384	0.99965	0.864	0.99112	0.74677
Dress-False	0.99956	0.60088	0.39912	0.63162	0.98449	0.99956
Dress-True	0.39912	0.00043683	0.99956	0.63162	0.95992	0.39912
Eat-False	0.99972	0.10175	0.89825	0.94763	0.99651	0.99972
Eat-True	0.89825	0.00027809	0.99972	0.94763	0.99108	0.89825
Enter_Home-False	0.99993	0.6276	0.3724	0.61023	0.98499	0.99993
Enter_Home-True	0.3724	6.8844e-05	0.99993	0.61023	0.99244	0.3724
Housekeeping-False	1	0.12621	0.87379	0.93477	0.99971	1
Housekeeping-True	0.87379	0	1	0.93477	1	0.87379
Leave_Home-False	0.94776	0.022509	0.97749	0.96251	0.98932	0.94776
Leave_Home-True	0.97749	0.052241	0.94776	0.96251	0.89481	0.97749
Other_Activity-False	0.99515	0.23582	0.76418	0.87205	0.93747	0.99515
Other_Activity-True	0.76418	0.004852	0.99515	0.87205	0.97794	0.76418
Personal_Hygiene-False	0.9992	0.39215	0.60785	0.77934	0.97024	0.9992
Personal_Hygiene-True	0.60785	0.00079712	0.9992	0.77934	0.9835	0.60785
Relax-False	0.99993	0.11039	0.88961	0.94316	0.99846	0.99993
Relax-True	0.88961	6.8152e-05	0.99993	0.94316	0.99456	0.88961
Sleep-False	0.89935	0.0098158	0.99018	0.94367	0.99723	0.89935
Sleep-True	0.99018	0.10065	0.89935	0.94367	0.71492	0.99018
Take_Medicine-False	1	0.7812	0.2188	0.46776	0.9886	1
Take_Medicine-True	0.2188	0	1	0.46776	1	0.2188
Wash_Dishes-False	1	0.41828	0.58172	0.76271	0.99264	1
Wash_Dishes-True	0.58172	0	1	0.76271	1	0.58172
Work-False	0.98848	0.031443	0.96856	0.97847	0.98691	0.98848
Work-True	0.96856	0.011524	0.98848	0.97847	0.97226	0.96856

Table E.18: *hh119* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	0.99999	0.37007	0.62993	0.79368	0.99652	0.99999
Bathe-True	0.62993	1.0954e-05	0.99999	0.79368	0.99816	0.62993
Bed_Toilet_Transition-False	1	0.8471	0.1529	0.39102	0.98505	1
Bed_Toilet_Transition-True	0.1529	0	1	0.39102	1	0.1529
Cook-False	0.99991	0.16822	0.83178	0.91198	0.9956	0.99991
Cook-True	0.83178	8.9093e-05	0.99991	0.91198	0.99594	0.83178
Dress-False	0.99998	0.38294	0.61706	0.78553	0.99151	0.99998
Dress-True	0.61706	2.2188e-05	0.99998	0.78553	0.99839	0.61706
Eat-False	0.9999	0.11793	0.88207	0.93914	0.99786	0.9999
Eat-True	0.88207	9.9438e-05	0.9999	0.93914	0.99384	0.88207
Enter_Home-False	0.99999	0.73173	0.26827	0.51795	0.9814	0.99999
Enter_Home-True	0.26827	1.1132e-05	0.99999	0.51795	0.9984	0.26827
Leave_Home-False	0.99947	0.31355	0.68645	0.82831	0.98206	0.99947
Leave_Home-True	0.68645	0.00052823	0.99947	0.82831	0.98696	0.68645
Other_Activity-False	0.99366	0.13278	0.86722	0.92829	0.94026	0.99366
Other_Activity-True	0.86722	0.0063403	0.99366	0.92829	0.98486	0.86722
Personal_Hygiene-False	0.99967	0.40578	0.59422	0.77073	0.96978	0.99967
Personal_Hygiene-True	0.59422	0.00032716	0.99967	0.77073	0.99288	0.59422
Relax-False	0.99991	0.12742	0.87258	0.93408	0.99701	0.99991
Relax-True	0.87258	8.8854e-05	0.99991	0.93408	0.99569	0.87258
Sleep-False	0.98327	0.45829	0.54171	0.72982	0.86688	0.98327
Sleep-True	0.54171	0.016735	0.98327	0.72982	0.91427	0.54171
Take_Medicine-False	1	0.62418	0.37582	0.61304	0.98439	1
Take_Medicine-True	0.37582	0	1	0.61304	1	0.37582
Wash_Dishes-False	0.99993	0.18844	0.81156	0.90084	0.9971	0.99993
Wash_Dishes-True	0.81156	6.6114e-05	0.99993	0.90084	0.99475	0.81156
Watch_TV-False	0.99459	0.072666	0.92733	0.96038	0.98911	0.99459
Watch_TV-True	0.92733	0.0054068	0.99459	0.96038	0.96275	0.92733
Work-False	0.9971	0.08185	0.91815	0.95681	0.98879	0.9971
Work-True	0.91815	0.0029021	0.9971	0.95681	0.97762	0.91815

Table E.19: *hh120* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	1	0.20343	0.79657	0.89251	0.99806	1
Bathe-True	0.79657	0	1	0.89251	1	0.79657
Bed_Toilet_Transition-False	1	0.95285	0.047149	0.21714	0.97985	1
Bed_Toilet_Transition-True	0.047149	0	1	0.21714	1	0.047149
Cook-False	0.99983	0.16277	0.83723	0.91493	0.99555	0.99983
Cook-True	0.83723	0.00016657	0.99983	0.91493	0.99281	0.83723
Dress-False	0.99998	0.34822	0.65178	0.80732	0.99287	0.99998
Dress-True	0.65178	2.3637e-05	0.99998	0.80732	0.99825	0.65178
Eat-False	0.99976	0.06671	0.93329	0.96595	0.99753	0.99976
Eat-True	0.93329	0.00024018	0.99976	0.96595	0.99311	0.93329
Enter_Home-False	0.99995	0.56582	0.43418	0.65891	0.98956	0.99995
Enter_Home-True	0.43418	4.7181e-05	0.99995	0.65891	0.9942	0.43418
Leave_Home-False	1	0.51086	0.48914	0.69939	0.99065	1
Leave_Home-True	0.48914	0	1	0.69939	1	0.48914
Other_Activity-False	0.98824	0.093516	0.90648	0.94648	0.91784	0.98824
Other_Activity-True	0.90648	0.011763	0.98824	0.94648	0.98647	0.90648
Personal_Hygiene-False	0.99931	0.25031	0.74969	0.86555	0.97488	0.99931
Personal_Hygiene-True	0.74969	0.0006896	0.99931	0.86555	0.99114	0.74969
Relax-False	0.99981	0.10878	0.89122	0.94395	0.99742	0.99981
Relax-True	0.89122	0.00018967	0.99981	0.94395	0.99112	0.89122
Sleep-False	0.85723	0.014295	0.9857	0.91923	0.99365	0.85723
Sleep-True	0.9857	0.14277	0.85723	0.91923	0.72569	0.9857
Take_Medicine-False	1	0.6994	0.3006	0.54827	0.99189	1
Take_Medicine-True	0.3006	0	1	0.54827	1	0.3006
Wash_Dishes-False	0.99988	0.1458	0.8542	0.92417	0.99563	0.99988
Wash_Dishes-True	0.8542	0.00011928	0.99988	0.92417	0.99538	0.8542
Watch_TV-False	0.99351	0.026108	0.97389	0.98365	0.9972	0.99351
Watch_TV-True	0.97389	0.0064863	0.99351	0.98365	0.94142	0.97389
Work-False	0.99937	0.1163	0.8837	0.93975	0.989	0.99937
Work-True	0.8837	0.00063429	0.99937	0.93975	0.99254	0.8837

Table E.20: *hh122* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	0.99998	0.35955	0.64045	0.80027	0.99783	0.99998
Bathe-True	0.64045	2.2627e-05	0.99998	0.80027	0.99419	0.64045
Bed_Toilet_Transition-False	1	0.79006	0.20994	0.4582	0.99356	1
Bed_Toilet_Transition-True	0.20994	0	1	0.4582	1	0.20994
Cook-False	0.99986	0.26407	0.73593	0.8578	0.9898	0.99986
Cook-True	0.73593	0.00014021	0.99986	0.8578	0.99514	0.73593
Dress-False	1	0.36964	0.63036	0.79395	0.99054	1
Dress-True	0.63036	0	1	0.79395	1	0.63036
Eat-False	0.99972	0.11241	0.88759	0.94199	0.9955	0.99972
Eat-True	0.88759	0.00028073	0.99972	0.94199	0.99219	0.88759
Enter_Home-False	1	0.47955	0.52045	0.72142	0.98825	1
Enter_Home-True	0.52045	0	1	0.72142	1	0.52045
Leave_Home-False	0.99998	0.44528	0.55472	0.74479	0.98915	0.99998
Leave_Home-True	0.55472	2.3045e-05	0.99998	0.74479	0.99832	0.55472
Other_Activity-False	0.99053	0.030551	0.96945	0.97993	0.97932	0.99053
Other_Activity-True	0.96945	0.0094718	0.99053	0.97993	0.98593	0.96945
Personal_Hygiene-False	0.99988	0.37078	0.62922	0.79319	0.97877	0.99988
Personal_Hygiene-True	0.62922	0.00011903	0.99988	0.79319	0.99678	0.62922
Relax-False	0.99988	0.17068	0.82932	0.91062	0.99273	0.99988
Relax-True	0.82932	0.00011728	0.99988	0.91062	0.99671	0.82932
Sleep-False	0.98073	0.39733	0.60267	0.76881	0.87214	0.98073
Sleep-True	0.60267	0.019266	0.98073	0.76881	0.91883	0.60267
Take_Medicine-False	1	0.51129	0.48871	0.69908	0.99282	1
Take_Medicine-True	0.48871	0	1	0.69908	1	0.48871
Wash_Dishes-False	0.99974	0.2431	0.7569	0.86989	0.99041	0.99974
Wash_Dishes-True	0.7569	0.00025726	0.99974	0.86989	0.99154	0.7569
Watch_TV-False	0.99755	0.039356	0.96064	0.97893	0.99386	0.99755
Watch_TV-True	0.96064	0.0024454	0.99755	0.97893	0.98401	0.96064
Work-False	1	0.05	0.95	0.97468	0.99998	1
Work-True	0.95	0	1	0.97468	1	0.95

Table E.21: *hh123* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	0.99998	0.21178	0.78822	0.88781	0.99785	0.99998
Bathe-True	0.78822	2.3024e-05	0.99998	0.88781	0.99713	0.78822
Bed_Toilet_Transition-False	1	0.86234	0.13766	0.37103	0.99621	1
Bed_Toilet_Transition-True	0.13766	0	1	0.37103	1	0.13766
Cook-False	0.99977	0.22401	0.77599	0.8808	0.9893	0.99977
Cook-True	0.77599	0.00022698	0.99977	0.8808	0.99398	0.77599
Dress-False	0.99993	0.50918	0.49082	0.70056	0.98881	0.99993
Dress-True	0.49082	6.9896e-05	0.99993	0.70056	0.99363	0.49082
Eat-False	0.99952	0.091677	0.90832	0.95283	0.99547	0.99952
Eat-True	0.90832	0.00047845	0.99952	0.95283	0.98949	0.90832
Enter_Home-False	0.99996	0.52706	0.47294	0.6877	0.98355	0.99996
Enter_Home-True	0.47294	3.5273e-05	0.99996	0.6877	0.99765	0.47294
Leave_Home-False	0.99574	0.065689	0.93431	0.96454	0.98715	0.99574
Leave_Home-True	0.93431	0.0042572	0.99574	0.96454	0.97743	0.93431
Other_Activity-False	0.99264	0.17359	0.82641	0.90572	0.94391	0.99264
Other_Activity-True	0.82641	0.0073592	0.99264	0.90572	0.97446	0.82641
Personal_Hygiene-False	0.99864	0.39629	0.60371	0.77646	0.96809	0.99864
Personal_Hygiene-True	0.60371	0.0013577	0.99864	0.77646	0.97364	0.60371
Relax-False	0.97738	0.079358	0.92064	0.94859	0.98519	0.97738
Relax-True	0.92064	0.022623	0.97738	0.94859	0.88284	0.92064
Sleep-False	0.99639	0.32014	0.67986	0.82304	0.9593	0.99639
Sleep-True	0.67986	0.0036123	0.99639	0.82304	0.96132	0.67986
Take_Medicine-False	0.99995	0.69171	0.30829	0.55523	0.98681	0.99995
Take_Medicine-True	0.30829	4.6466e-05	0.99995	0.55523	0.99226	0.30829
Wash_Dishes-False	0.99985	0.21653	0.78347	0.88507	0.991	0.99985
Wash_Dishes-True	0.78347	0.00015436	0.99985	0.88507	0.99533	0.78347
Watch_TV-False	0.99512	0.04856	0.95144	0.97304	0.99347	0.99512
Watch_TV-True	0.95144	0.0048753	0.99512	0.97304	0.96337	0.95144
Work-False	0.99835	0.059824	0.94018	0.96883	0.99369	0.99835
Work-True	0.94018	0.0016511	0.99835	0.96883	0.9837	0.94018

Table E.22: *hh125* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	1	0.50515	0.49485	0.70345	0.99813	1
Bathe-True	0.49485	0	1	0.70345	1	0.49485
Bed_Toilet_Transition-False	1	1	0	0	0.99222	1
Bed_Toilet_Transition-True	0	0	1	0	-	0
Cook-False	0.9999	0.33356	0.66644	0.81632	0.99064	0.9999
Cook-True	0.66644	9.7851e-05	0.9999	0.81632	0.99485	0.66644
Dress-False	0.99994	0.54367	0.45633	0.6755	0.98936	0.99994
Dress-True	0.45633	5.8222e-05	0.99994	0.6755	0.99359	0.45633
Eat-False	0.9997	0.17076	0.82924	0.91049	0.99429	0.9997
Eat-True	0.82924	0.00029507	0.9997	0.91049	0.98953	0.82924
Enter_Home-False	0.99996	0.61807	0.38193	0.61799	0.97783	0.99996
Enter_Home-True	0.38193	3.9458e-05	0.99996	0.61799	0.99719	0.38193
Leave_Home-False	0.99994	0.52932	0.47068	0.68604	0.98096	0.99994
Leave_Home-True	0.47068	5.9187e-05	0.99994	0.68604	0.99658	0.47068
Other_Activity-False	0.99166	0.051931	0.94807	0.96962	0.96069	0.99166
Other_Activity-True	0.94807	0.0083401	0.99166	0.96962	0.98887	0.94807
Personal_Hygiene-False	0.99971	0.32656	0.67344	0.82051	0.96733	0.99971
Personal_Hygiene-True	0.67344	0.00029398	0.99971	0.82051	0.9958	0.67344
Relax-False	0.99972	0.21322	0.78678	0.88688	0.98653	0.99972
Relax-True	0.78678	0.00028349	0.99972	0.88688	0.9944	0.78678
Sleep-False	0.99769	0.55455	0.44545	0.66665	0.93461	0.99769
Sleep-True	0.44545	0.0023141	0.99769	0.66665	0.96037	0.44545
Take_Medicine-False	0.99996	0.65487	0.34513	0.58747	0.99293	0.99996
Take_Medicine-True	0.34513	3.8476e-05	0.99996	0.58747	0.98985	0.34513
Wash_Dishes-False	1	0.5787	0.4213	0.64908	0.99304	1
Wash_Dishes-True	0.4213	0	1	0.64908	1	0.4213
Watch_TV-False	0.99589	0.044763	0.95524	0.97535	0.99046	0.99589
Watch_TV-True	0.95524	0.0041132	0.99589	0.97535	0.9803	0.95524
Work-False	0.99895	0.070577	0.92942	0.96356	0.98918	0.99895
Work-True	0.92942	0.0010549	0.99895	0.96356	0.99272	0.92942

Table E.23: *hh126* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	0.99993	0.059451	0.94055	0.96979	0.99913	0.99993
Bathe-True	0.94055	6.7123e-05	0.99993	0.96979	0.99516	0.94055
Bed_Toilet_Transition-False	1	0.74194	0.25806	0.508	0.99899	1
Bed_Toilet_Transition-True	0.25806	0	1	0.508	1	0.25806
Cook-False	0.99993	0.19667	0.80333	0.89626	0.99441	0.99993
Cook-True	0.80333	6.8044e-05	0.99993	0.89626	0.99705	0.80333
Dress-False	0.99975	0.2838	0.7162	0.84618	0.99336	0.99975
Dress-True	0.7162	0.00024827	0.99975	0.84618	0.98549	0.7162
Eat-False	0.99993	0.16	0.84	0.91648	0.99371	0.99993
Eat-True	0.84	6.8768e-05	0.99993	0.91648	0.99793	0.84
Enter_Home-False	0.99996	0.43979	0.56021	0.74845	0.99814	0.99996
Enter_Home-True	0.56021	4.4288e-05	0.99996	0.74845	0.98165	0.56021
Leave_Home-False	0.99845	0.093314	0.90669	0.95146	0.97705	0.99845
Leave_Home-True	0.90669	0.0015452	0.99845	0.95146	0.99327	0.90669
Other_Activity-False	0.99857	0.18946	0.81054	0.89966	0.97456	0.99857
Other_Activity-True	0.81054	0.0014298	0.99857	0.89966	0.98734	0.81054
Personal_Hygiene-False	0.99968	0.23495	0.76505	0.87453	0.99178	0.99968
Personal_Hygiene-True	0.76505	0.0003196	0.99968	0.87453	0.98829	0.76505
Relax-False	0.99955	0.22096	0.77904	0.88243	0.98221	0.99955
Relax-True	0.77904	0.0004533	0.99955	0.88243	0.99295	0.77904
Sleep-False	0.99888	0.040647	0.95935	0.97892	0.98508	0.99888
Sleep-True	0.95935	0.0011195	0.99888	0.97892	0.99687	0.95935
Wash_Dishes-False	1	0.24625	0.75375	0.86819	0.99634	1
Wash_Dishes-True	0.75375	0	1	0.86819	1	0.75375
Watch_TV-False	0.99923	0.2387	0.7613	0.87219	0.97872	0.99923
Watch_TV-True	0.7613	0.00076984	0.99923	0.87219	0.98901	0.7613
Work-False	1	0.39474	0.60526	0.77799	0.99601	1
Work-True	0.60526	0	1	0.77799	1	0.60526

Table E.24: *hh127* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bathe-False	1	0.19355	0.80645	0.89803	0.99952	1
Bathe-True	0.80645	0	1	0.89803	1	0.80645
Bed_Toilet_Transition-False	1	1	0	0	0.99283	1
Bed_Toilet_Transition-True	0	0	1	0	-	0
Cook-False	0.99969	0.17353	0.82647	0.90897	0.99336	0.99969
Cook-True	0.82647	0.00030749	0.99969	0.90897	0.99043	0.82647
Dress-False	0.99992	0.43033	0.56967	0.75473	0.98581	0.99992
Dress-True	0.56967	8.2383e-05	0.99992	0.75473	0.99569	0.56967
Eat-False	0.99989	0.079086	0.92091	0.95959	0.99736	0.99989
Eat-True	0.92091	0.00010592	0.99989	0.95959	0.99658	0.92091
Enter_Home-False	0.99987	0.53289	0.46711	0.68341	0.98125	0.99987
Enter_Home-True	0.46711	0.00012976	0.99987	0.68341	0.99231	0.46711
Leave_Home-False	1	0.45452	0.54548	0.73857	0.98388	1
Leave_Home-True	0.54548	0	1	0.73857	1	0.54548
Other_Activity-False	0.98194	0.058421	0.94158	0.96155	0.95244	0.98194
Other_Activity-True	0.94158	0.018056	0.98194	0.96155	0.97766	0.94158
Personal_Hygiene-False	0.99758	0.14797	0.85203	0.92194	0.97096	0.99758
Personal_Hygiene-True	0.85203	0.0024221	0.99758	0.92194	0.9861	0.85203
Relax-False	0.99986	0.1536	0.8464	0.91993	0.99247	0.99986
Relax-True	0.8464	0.00014341	0.99986	0.91993	0.99658	0.8464
Sleep-False	0.9973	0.5988	0.4012	0.63255	0.89919	0.9973
Sleep-True	0.4012	0.0027029	0.9973	0.63255	0.96517	0.4012
Take_Medicine-False	1	0.5761	0.4239	0.65107	0.98725	1
Take_Medicine-True	0.4239	0	1	0.65107	1	0.4239
Wash_Dishes-False	0.99971	0.13492	0.86508	0.92996	0.99603	0.99971
Wash_Dishes-True	0.86508	0.00029311	0.99971	0.92996	0.98866	0.86508
Watch_TV-False	0.99694	0.033175	0.96683	0.98177	0.99559	0.99694
Watch_TV-True	0.96683	0.003058	0.99694	0.98177	0.97677	0.96683
Work-False	0.99891	0.051641	0.94836	0.97331	0.99539	0.99891
Work-True	0.94836	0.001092	0.99891	0.97331	0.98732	0.94836

Table E.25: *hh128* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Bed_Toilet_Transition-False	1	0.66375	0.33625	0.57987	0.98801	1
Bed_Toilet_Transition-True	0.33625	0	1	0.57987	1	0.33625
Cook-False	0.99972	0.25036	0.74964	0.86569	0.988	0.99972
Cook-True	0.74964	0.00028243	0.99972	0.86569	0.99229	0.74964
Eat-False	0.99989	0.30754	0.69246	0.8321	0.99312	0.99989
Eat-True	0.69246	0.00011476	0.99989	0.8321	0.9927	0.69246
Enter_Home-False	0.99998	0.52212	0.47788	0.69128	0.99734	0.99998
Enter_Home-True	0.47788	2.2561e-05	0.99998	0.69128	0.99083	0.47788
Leave_Home-False	0.99676	0.16667	0.83333	0.91139	0.96539	0.99676
Leave_Home-True	0.83333	0.0032439	0.99676	0.91139	0.98217	0.83333
Other_Activity-False	0.9981	0.20639	0.79361	0.89	0.9686	0.9981
Other_Activity-True	0.79361	0.0018955	0.9981	0.89	0.98499	0.79361
Personal_Hygiene-False	0.99959	0.31144	0.68856	0.82963	0.98115	0.99959
Personal_Hygiene-True	0.68856	0.00040513	0.99959	0.82963	0.99055	0.68856
Relax-False	0.99957	0.2824	0.7176	0.84693	0.98108	0.99957
Relax-True	0.7176	0.00043162	0.99957	0.84693	0.99127	0.7176
Sleep-False	0.99599	0.071963	0.92804	0.96142	0.95793	0.99599
Sleep-True	0.92804	0.0040061	0.99599	0.96142	0.99295	0.92804
Wash_Dishes-False	0.99995	0.62808	0.37192	0.60984	0.99426	0.99995
Wash_Dishes-True	0.37192	4.5306e-05	0.99995	0.60984	0.98693	0.37192
Watch_TV-False	0.99986	0.094708	0.90529	0.9514	0.99923	0.99986
Watch_TV-True	0.90529	0.00013577	0.99986	0.9514	0.98187	0.90529
Work-False	0.99998	0.31818	0.68182	0.82571	0.99953	0.99998
Work-True	0.68182	2.248e-05	0.99998	0.82571	0.97826	0.68182

Table E.26: *hh129* activity forecasting accuracies.

F ACTIVITY DISCOVERY RESULTS

0	1	2	3	4	5	6	7	←guessed
8163	0	11	25	51	2116	1018	771	0 = Other_Activity
0	0	0	0	0	0	0	0	1 = Pat_0
836	0	68	0	0	5	1350	0	2 = Pat_11
1138	0	0	87	0	11	0	0	3 = Pat_12
689	0	0	0	345	156	0	1036	4 = Pat_13
1459	0	0	0	5	7531	0	23	5 = Pat_3
698	0	35	0	0	0	3025	0	6 = Pat_5
750	0	0	0	89	118	0	2293	7 = Pat_6

Table F.1: Results for *navan_week.AD* activity recognition, with an accuracy of 63.453.

0	1	2	3	4	5	6	7	←guessed
45239	32015	17363	307	0	12449	5609	1385	0 = Other_Activity
5987	305664	5111	36	0	2683	1280	183	1 = Pat_0
1793	4905	133561	80	0	114	48	2	2 = Pat_1
2017	5940	5452	2537	0	237	68	15	3 = Pat_11
824	3358	5369	4	10	34	7	2	4 = Pat_14
6580	1882	337	27	0	102431	124	37	5 = Pat_2
3209	5327	345	4	0	602	66186	131	6 = Pat_3
3688	3455	319	9	0	697	652	15217	7 = Pat_8

Table F.2: Results for *navan_2012.AD* activity recognition, with an accuracy of 82.52.

0	1	2	3	4	5	6	7	←guessed
9416	3410	0	21	1285	5588	1248	12	0 = Other_Activity
555	78896	0	0	130	124	8	0	1 = Pat_0
5	4	0	0	0	0	0	0	2 = Pat_1
104	204	0	293	5166	10	130	1	3 = Pat_11
106	292	0	118	42089	10	255	0	4 = Pat_2
284	407	0	0	76	37859	8	0	5 = Pat_3
51	91	0	0	103	3	26836	118	6 = Pat_4
76	120	0	2	164	1	6606	420	7 = Pat_9

Table F.3: Results for *hh101.AD* activity recognition, with an accuracy of 87.923.

0	1	2	3	4	5	6	7	←guessed
14217	9734	0	1779	1525	13487	4776	6132	0 = Other_Activity
802	50786	0	0	18	0	7	240	1 = Pat_0
0	0	0	1	0	0	0	0	2 = Pat_1
959	4	0	8802	4	123	1307	1901	3 = Pat_12
1414	756	0	5	8019	0	12	1018	4 = Pat_13
620	10	0	23	0	49121	685	203	5 = Pat_2
833	28	0	278	1	798	61711	152	6 = Pat_3
2835	749	0	322	447	98	181	35015	7 = Pat_5

Table F.4: Results for *hh102.AD* activity recognition, with an accuracy of 80.752.

0	1	2	3	4	5	6	7	←guessed
14117	1938	1020	175	325	426	0	1530	0 = Other_Activity
143	23576	0	0	0	0	0	65	1 = Pat_0
38	0	37115	0	0	2	0	2	2 = Pat_1
2855	3	63	724	0	0	0	3	3 = Pat_11
1135	0	0	0	1149	0	0	22	4 = Pat_12
747	0	780	5	0	1557	0	7	5 = Pat_13
1069	105	2	4	0	0	33	2326	6 = Pat_2
1101	245	11	13	0	0	1	18083	7 = Pat_3

Table F.5: Results for *hh103.AD* activity recognition, with an accuracy of 85.637.

0	1	2	3	4	5	6	7	←guessed
21743	8377	5199	1979	1381	0	6433	345	0 = Other_Activity
1841	89317	64	442	38	0	28	578	1 = Pat_0
3238	116	108857	71	230	0	160	1	2 = Pat_1
637	2547	124	19007	25	0	18	147	3 = Pat_10
7627	617	1148	34	6869	0	373	28	4 = Pat_11
4	0	0	0	0	0	1	0	5 = Pat_2
855	82	215	20	13	0	31377	0	6 = Pat_5
2368	16086	82	1299	42	0	9	2614	7 = Pat_7

Table F.6: Results for *hh104.AD* activity recognition, with an accuracy of 81.166.

0	1	2	3	4	5	6	7	←guessed
9758	5843	2	34	1957	3179	2010	317	0 = Other_Activity
145	51711	0	0	43	0	27	19	1 = Pat_0
1021	322	36	26	2292	35	384	13	2 = Pat_1
478	55	2	258	164	308	2157	0	3 = Pat_10
1204	844	9	2	17355	55	845	54	4 = Pat_2
393	19	0	4	10	17177	148	0	5 = Pat_4
617	64	0	83	315	339	17999	1	6 = Pat_6
596	1726	0	0	1034	8	198	3410	7 = Pat_9

Table F.7: Results for *hh105.AD* activity recognition, with an accuracy of 80.014.

0	1	2	3	4	5	6	7	←guessed
21624	0	3280	24	3726	4958	2717	2624	0 = Other_Activity
1	0	0	0	0	0	0	0	1 = Pat_0
2267	0	55226	0	198	1093	28	62	2 = Pat_1
3453	0	125	132	5	147	7	835	3 = Pat_13
478	0	229	0	37188	557	15	27	4 = Pat_2
5540	0	2087	0	2230	23554	812	119	5 = Pat_3
1376	0	77	0	30	1141	12338	14	6 = Pat_6
1193	0	28	2	10	142	8	11743	7 = Pat_7

Table F.8: Results for *hh106.AD* activity recognition, with an accuracy of 79.523.

0	1	2	3	4	5	6	7	←guessed
16081	9056	4732	1020	2	627	2587	1645	0 = Other_Activity
729	54036	770	2	1	217	256	75	1 = Pat_0
1712	1250	43917	10	0	238	111	148	2 = Pat_1
2377	41	85	2365	0	15	0	21	3 = Pat_11
346	666	769	13	53	1745	54	54	4 = Pat_2
513	724	1278	33	25	22145	62	106	5 = Pat_4
457	1280	816	0	0	85	15800	44	6 = Pat_5
1855	236	497	10	0	48	7	9635	7 = Pat_9

Table F.9: Results for *hh107.AD* activity recognition, with an accuracy of 80.613.

0	1	2	3	4	5	6	7	←guessed
14945	13844	0	0	54	4123	10132	3142	0 = Other_Activity
2080	77418	0	0	6	190	1359	51	1 = Pat_0
304	706	23	0	0	15	300	17	2 = Pat_1
1014	240	0	29	0	67	2402	3516	3 = Pat_11
2824	1550	1	0	334	43	228	8	4 = Pat_14
519	174	0	0	0	57660	850	34	5 = Pat_2
2220	3103	0	2	0	1607	53373	1306	6 = Pat_3
1392	331	0	1	0	172	2886	22262	7 = Pat_5

Table F.10: Results for *hh108.AD* activity recognition, with an accuracy of 78.255.

0	1	2	3	4	5	6	7	←guessed
67643	18974	5837	3	1	0	1132	854	0 = Other_Activity
4910	99777	19	0	0	0	2	128	1 = Pat_0
3332	5	107479	0	0	0	571	4	2 = Pat_1
12960	3047	29	25	0	0	6	1844	3 = Pat_10
1189	1	1957	0	6	0	3738	2	4 = Pat_13
2	0	0	0	0	0	0	0	5 = Pat_2
1179	2	2965	0	0	0	32657	3	6 = Pat_5
3097	2042	6	3	0	0	2	21964	7 = Pat_6

Table F.11: Results for *hh109.AD* activity recognition, with an accuracy of 82.512.

0	1	2	3	4	5	6	7	←guessed
16496	72	3375	34	3066	3179	3705	1505	0 = Other_Activity
2264	334	4968	22	1016	809	318	2426	1 = Pat_0
1456	51	55152	0	285	244	161	209	2 = Pat_1
398	6	39	214	5595	174	69	125	3 = Pat_10
560	0	175	54	41625	142	76	282	4 = Pat_2
2005	35	425	7	280	24590	954	581	5 = Pat_4
892	11	114	1	212	365	20157	116	6 = Pat_6
1281	62	274	21	2301	775	275	14873	7 = Pat_7

Table F.12: Results for *hh111.AD* activity recognition, with an accuracy of 78.378.

0	1	2	3	4	5	6	7	←guessed
64834	12940	2107	473	99	1342	2539	1517	0 = Other_Activity
2299	200989	4	41	1	3288	236	2	1 = Pat_0
2814	46	9923	0	2	0	302	19	2 = Pat_12
4023	3539	2	3201	0	109	188	0	3 = Pat_14
11233	1645	84	6	1143	753	3563	4096	4 = Pat_2
3280	33749	2	39	22	12527	249	4	5 = Pat_3
12966	3746	630	12	164	282	25488	162	6 = Pat_5
3767	119	7	0	186	20	99	31844	7 = Pat_6

Table F.13: Results for *hh112.AD* activity recognition, with an accuracy of 74.653.

0	1	2	3	4	5	6	7	←guessed
193269	50738	19354	945	0	39012	39620	7083	0 = Other_Activity
9947	517603	271	0	0	129	377	5377	1 = Pat_0
5031	515	633175	0	0	317	2958	34	2 = Pat_1
8139	360	522	1968	0	32783	36	10	3 = Pat_11
9	0	0	0	0	0	0	0	4 = Pat_2
4674	206	520	306	0	224740	30	0	5 = Pat_3
10134	311	3768	0	0	63	271435	11	6 = Pat_4
20274	144581	646	0	0	209	892	29920	7 = Pat_5

Table F.14: Results for *hh113.AD* activity recognition, with an accuracy of 82.027.

0	1	2	3	4	5	6	7	←guessed
12777	4758	1	1191	0	4853	42	1517	0 = Other_Activity
303	53725	0	31	0	35	2	2	1 = Pat_0
326	79	15	2784	0	60	0	31	2 = Pat_10
344	68	1	16815	0	65	0	21	3 = Pat_2
2	0	0	0	0	0	0	0	4 = Pat_3
3315	806	0	143	0	14542	32	26	5 = Pat_4
3599	1575	0	110	0	3293	260	29	6 = Pat_6
325	42	0	267	0	10	0	7232	7 = Pat_8

Table F.15: Results for *hh114.AD* activity recognition, with an accuracy of 77.787.

0	1	2	3	4	5	6	7	←guessed
126276	30702	32819	5	0	18165	9985	3829	0 = Other_Activity
2693	443803	155	0	0	431	533	4217	1 = Pat_0
2826	45	377120	0	0	814	19	3	2 = Pat_1
7523	613	2376	118	0	26227	385	46	3 = Pat_10
4	0	0	0	0	0	0	0	4 = Pat_2
12898	1387	4672	16	0	163687	675	21	5 = Pat_3
1614	1690	161	0	0	739	205858	9	6 = Pat_4
5613	80922	491	0	0	1247	2617	22342	7 = Pat_6

Table F.16: Results for *hh115.AD* activity recognition, with an accuracy of 83.785.

0	1	2	3	4	5	6	7	←guessed
53048	5590	2936	336	4234	139	0	4	0 = Other_Activity
3304	159033	471	46	820	35	0	6	1 = Pat_0
3702	840	64561	2	57	438	0	0	2 = Pat_1
9033	664	421	3264	929	3	0	0	3 = Pat_11
3710	1634	166	15	34627	23	0	21	4 = Pat_4
3792	777	20237	3	86	1966	0	1	5 = Pat_5
1	0	0	0	0	0	0	0	6 = Pat_6
1954	925	51	7	4671	11	0	64	7 = Pat_9

Table F.17: Results for *hh116.AD* activity recognition, with an accuracy of 81.45.

0	1	2	3	4	5	6	7	←guessed
18549	20868	21884	5494	0	9582	8384	167	0 = Other_Activity
1623	219256	811	46	0	804	60	42	1 = Pat_0
2589	3801	221291	538	0	414	255	20	2 = Pat_1
2696	2294	9556	37073	0	533	779	101	3 = Pat_10
9	6	4	0	0	1	0	0	4 = Pat_2
1660	2893	709	35	0	66547	122	6	5 = Pat_4
598	479	1119	64	0	651	65297	0	6 = Pat_6
3943	28669	6411	7166	0	641	546	1237	7 = Pat_9

Table F.18: Results for *hh117.AD* activity recognition, with an accuracy of 80.847.

0	1	2	3	4	5	6	7	←guessed
18916	4781	2141	200	2	5025	1476	3435	0 = Other_Activity
652	44431	651	0	0	1	24	6	1 = Pat_0
1765	2138	30896	0	2	10	590	0	2 = Pat_1
2992	7	47	861	0	19	44	0	3 = Pat_14
1337	121	409	5	45	12	2273	4	4 = Pat_2
1693	1	0	0	0	21583	5	120	5 = Pat_3
2475	249	749	2	15	60	13988	4	6 = Pat_5
943	10	0	0	0	214	2	12263	7 = Pat_6

Table F.19: Results for *hh118.AD* activity recognition, with an accuracy of 79.57.

0	1	2	3	4	5	6	7	←guessed
8593	1745	1205	66	0	2814	520	681	0 = Other_Activity
258	9513	36	2	0	328	1481	8	1 = Pat_0
462	27	23422	1	0	177	35	50	2 = Pat_1
1487	18	103	293	0	184	56	13	3 = Pat_14
0	0	0	0	0	0	0	0	4 = Pat_2
216	12	39	0	0	20132	108	11	5 = Pat_3
311	3694	29	0	0	297	8066	7	6 = Pat_4
1489	2	187	0	0	667	14	3881	7 = Pat_8

Table F.20: Results for *hh119.AD* activity recognition, with an accuracy of 79.685.

0	1	2	3	4	5	6	7	←guessed
23500	5900	0	4886	2322	755	2490	2078	0 = Other_Activity
387	65399	0	14	23	767	38	0	1 = Pat_0
0	0	0	0	0	0	0	0	2 = Pat_1
691	193	0	29330	10	15	30	0	3 = Pat_2
869	14	0	12	26662	0	238	8	4 = Pat_3
903	12469	0	99	36	3872	99	4	5 = Pat_4
3965	240	0	65	1316	22	16940	464	6 = Pat_5
2152	45	0	8	191	2	399	9459	7 = Pat_8

Table F.21: Results for *hh120.AD* activity recognition, with an accuracy of 79.844.

0	1	2	3	4	5	6	7	←guessed
18366	3322	2	515	1	1446	3299	799	0 = Other_Activity
3573	47977	0	59	0	412	59	5	1 = Pat_0
897	214	18	0	0	1871	111	0	2 = Pat_1
849	417	0	4099	0	38	7	14	3 = Pat_12
1217	35	0	4	32	1	0	1157	4 = Pat_13
1164	405	5	2	0	15374	134	8	5 = Pat_3
1070	92	0	4	0	222	12000	10	6 = Pat_6
1838	62	0	17	16	15	0	6682	7 = Pat_8

Table F.22: Results for *hh122.AD* activity recognition, with an accuracy of 80.461.

0	1	2	3	4	5	6	7	←guessed
4674	3037	0	619	6435	1152	349	1662	0 = Other_Activity
38	32597	0	0	0	6	351	0	1 = Pat_0
0	0	0	0	0	0	0	0	2 = Pat_1
409	258	0	3427	125	20	4	75	3 = Pat_12
71	68	0	19	22382	967	0	1	4 = Pat_2
271	344	0	50	5114	8319	8	5	5 = Pat_3
77	7231	0	3	2	11	1737	0	6 = Pat_4
1072	7	0	11	6	0	0	3822	7 = Pat_6

Table F.23: Results for *hh123.AD* activity recognition, with an accuracy of 72.034.

0	1	2	3	4	5	6	7	←guessed
14848	8183	1847	0	1787	2582	0	4	0 = Other_Activity
120	94155	18	0	15	476	0	0	1 = Pat_0
909	68	9599	0	486	506	0	0	2 = Pat_10
356	1360	12	0	10	2302	0	0	3 = Pat_13
358	41	114	0	38650	102	0	19	4 = Pat_2
1153	2884	93	0	64	25872	0	0	5 = Pat_3
1	0	0	0	0	0	0	0	6 = Pat_4
234	18	84	0	6792	35	0	88	7 = Pat_8

Table F.24: Results for *hh125.AD* activity recognition, with an accuracy of 84.724.

0	1	2	3	4	5	6	7	←guessed
9755	0	4546	346	6216	1383	1269	699	0 = Other_Activity
332	3	5	0	21	0	299	2	1 = Pat_0
124	0	28613	1	256	0	29	41	2 = Pat_1
438	0	23	3811	78	1664	11	111	3 = Pat_11
528	0	289	0	23250	3	18	44	4 = Pat_2
490	0	25	1064	100	7394	43	60	5 = Pat_3
3595	0	780	34	3104	167	4202	522	6 = Pat_4
1658	0	61	20	534	78	809	3784	7 = Pat_8

Table F.25: Results for *hh126.AD* activity recognition, with an accuracy of 71.685.

0	1	2	3	4	5	6	7	←guessed
6625	0	1892	7	2029	517	567	424	0 = Other_Activity
555	7	15	0	1	2	0	0	1 = Pat_0
123	0	20082	0	24	30	12	9	2 = Pat_1
749	0	160	67	8	12	19	30	3 = Pat_11
286	0	300	0	9795	954	2	21	4 = Pat_2
187	0	265	0	2260	5365	4	15	5 = Pat_4
452	0	215	0	32	13	2664	912	6 = Pat_5
465	0	222	0	28	27	785	3565	7 = Pat_7

Table F.26: Results for *hh127.AD* activity recognition, with an accuracy of 76.704.

0	1	2	3	4	5	6	7	←guessed
40844	9112	16071	1659	4862	89	36	2413	0 = Other_Activity
422	121392	665	3	113	28	0	1	1 = Pat_0
1607	73	79245	132	118	0	0	5	2 = Pat_1
3017	109	2866	11161	576	0	0	161	3 = Pat_12
1754	2184	255	5	56898	0	59	13	4 = Pat_2
1800	5831	50	10	501	1520	2	6	5 = Pat_3
2234	1244	315	11	13644	0	409	15	6 = Pat_6
13072	1698	4661	2370	828	0	4	6969	7 = Pat_8

Table F.27: Results for *hh128.AD* activity recognition, with an accuracy of 76.706.

0	1	2	3	4	5	6	7	←guessed
10060	4560	954	1998	0	568	2631	95	0 = Other_Activity
789	48514	901	39	0	73	28	4	1 = Pat_0
1100	12481	7352	89	0	105	71	8	2 = Pat_1
326	240	12	22122	0	2	1180	58	3 = Pat_2
0	0	0	0	0	0	0	0	4 = Pat_4
247	304	45	7	0	11091	0	20	5 = Pat_5
1205	416	35	4872	0	38	12687	79	6 = Pat_6
2142	1813	834	4359	0	1594	1526	1019	7 = Pat_7

Table F.28: Results for *hh129.AD* activity recognition, with an accuracy of 70.224.

G ACTIVITY DISCOVERY RESULTS PER ACTIVITY

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.44881	0.0058545	0.99415	0.66797	0.88855	0.44881
Pat_0	0.98975	0.031666	0.96833	0.97898	0.94572	0.98975
Pat_1	0	0	1	0	-	0
Pat_11	0.049594	0.00065038	0.99935	0.22262	0.67512	0.049594
Pat_2	0.98178	0.038502	0.9615	0.97159	0.85873	0.98178
Pat_3	0.97994	0.031162	0.96884	0.97437	0.86843	0.97994
Pat_4	0.98655	0.042224	0.95778	0.97205	0.76475	0.98655
Pat_9	0.056841	0.00060841	0.99939	0.23834	0.76225	0.056841

Table G.1: *hh101.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.27526	0.032407	0.96759	0.51608	0.65577	0.27526
Pat_0	0.97942	0.04903	0.95097	0.96509	0.81824	0.97942
Pat_1	0	0	1	0	-	0
Pat_12	0.67191	0.0089571	0.99104	0.81602	0.78519	0.67191
Pat_13	0.71445	0.0073694	0.99263	0.84213	0.80078	0.71445
Pat_2	0.96958	0.062722	0.93728	0.95329	0.77202	0.96958
Pat_3	0.96724	0.031943	0.96806	0.96765	0.89854	0.96724
Pat_5	0.88317	0.039812	0.96019	0.92087	0.78402	0.88317

Table G.2: *hh102.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.7228	0.076228	0.92377	0.81713	0.66574	0.7228
Pat_0	0.99125	0.02582	0.97418	0.98268	0.91143	0.99125
Pat_1	0.99887	0.024895	0.97511	0.98692	0.95189	0.99887
Pat_11	0.19846	0.0018095	0.99819	0.44509	0.7861	0.19846
Pat_12	0.49827	0.0029489	0.99705	0.70484	0.77951	0.49827
Pat_13	0.50291	0.0039116	0.99609	0.70777	0.78438	0.50291
Pat_2	0.0093247	9.1763e-06	0.99999	0.096564	0.97059	0.0093247
Pat_3	0.92953	0.042499	0.9575	0.94341	0.82054	0.92953

Table G.3: *hh103.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.47832	0.055372	0.94463	0.67219	0.56751	0.47832
Pat_0	0.9676	0.11024	0.88976	0.92786	0.76247	0.9676
Pat_1	0.96613	0.029444	0.97056	0.96834	0.94095	0.96613
Pat_10	0.84457	0.011934	0.98807	0.9135	0.83174	0.84457
Pat_11	0.41142	0.0052712	0.99473	0.63972	0.79891	0.41142
Pat_2	0	0	1	0	-	0
Pat_5	0.96361	0.022496	0.9775	0.97053	0.81713	0.96361
Pat_7	0.11618	0.0034109	0.99659	0.34027	0.70401	0.11618

Table G.4: *hh104.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.42242	0.035918	0.96408	0.63816	0.6866	0.42242
Pat_0	0.9955	0.093243	0.90676	0.95009	0.85354	0.9955
Pat_1	0.0087188	9.0924e-05	0.99991	0.09337	0.73469	0.0087188
Pat_10	0.075395	0.001037	0.99896	0.27444	0.63391	0.075395
Pat_2	0.85207	0.045882	0.95412	0.90165	0.74903	0.85207
Pat_4	0.96766	0.030335	0.96966	0.96866	0.81404	0.96766
Pat_6	0.92692	0.045181	0.95482	0.94077	0.75728	0.92692
Pat_9	0.4891	0.002883	0.99712	0.69835	0.89407	0.4891

Table G.5: *hh105.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.55513	0.08697	0.91303	0.71193	0.6018	0.55513
Pat_0	0	0	1	0	-	0
Pat_1	0.93804	0.040292	0.95971	0.94881	0.90457	0.93804
Pat_13	0.028061	0.00013081	0.99987	0.1675	0.83544	0.028061
Pat_2	0.96607	0.037575	0.96242	0.96425	0.85712	0.96607
Pat_3	0.68587	0.047526	0.95247	0.80825	0.74557	0.68587
Pat_6	0.82385	0.01903	0.98097	0.89898	0.77476	0.82385
Pat_7	0.89464	0.019339	0.98066	0.93666	0.76135	0.89464

Table G.6: *hh106.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.44982	0.04763	0.95237	0.65452	0.66809	0.44982
Pat_0	0.96345	0.089914	0.91009	0.93639	0.80304	0.96345
Pat_1	0.92679	0.057317	0.94268	0.9347	0.83075	0.92679
Pat_11	0.48226	0.005479	0.99452	0.69254	0.68491	0.48226
Pat_2	0.014324	0.00014015	0.99986	0.11968	0.65432	0.014324
Pat_4	0.88986	0.016658	0.98334	0.93543	0.88157	0.88986
Pat_5	0.85489	0.016632	0.98337	0.91688	0.837	0.85489
Pat_9	0.7841	0.010947	0.98905	0.88063	0.82154	0.7841

Table G.7: *hh107.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.32321	0.042672	0.95733	0.55625	0.59076	0.32321
Pat_0	0.95455	0.096018	0.90398	0.92892	0.79512	0.95455
Pat_1	0.01685	3.4784e-06	1	0.12981	0.95833	0.01685
Pat_11	0.0039901	1.0654e-05	0.99999	0.063167	0.90625	0.0039901
Pat_14	0.066961	0.00021137	0.99979	0.25874	0.84772	0.066961
Pat_2	0.97338	0.027075	0.97292	0.97315	0.90267	0.97338
Pat_3	0.86629	0.0799	0.9201	0.89279	0.74616	0.86629
Pat_5	0.82318	0.030839	0.96916	0.89319	0.73385	0.82318

Table G.8: *hh108.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.71622	0.087453	0.91255	0.80845	0.71723	0.71622
Pat_0	0.95174	0.081718	0.91828	0.93486	0.80564	0.95174
Pat_1	0.96488	0.037544	0.96246	0.96367	0.90859	0.96488
Pat_10	0.0013958	1.5728e-05	0.99998	0.03736	0.80645	0.0013958
Pat_13	0.00087045	2.5477e-06	1	0.029503	0.85714	0.00087045
Pat_2	0	0	1	0	-	0
Pat_5	0.88727	0.015033	0.98497	0.93484	0.85696	0.88727
Pat_6	0.81006	0.0076152	0.99238	0.8966	0.88568	0.81006

Table G.9: *hh109.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.52482	0.046646	0.95335	0.70734	0.65068	0.52482
Pat_0	0.027474	0.0011333	0.99887	0.16566	0.58494	0.027474
Pat_1	0.9582	0.057228	0.94277	0.95045	0.85478	0.9582
Pat_10	0.032326	0.00064751	0.99935	0.17974	0.60623	0.032326
Pat_2	0.96996	0.071507	0.92849	0.949	0.76545	0.96996
Pat_4	0.85154	0.029562	0.97044	0.90905	0.81214	0.85154
Pat_6	0.92176	0.027871	0.97213	0.94661	0.78386	0.92176
Pat_7	0.74882	0.026034	0.97397	0.854	0.73932	0.74882

Table G.10: *hh111.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.75519	0.10546	0.89454	0.82192	0.6162	0.75519
Pat_0	0.97162	0.21299	0.78701	0.87445	0.78275	0.97162
Pat_12	0.75713	0.0062239	0.99378	0.86742	0.77773	0.75713
Pat_14	0.28937	0.0012475	0.99875	0.53759	0.84862	0.28937
Pat_2	0.050748	0.0010622	0.99894	0.22515	0.70686	0.050748
Pat_3	0.25118	0.013832	0.98617	0.4977	0.68375	0.25118
Pat_5	0.58661	0.016872	0.98313	0.75941	0.78031	0.58661
Pat_6	0.88352	0.013403	0.9866	0.93364	0.84592	0.88352

Table G.11: *hh112.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.55216	0.030124	0.96988	0.7318	0.76854	0.55216
Pat_0	0.96983	0.1125	0.8875	0.92775	0.72462	0.96983
Pat_1	0.98621	0.015291	0.98471	0.98546	0.9619	0.98621
Pat_11	0.044913	0.00055886	0.99944	0.21187	0.61137	0.044913
Pat_2	0	0	1	0	-	0
Pat_3	0.97511	0.035341	0.96466	0.96987	0.75606	0.97511
Pat_4	0.95	0.021994	0.97801	0.9639	0.86075	0.95
Pat_5	0.15225	0.0060002	0.994	0.38902	0.70508	0.15225

Table G.12: *hh113.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.50825	0.07446	0.92554	0.68586	0.60869	0.50825
Pat_0	0.99311	0.090073	0.90993	0.95061	0.87997	0.99311
Pat_10	0.0045524	1.5133e-05	0.99998	0.067471	0.88235	0.0045524
Pat_2	0.97118	0.03831	0.96169	0.96642	0.78792	0.97118
Pat_3	0	0	1	0	-	0
Pat_4	0.77089	0.071327	0.92867	0.84611	0.63619	0.77089
Pat_6	0.029326	0.00060037	0.9994	0.1712	0.77381	0.029326
Pat_8	0.91823	0.012745	0.98725	0.95212	0.81644	0.91823

Table G.13: *hh114.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.56937	0.024096	0.9759	0.74542	0.79196	0.56937
Pat_0	0.98223	0.10061	0.89939	0.9399	0.79369	0.98223
Pat_1	0.99027	0.033406	0.96659	0.97836	0.90265	0.99027
Pat_10	0.0031646	1.3452e-05	0.99999	0.056254	0.84892	0.0031646
Pat_2	0	0	1	0	-	0
Pat_3	0.89273	0.033655	0.96635	0.92881	0.77463	0.89273
Pat_4	0.97994	0.010238	0.98976	0.98484	0.93541	0.97994
Pat_6	0.19731	0.0054708	0.99453	0.44298	0.73332	0.19731

Table G.14: *hh115.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.80028	0.079089	0.92091	0.85848	0.67539	0.80028
Pat_0	0.9714	0.046367	0.95363	0.96248	0.93845	0.9714
Pat_1	0.9276	0.076105	0.92389	0.92575	0.72669	0.9276
Pat_11	0.22803	0.0010926	0.99891	0.47726	0.88865	0.22803
Pat_4	0.86145	0.030985	0.96902	0.91365	0.76231	0.86145
Pat_5	0.073189	0.0017938	0.99821	0.27029	0.75182	0.073189
Pat_6	0	0	1	0	-	0
Pat_9	0.0083301	8.3995e-05	0.99992	0.091265	0.66667	0.0083301

Table G.15: *hh116.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.21841	0.018919	0.98108	0.4629	0.58575	0.21841
Pat_0	0.98479	0.10619	0.89381	0.9382	0.78794	0.98479
Pat_1	0.96672	0.073704	0.9263	0.94629	0.84532	0.96672
Pat_10	0.69907	0.018397	0.9816	0.82838	0.73534	0.69907
Pat_2	0	0	1	0	-	0
Pat_4	0.92462	0.017875	0.98213	0.95294	0.84053	0.92462
Pat_6	0.95732	0.014288	0.98571	0.97141	0.86551	0.95732
Pat_9	0.025446	0.00046046	0.99954	0.15948	0.7864	0.025446

Table G.16: *hh117.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.52579	0.082502	0.9175	0.69456	0.61469	0.52579
Pat_0	0.97085	0.054559	0.94544	0.95806	0.85877	0.97085
Pat_1	0.87274	0.027701	0.9723	0.92118	0.88545	0.87274
Pat_14	0.21688	0.001178	0.99882	0.46543	0.80618	0.21688
Pat_2	0.010699	0.00010827	0.99989	0.10343	0.70312	0.010699
Pat_3	0.92227	0.034173	0.96583	0.9438	0.80163	0.92227
Pat_5	0.7974	0.027221	0.97278	0.88074	0.76013	0.7974
Pat_6	0.91297	0.021466	0.97853	0.94518	0.77457	0.91297

Table G.17: *hh118.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.54999	0.054762	0.94524	0.72102	0.67049	0.54999
Pat_0	0.81825	0.067781	0.93222	0.87338	0.63374	0.81825
Pat_1	0.96889	0.023321	0.97668	0.97278	0.93609	0.96889
Pat_14	0.13603	0.00076171	0.99924	0.36868	0.80939	0.13603
Pat_2	-	0	1	-	-	-
Pat_3	0.98119	0.061851	0.93815	0.95943	0.81841	0.98119
Pat_4	0.65027	0.027559	0.97244	0.79521	0.78463	0.65027
Pat_8	0.62196	0.0089017	0.9911	0.78512	0.83444	0.62196

Table G.18: *hh119.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.56044	0.050533	0.94947	0.72947	0.72381	0.56044
Pat_0	0.98155	0.12347	0.87653	0.92755	0.77616	0.98155
Pat_1	-	0	1	-	-	-
Pat_2	0.96898	0.026884	0.97312	0.97105	0.85227	0.96898
Pat_3	0.95896	0.020347	0.97965	0.96925	0.87245	0.95896
Pat_4	0.22148	0.0077316	0.99227	0.4688	0.71268	0.22148
Pat_5	0.73614	0.016775	0.98323	0.85076	0.8372	0.73614
Pat_8	0.77179	0.012331	0.98767	0.87308	0.7874	0.77179

Table G.19: *hh120.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.66184	0.10381	0.89619	0.77015	0.63388	0.66184
Pat_0	0.92113	0.058406	0.94159	0.93131	0.91343	0.92113
Pat_1	0.0057859	5.5194e-05	0.99994	0.076063	0.72	0.0057859
Pat_12	0.75572	0.0048268	0.99517	0.86722	0.87213	0.75572
Pat_13	0.013083	0.00013334	0.99987	0.11437	0.65306	0.013083
Pat_3	0.89949	0.035491	0.96451	0.93143	0.79333	0.89949
Pat_6	0.89566	0.030977	0.96902	0.93162	0.76874	0.89566
Pat_8	0.77428	0.01643	0.98357	0.87267	0.77026	0.77428

Table G.20: *hh122.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.26071	0.021798	0.9782	0.505	0.7069	0.26071
Pat_0	0.98803	0.14822	0.85178	0.91738	0.74863	0.98803
Pat_1	-	0	1	-	-	-
Pat_12	0.79365	0.0068476	0.99315	0.88782	0.82998	0.79365
Pat_2	0.9521	0.14019	0.85981	0.90478	0.65706	0.9521
Pat_3	0.58954	0.023252	0.97675	0.75884	0.79418	0.58954
Pat_4	0.1917	0.007282	0.99272	0.43624	0.70927	0.1917
Pat_6	0.77715	0.017102	0.9829	0.87399	0.68679	0.77715

Table G.21: *hh123.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.50761	0.016744	0.98326	0.70648	0.82585	0.50761
Pat_0	0.99336	0.10336	0.89664	0.94376	0.88235	0.99336
Pat_10	0.82979	0.010592	0.98941	0.90609	0.81576	0.82979
Pat_13	0	0	1	0	-	0
Pat_2	0.98386	0.051729	0.94827	0.9659	0.80851	0.98386
Pat_3	0.86051	0.032243	0.96776	0.91256	0.81167	0.86051
Pat_4	0	0	1	0	-	0
Pat_8	0.012136	0.00011005	0.99989	0.11016	0.79279	0.012136

Table G.22: *hh125.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.40287	0.080944	0.91906	0.60849	0.57654	0.40287
Pat_0	0.0045317	0	1	0.067318	1	0.0045317
Pat_1	0.98448	0.068473	0.93153	0.95764	0.83318	0.98448
Pat_11	0.62109	0.013743	0.98626	0.78266	0.72233	0.62109
Pat_2	0.96345	0.11635	0.88365	0.92269	0.69281	0.96345
Pat_3	0.8058	0.031819	0.96818	0.88327	0.69174	0.8058
Pat_4	0.33876	0.024699	0.9753	0.5748	0.62904	0.33876
Pat_8	0.54493	0.013981	0.98602	0.73302	0.71898	0.54493

Table G.23: *hh126.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.54929	0.055519	0.94448	0.72027	0.70165	0.54929
Pat_0	0.012069	0	1	0.10986	1	0.012069
Pat_1	0.99024	0.072178	0.92782	0.95852	0.86744	0.99024
Pat_11	0.064115	0.00011335	0.99989	0.25319	0.90541	0.064115
Pat_2	0.86239	0.085183	0.91482	0.88822	0.69091	0.86239
Pat_4	0.66267	0.028426	0.97157	0.80239	0.77529	0.66267
Pat_5	0.62127	0.023739	0.97626	0.77879	0.65729	0.62127
Pat_7	0.70012	0.024451	0.97555	0.82644	0.71644	0.70012

Table G.24: *hh127.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.54396	0.0703	0.9297	0.71114	0.6308	0.54396
Pat_0	0.98995	0.06923	0.93077	0.95991	0.85703	0.98995
Pat_1	0.97616	0.074508	0.92549	0.95049	0.76103	0.97616
Pat_12	0.62387	0.010547	0.98945	0.78568	0.72705	0.62387
Pat_2	0.93019	0.058315	0.94168	0.93592	0.73379	0.93019
Pat_3	0.15638	0.00028859	0.99971	0.39539	0.92853	0.15638
Pat_6	0.022885	0.00025424	0.99975	0.15126	0.80196	0.022885
Pat_8	0.23542	0.0067801	0.99322	0.48356	0.72723	0.23542

Table G.25: *hh128.AD* activity recognition accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity	0.48212	0.041544	0.95846	0.67978	0.63394	0.48212
Pat_0	0.96357	0.17956	0.82044	0.88913	0.71002	0.96357
Pat_1	0.34669	0.019937	0.98006	0.58291	0.72555	0.34669
Pat_2	0.92406	0.083099	0.9169	0.92047	0.66063	0.92406
Pat_4	-	0	1	-	-	-
Pat_5	0.94682	0.015975	0.98402	0.96524	0.82332	0.94682
Pat_6	0.65627	0.038455	0.96155	0.79438	0.70005	0.65627
Pat_7	0.076692	0.001791	0.99821	0.27668	0.79423	0.076692

Table G.26: *hh129.AD* activity recognition accuracies.

H ACTIVITY DISCOVERY FORECASTING RESULTS

0	1	←guessed
127	856	0 = False
0	9606	1 = True

Table H.1: Results for *navan_week.AD* Other_Activity forecasting, with an accuracy of 91.916.

0	1	←guessed
201	6	0 = False
0	10382	1 = True

Table H.2: Results for *navan_week.AD* Pat_0 forecasting, with an accuracy of 99.943.

0	1	←guessed
8341	9	0 = False
538	1701	1 = True

Table H.3: Results for *navan_week.AD* Pat_11 forecasting, with an accuracy of 94.834.

0	1	←guessed
8383	26	0 = False
1357	823	1 = True

Table H.4: Results for *navan_week.AD* Pat_12 forecasting, with an accuracy of 86.939.

0	1	←guessed
8814	45	0 = False
424	1306	1 = True

Table H.5: Results for *navan_week.AD* Pat_13 forecasting, with an accuracy of 95.571.

0	1	←guessed
6217	99	0 = False
653	3620	1 = True

Table H.6: Results for *navan_week.AD* Pat_3 forecasting, with an accuracy of 92.898.

0	1	←guessed
8731	14	0 = False
255	1589	1 = True

Table H.7: Results for *navan_week.AD* Pat_5 forecasting, with an accuracy of 97.46.

0	1	←guessed
8829	43	0 = False
390	1327	1 = True

Table H.8: Results for *navan_week.AD* Pat_6 forecasting, with an accuracy of 95.911.

0	1	←guessed
207	539	0 = False
9	63714	1 = True

Table H.9: Results for *navan_2014.AD* Other_Activity forecasting, with an accuracy of 99.15.

0	1	←guessed
585	139	0 = False
26	63719	1 = True

Table H.10: Results for *navan_2014.AD* Pat_0 forecasting, with an accuracy of 99.744.

0	1	←guessed
49902	277	0 = False
1979	12311	1 = True

Table H.11: Results for *navan_2014.AD* Pat_10 forecasting, with an accuracy of 96.501.

0	1	←guessed
44451	3080	0 = False
3433	13505	1 = True

Table H.12: Results for *navan_2014.AD* Pat_12 forecasting, with an accuracy of 89.897.

0	1	←guessed
49844	284	0 = False
1855	12486	1 = True

Table H.13: Results for *navan_2014.AD* Pat_4 forecasting, with an accuracy of 96.682.

0	1	←guessed
34728	1333	0 = False
3873	24535	1 = True

Table H.14: Results for *navan_2014.AD* Pat_5 forecasting, with an accuracy of 91.925.

0	1	←guessed
47965	234	0 = False
2856	13414	1 = True

Table H.15: Results for *navan_2014.AD* Pat_7 forecasting, with an accuracy of 95.207.

0	1	←guessed
20172	3449	0 = False
4526	36322	1 = True

Table H.16: Results for *navan_2014.AD* Pat_9 forecasting, with an accuracy of 87.63.

0	1	←guessed
5119	24725	0 = False
136	200419	1 = True

Table H.17: Results for *navan_2012.AD* Other_Activity forecasting, with an accuracy of 89.21.

0	1	←guessed
136981	2958	0 = False
12421	78039	1 = True

Table H.18: Results for *navan_2012.AD* Pat_0 forecasting, with an accuracy of 93.325.

0	1	←guessed
188846	709	0 = False
19393	21451	1 = True

Table H.19: Results for *navan_2012.AD* Pat_1 forecasting, with an accuracy of 91.275.

0	1	←guessed
209401	195	0 = False
11155	9648	1 = True

Table H.20: Results for *navan_2012.AD* Pat_11 forecasting, with an accuracy of 95.074.

0	1	←guessed
209817	175	0 = False
12737	7670	1 = True

Table H.21: Results for *navan_2012.AD* Pat_14 forecasting, with an accuracy of 94.396.

0	1	←guessed
179690	590	0 = False
24312	25807	1 = True

Table H.22: Results for *navan_2012.AD* Pat_2 forecasting, with an accuracy of 89.192.

0	1	←guessed
139099	13301	0 = False
10290	67709	1 = True

Table H.23: Results for *navan_2012.AD* Pat_3 forecasting, with an accuracy of 89.761.

0	1	←guessed
200431	84	0 = False
21414	8470	1 = True

Table H.24: Results for *navan_2012.AD* Pat_8 forecasting, with an accuracy of 90.669.

.

I ACTIVITY DISCOVERY FORECASTING RESULTS PER ACTIVITY

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.97442	0.13772	0.86228	0.91663	0.9087	0.97442
Other_Activity-True	0.86228	0.025583	0.97442	0.91663	0.95993	0.86228
Pat_0-False	0.96846	0.0458	0.9542	0.9613	0.96098	0.96846
Pat_0-True	0.9542	0.031544	0.96846	0.9613	0.96293	0.9542
Pat_1-False	0.94113	0.077693	0.92231	0.93167	0.83472	0.94113
Pat_1-True	0.92231	0.058868	0.94113	0.93167	0.97408	0.92231
Pat_11-False	0.99844	0.35214	0.64786	0.80427	0.96935	0.99844
Pat_11-True	0.64786	0.0015633	0.99844	0.80427	0.97379	0.64786
Pat_2-False	0.99813	0.54399	0.45601	0.67465	0.91114	0.99813
Pat_2-True	0.45601	0.0018702	0.99813	0.67465	0.97759	0.45601
Pat_3-False	0.99938	0.46357	0.53643	0.73219	0.95294	0.99938
Pat_3-True	0.53643	0.00061948	0.99938	0.73219	0.98927	0.53643
Pat_4-False	0.99887	0.38775	0.61225	0.78202	0.95757	0.99887
Pat_4-True	0.61225	0.0011306	0.99887	0.78202	0.98408	0.61225
Pat_9-False	0.999	0.3733	0.6267	0.79125	0.96502	0.999
Pat_9-True	0.6267	0.00099806	0.999	0.79125	0.98385	0.6267

Table I.1: *hh101.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.98018	0.11629	0.88371	0.93069	0.93419	0.98018
Other_Activity-True	0.88371	0.019824	0.98018	0.93069	0.96359	0.88371
Pat_0-False	0.99669	0.21231	0.78769	0.88605	0.9728	0.99669
Pat_0-True	0.78769	0.0033087	0.99669	0.88605	0.96899	0.78769
Pat_1-False	0.90374	0.053334	0.94667	0.92495	0.87795	0.90374
Pat_1-True	0.94667	0.096262	0.90374	0.92495	0.95862	0.94667
Pat_12-False	0.99797	0.29939	0.70061	0.83617	0.96122	0.99797
Pat_12-True	0.70061	0.0020341	0.99797	0.83617	0.97887	0.70061
Pat_13-False	0.99796	0.2216	0.7784	0.88137	0.97455	0.99796
Pat_13-True	0.7784	0.0020414	0.99796	0.88137	0.97819	0.7784
Pat_2-False	0.99796	0.25032	0.74968	0.86496	0.96307	0.99796
Pat_2-True	0.74968	0.0020412	0.99796	0.86496	0.9825	0.74968
Pat_3-False	0.98984	0.28701	0.71299	0.84009	0.92296	0.98984
Pat_3-True	0.71299	0.01016	0.98984	0.84009	0.95283	0.71299
Pat_5-False	0.98026	0.068953	0.93105	0.95533	0.97733	0.98026
Pat_5-True	0.93105	0.019745	0.98026	0.95533	0.93958	0.93105

Table I.2: *hh102.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.99557	0.35689	0.64311	0.80016	0.90265	0.99557
Other_Activity-True	0.64311	0.0044346	0.99557	0.80016	0.97759	0.64311
Pat_0-False	0.99783	0.50179	0.49821	0.70507	0.93481	0.99783
Pat_0-True	0.49821	0.0021748	0.99783	0.70507	0.96948	0.49821
Pat_1-False	0.99789	0.3163	0.6837	0.82599	0.97327	0.99789
Pat_1-True	0.6837	0.0021149	0.99789	0.82599	0.96552	0.6837
Pat_11-False	0.99907	0.49843	0.50157	0.70789	0.95178	0.99907
Pat_11-True	0.50157	0.00093213	0.99907	0.70789	0.98203	0.50157
Pat_12-False	0.99997	0.74736	0.25264	0.50263	0.96101	0.99997
Pat_12-True	0.25264	2.5489e-05	0.99997	0.50263	0.99814	0.25264
Pat_13-False	0.99887	0.45651	0.54349	0.7368	0.96843	0.99887
Pat_13-True	0.54349	0.0011267	0.99887	0.7368	0.97175	0.54349
Pat_2-False	0.95974	0.046741	0.95326	0.95649	0.90843	0.95974
Pat_2-True	0.95326	0.040263	0.95974	0.95649	0.98	0.95326
Pat_3-False	0.99652	0.56311	0.43689	0.65983	0.86781	0.99652
Pat_3-True	0.43689	0.0034838	0.99652	0.65983	0.97127	0.43689

Table I.3: *hh103.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.96545	0.21251	0.78749	0.87194	0.79981	0.96545
Other_Activity-True	0.78749	0.034549	0.96545	0.87194	0.96285	0.78749
Pat_0-False	0.96813	0.22118	0.77882	0.86833	0.87624	0.96813
Pat_0-True	0.77882	0.031871	0.96813	0.86833	0.93791	0.77882
Pat_1-False	0.99801	0.20484	0.79516	0.89083	0.94979	0.99801
Pat_1-True	0.79516	0.0019901	0.99801	0.89083	0.99038	0.79516
Pat_10-False	0.99429	0.37594	0.62406	0.78772	0.92429	0.99429
Pat_10-True	0.62406	0.0057067	0.99429	0.78772	0.9595	0.62406
Pat_11-False	0.99832	0.30594	0.69406	0.8324	0.94024	0.99832
Pat_11-True	0.69406	0.001677	0.99832	0.8324	0.98848	0.69406
Pat_2-False	0.9034	0.098597	0.9014	0.9024	0.75097	0.9034
Pat_2-True	0.9014	0.096598	0.9034	0.9024	0.96593	0.9014
Pat_5-False	0.99243	0.17869	0.82131	0.90283	0.97163	0.99243
Pat_5-True	0.82131	0.007568	0.99243	0.90283	0.94623	0.82131
Pat_7-False	0.98653	0.303	0.697	0.82922	0.88525	0.98653
Pat_7-True	0.697	0.01347	0.98653	0.82922	0.95622	0.697

Table I.4: *hh104.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.99222	0.17484	0.82516	0.90484	0.95345	0.99222
Other_Activity-True	0.82516	0.0077801	0.99222	0.90484	0.96709	0.82516
Pat_0-False	0.99647	0.19402	0.80598	0.89618	0.97535	0.99647
Pat_0-True	0.80598	0.0035317	0.99647	0.89618	0.96735	0.80598
Pat_1-False	0.98595	0.057277	0.94272	0.9641	0.94223	0.98595
Pat_1-True	0.94272	0.014046	0.98595	0.9641	0.98608	0.94272
Pat_10-False	0.99931	0.31915	0.68085	0.82485	0.97302	0.99931
Pat_10-True	0.68085	0.00069435	0.99931	0.82485	0.98839	0.68085
Pat_2-False	0.98757	0.11346	0.88654	0.93569	0.97635	0.98757
Pat_2-True	0.88654	0.012433	0.98757	0.93569	0.93764	0.88654
Pat_4-False	0.99942	0.36436	0.63564	0.79704	0.97315	0.99942
Pat_4-True	0.63564	0.00057678	0.99942	0.79704	0.98815	0.63564
Pat_6-False	0.99816	0.40288	0.59712	0.77202	0.95025	0.99816
Pat_6-True	0.59712	0.001843	0.99816	0.77202	0.97676	0.59712
Pat_9-False	0.99692	0.19753	0.80247	0.89443	0.97676	0.99692
Pat_9-True	0.80247	0.0030796	0.99692	0.89443	0.96903	0.80247

Table I.5: *hh105.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.98572	0.17862	0.82138	0.8998	0.91302	0.98572
Other_Activity-True	0.82138	0.014282	0.98572	0.8998	0.96798	0.82138
Pat_0-False	0.96136	0.10635	0.89365	0.92689	0.76212	0.96136
Pat_0-True	0.89365	0.038644	0.96136	0.92689	0.98491	0.89365
Pat_1-False	0.99502	0.17673	0.82327	0.90508	0.96519	0.99502
Pat_1-True	0.82327	0.0049768	0.99502	0.90508	0.97109	0.82327
Pat_13-False	0.99633	0.31792	0.68208	0.82436	0.95366	0.99633
Pat_13-True	0.68208	0.0036687	0.99633	0.82436	0.96589	0.68208
Pat_2-False	0.99744	0.11377	0.88623	0.94019	0.98232	0.99744
Pat_2-True	0.88623	0.0025569	0.99744	0.94019	0.98204	0.88623
Pat_3-False	0.98744	0.13394	0.86606	0.92476	0.9643	0.98744
Pat_3-True	0.86606	0.012558	0.98744	0.92476	0.94956	0.86606
Pat_6-False	0.99633	0.14357	0.85643	0.92373	0.98166	0.99633
Pat_6-True	0.85643	0.0036727	0.99633	0.92373	0.96799	0.85643
Pat_7-False	0.99781	0.53805	0.46195	0.67893	0.92358	0.99781
Pat_7-True	0.46195	0.0021853	0.99781	0.67893	0.97009	0.46195

Table I.6: *hh106.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.97987	0.11307	0.88693	0.93224	0.90002	0.97987
Other_Activity-True	0.88693	0.020135	0.97987	0.93224	0.97696	0.88693
Pat_0-False	0.99307	0.064351	0.93565	0.96393	0.98126	0.99307
Pat_0-True	0.93565	0.0069314	0.99307	0.96393	0.97548	0.93565
Pat_1-False	0.98706	0.023816	0.97618	0.98161	0.9878	0.98706
Pat_1-True	0.97618	0.012937	0.98706	0.98161	0.97477	0.97618
Pat_11-False	0.99906	0.27135	0.72865	0.85321	0.98051	0.99906
Pat_11-True	0.72865	0.0009375	0.99906	0.85321	0.98272	0.72865
Pat_2-False	0.98616	0.090066	0.90993	0.94728	0.80081	0.98616
Pat_2-True	0.90993	0.013845	0.98616	0.94728	0.99444	0.90993
Pat_4-False	0.91486	0.14534	0.85466	0.88424	0.92721	0.91486
Pat_4-True	0.85466	0.085143	0.91486	0.88424	0.83222	0.85466
Pat_5-False	0.99779	0.1263	0.8737	0.93369	0.98017	0.99779
Pat_5-True	0.8737	0.0022083	0.99779	0.93369	0.98443	0.8737
Pat_9-False	0.99781	0.13804	0.86196	0.9274	0.97984	0.99781
Pat_9-True	0.86196	0.0021872	0.99781	0.9274	0.98323	0.86196

Table I.7: *hh107.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.97652	0.16119	0.83881	0.90505	0.89806	0.97652
Other_Activity-True	0.83881	0.023485	0.97652	0.90505	0.96088	0.83881
Pat_0-False	0.99337	0.16786	0.83214	0.90919	0.95873	0.99337
Pat_0-True	0.83214	0.0066297	0.99337	0.90919	0.96968	0.83214
Pat_1-False	0.47877	0.040609	0.95939	0.67774	0.72555	0.47877
Pat_1-True	0.95939	0.52123	0.47877	0.67774	0.8914	0.95939
Pat_11-False	0.9911	0.091651	0.90835	0.94882	0.97956	0.9911
Pat_11-True	0.90835	0.0089046	0.9911	0.94882	0.95837	0.90835
Pat_14-False	0.99939	0.32376	0.67624	0.82208	0.96126	0.99939
Pat_14-True	0.67624	0.00061459	0.99939	0.82208	0.99275	0.67624
Pat_2-False	0.99051	0.29027	0.70973	0.83845	0.90092	0.99051
Pat_2-True	0.70973	0.0094904	0.99051	0.83845	0.9656	0.70973
Pat_3-False	0.9867	0.11502	0.88498	0.93445	0.95501	0.9867
Pat_3-True	0.88498	0.013302	0.9867	0.93445	0.96413	0.88498
Pat_5-False	0.99023	0.094518	0.90548	0.94691	0.97642	0.99023
Pat_5-True	0.90548	0.0097737	0.99023	0.94691	0.95908	0.90548

Table I.8: *hh108.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.98871	0.11204	0.88796	0.93698	0.93566	0.98871
Other_Activity-True	0.88796	0.011289	0.98871	0.93698	0.97948	0.88796
Pat_0-False	0.9947	0.14833	0.85167	0.92041	0.96391	0.9947
Pat_0-True	0.85167	0.0052993	0.9947	0.92041	0.97581	0.85167
Pat_1-False	0.99499	0.36929	0.63071	0.79218	0.86901	0.99499
Pat_1-True	0.63071	0.0050115	0.99499	0.79218	0.98081	0.63071
Pat_10-False	0.99084	0.11644	0.88356	0.93566	0.96325	0.99084
Pat_10-True	0.88356	0.0091554	0.99084	0.93566	0.96907	0.88356
Pat_13-False	0.99707	0.18484	0.81516	0.90154	0.9657	0.99707
Pat_13-True	0.81516	0.0029308	0.99707	0.90154	0.98158	0.81516
Pat_2-False	0.96917	0.077056	0.92294	0.94578	0.8437	0.96917
Pat_2-True	0.92294	0.030828	0.96917	0.94578	0.98587	0.92294
Pat_5-False	0.99807	0.27217	0.72783	0.85231	0.95562	0.99807
Pat_5-True	0.72783	0.0019323	0.99807	0.85231	0.98465	0.72783
Pat_6-False	0.9956	0.11987	0.88013	0.93609	0.9778	0.9956
Pat_6-True	0.88013	0.0043985	0.9956	0.93609	0.97418	0.88013

Table I.9: *hh109.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.98056	0.14923	0.85077	0.91336	0.91131	0.98056
Other_Activity-True	0.85077	0.019438	0.98056	0.91336	0.96551	0.85077
Pat_0-False	0.98389	0.059164	0.94084	0.96212	0.85708	0.98389
Pat_0-True	0.94084	0.016114	0.98389	0.96212	0.99386	0.94084
Pat_1-False	0.98969	0.06652	0.93348	0.96117	0.97704	0.98969
Pat_1-True	0.93348	0.010314	0.98969	0.96117	0.96936	0.93348
Pat_10-False	0.99715	0.28548	0.71452	0.84409	0.95836	0.99715
Pat_10-True	0.71452	0.0028465	0.99715	0.84409	0.97442	0.71452
Pat_2-False	0.99075	0.36482	0.63518	0.79329	0.90118	0.99075
Pat_2-True	0.63518	0.0092526	0.99075	0.79329	0.95336	0.63518
Pat_4-False	0.99595	0.23683	0.76317	0.87183	0.95548	0.99595
Pat_4-True	0.76317	0.0040453	0.99595	0.87183	0.97366	0.76317
Pat_6-False	0.99889	0.36104	0.63896	0.7989	0.957	0.99889
Pat_6-True	0.63896	0.001114	0.99889	0.7989	0.98617	0.63896
Pat_7-False	0.99807	0.30292	0.69708	0.83411	0.95723	0.99807
Pat_7-True	0.69708	0.0019337	0.99807	0.83411	0.9815	0.69708

Table I.10: *hh111.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.98777	0.17332	0.82668	0.90364	0.92817	0.98777
Other_Activity-True	0.82668	0.012231	0.98777	0.90364	0.96754	0.82668
Pat_0-False	0.95426	0.2821	0.7179	0.82768	0.85022	0.95426
Pat_0-True	0.7179	0.045737	0.95426	0.82768	0.90342	0.7179
Pat_12-False	0.99784	0.19873	0.80127	0.89417	0.98727	0.99784
Pat_12-True	0.80127	0.0021566	0.99784	0.89417	0.96008	0.80127
Pat_14-False	0.99851	0.4013	0.5987	0.77318	0.95471	0.99851
Pat_14-True	0.5987	0.0014881	0.99851	0.77318	0.97938	0.5987
Pat_2-False	0.98796	0.05714	0.94286	0.96515	0.91219	0.98796
Pat_2-True	0.94286	0.012044	0.98796	0.96515	0.99238	0.94286
Pat_3-False	0.98984	0.27616	0.72384	0.84645	0.91999	0.98984
Pat_3-True	0.72384	0.010163	0.98984	0.84645	0.9569	0.72384
Pat_5-False	0.9899	0.16563	0.83437	0.90882	0.96073	0.9899
Pat_5-True	0.83437	0.010097	0.9899	0.90882	0.9528	0.83437
Pat_6-False	0.99779	0.25486	0.74514	0.86226	0.96778	0.99779
Pat_6-True	0.74514	0.0022096	0.99779	0.86226	0.97776	0.74514

Table I.11: *hh112.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.97887	0.14459	0.85541	0.91506	0.90935	0.97887
Other_Activity-True	0.85541	0.021132	0.97887	0.91506	0.96469	0.85541
Pat_0-False	0.99388	0.13968	0.86032	0.92469	0.97677	0.99388
Pat_0-True	0.86032	0.0061161	0.99388	0.92469	0.95968	0.86032
Pat_1-False	0.99566	0.17436	0.82564	0.90667	0.96497	0.99566
Pat_1-True	0.82564	0.0043419	0.99566	0.90667	0.97526	0.82564
Pat_11-False	0.99684	0.20686	0.79314	0.88917	0.98099	0.99684
Pat_11-True	0.79314	0.0031615	0.99684	0.88917	0.95905	0.79314
Pat_2-False	0.95008	0.12286	0.87714	0.91288	0.80637	0.95008
Pat_2-True	0.87714	0.049919	0.95008	0.91288	0.97026	0.87714
Pat_3-False	0.99714	0.1975	0.8025	0.89454	0.9808	0.99714
Pat_3-True	0.8025	0.0028583	0.99714	0.89454	0.96522	0.8025
Pat_4-False	0.99315	0.35809	0.64191	0.79844	0.9128	0.99315
Pat_4-True	0.64191	0.006853	0.99315	0.79844	0.96127	0.64191
Pat_5-False	0.99187	0.13573	0.86427	0.92588	0.97132	0.99187
Pat_5-True	0.86427	0.0081264	0.99187	0.92588	0.95824	0.86427

Table I.12: *hh113.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.98895	0.12746	0.87254	0.92892	0.93519	0.98895
Other_Activity-True	0.87254	0.011049	0.98895	0.92892	0.97699	0.87254
Pat_0-False	0.99603	0.16735	0.83265	0.91068	0.9663	0.99603
Pat_0-True	0.83265	0.0039665	0.99603	0.91068	0.97756	0.83265
Pat_10-False	0.99713	0.21307	0.78693	0.88581	0.96132	0.99713
Pat_10-True	0.78693	0.0028732	0.99713	0.88581	0.98098	0.78693
Pat_2-False	0.99647	0.26185	0.73815	0.85764	0.93441	0.99647
Pat_2-True	0.73815	0.0035263	0.99647	0.85764	0.98243	0.73815
Pat_3-False	0.89951	0.029759	0.97024	0.93421	0.91086	0.89951
Pat_3-True	0.97024	0.10049	0.89951	0.93421	0.96617	0.97024
Pat_4-False	0.99188	0.15424	0.84576	0.91591	0.95682	0.99188
Pat_4-True	0.84576	0.0081229	0.99188	0.91591	0.96797	0.84576
Pat_6-False	0.99078	0.13571	0.86429	0.92538	0.95791	0.99078
Pat_6-True	0.86429	0.0092194	0.99078	0.92538	0.96782	0.86429
Pat_8-False	0.99945	0.37865	0.62135	0.78804	0.96427	0.99945
Pat_8-True	0.62135	0.00055092	0.99945	0.78804	0.99102	0.62135

Table I.13: *hh114.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.97491	0.20142	0.79858	0.88235	0.87242	0.97491
Other_Activity-True	0.79858	0.025091	0.97491	0.88235	0.9575	0.79858
Pat_0-False	0.81866	0.070129	0.92987	0.87249	0.95018	0.81866
Pat_0-True	0.92987	0.18134	0.81866	0.87249	0.75836	0.92987
Pat_1-False	0.99861	0.34216	0.65784	0.81051	0.95705	0.99861
Pat_1-True	0.65784	0.001391	0.99861	0.81051	0.98411	0.65784
Pat_10-False	0.9921	0.22301	0.77699	0.87798	0.95027	0.9921
Pat_10-True	0.77699	0.0079042	0.9921	0.87798	0.95813	0.77699
Pat_2-False	0.94998	0.058388	0.94161	0.94579	0.90994	0.94998
Pat_2-True	0.94161	0.05002	0.94998	0.94579	0.96806	0.94161
Pat_3-False	0.98285	0.13644	0.86356	0.92127	0.95763	0.98285
Pat_3-True	0.86356	0.01715	0.98285	0.92127	0.94135	0.86356
Pat_4-False	0.99783	0.41195	0.58805	0.76601	0.92811	0.99783
Pat_4-True	0.58805	0.002171	0.99783	0.76601	0.9807	0.58805
Pat_6-False	0.99457	0.38646	0.61354	0.78116	0.90119	0.99457
Pat_6-True	0.61354	0.0054288	0.99457	0.78116	0.96959	0.61354

Table I.14: *hh115.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.97661	0.16769	0.83231	0.90158	0.91219	0.97661
Other_Activity-True	0.83231	0.023394	0.97661	0.90158	0.95226	0.83231
Pat_0-False	0.9974	0.17932	0.82068	0.90474	0.95603	0.9974
Pat_0-True	0.82068	0.0025999	0.9974	0.90474	0.98777	0.82068
Pat_1-False	0.99695	0.24043	0.75957	0.87021	0.96338	0.99695
Pat_1-True	0.75957	0.0030515	0.99695	0.87021	0.97515	0.75957
Pat_11-False	0.99645	0.29425	0.70575	0.8386	0.94279	0.99645
Pat_11-True	0.70575	0.0035459	0.99645	0.8386	0.97614	0.70575
Pat_4-False	0.99147	0.26199	0.73801	0.8554	0.93298	0.99147
Pat_4-True	0.73801	0.0085324	0.99147	0.8554	0.95921	0.73801
Pat_5-False	0.99748	0.22119	0.77881	0.88139	0.96656	0.99748
Pat_5-True	0.77881	0.0025241	0.99748	0.88139	0.97965	0.77881
Pat_6-False	0.92405	0.067412	0.93259	0.92831	0.87882	0.92405
Pat_6-True	0.93259	0.075952	0.92405	0.92831	0.95869	0.93259
Pat_9-False	0.99688	0.26886	0.73114	0.85373	0.95154	0.99688
Pat_9-True	0.73114	0.0031203	0.99688	0.85373	0.9779	0.73114

Table I.15: *hh116.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.99301	0.26693	0.73307	0.8532	0.93681	0.99301
Other_Activity-True	0.73307	0.0069852	0.99301	0.8532	0.96342	0.73307
Pat_0-False	0.99179	0.19828	0.80172	0.89171	0.96509	0.99179
Pat_0-True	0.80172	0.0082079	0.99179	0.89171	0.94645	0.80172
Pat_1-False	0.99715	0.32838	0.67162	0.81836	0.96084	0.99715
Pat_1-True	0.67162	0.0028473	0.99715	0.81836	0.96688	0.67162
Pat_10-False	0.99738	0.34507	0.65493	0.80821	0.96169	0.99738
Pat_10-True	0.65493	0.0026239	0.99738	0.80821	0.96637	0.65493
Pat_2-False	0.89234	0.052547	0.94745	0.91949	0.91174	0.89234
Pat_2-True	0.94745	0.10766	0.89234	0.91949	0.93535	0.94745
Pat_4-False	0.99851	0.52678	0.47322	0.6874	0.95604	0.99851
Pat_4-True	0.47322	0.0014898	0.99851	0.6874	0.96514	0.47322
Pat_6-False	0.9992	0.48485	0.51515	0.71746	0.96264	0.9992
Pat_6-True	0.51515	0.00079641	0.9992	0.71746	0.98104	0.51515
Pat_9-False	0.99491	0.26458	0.73542	0.85538	0.96204	0.99491
Pat_9-True	0.73542	0.0050857	0.99491	0.85538	0.95547	0.73542

Table I.16: *hh117.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.9865	0.13155	0.86845	0.9256	0.92014	0.9865
Other_Activity-True	0.86845	0.013496	0.9865	0.9256	0.97668	0.86845
Pat_0-False	0.9975	0.19792	0.80208	0.89447	0.96808	0.9975
Pat_0-True	0.80208	0.0025033	0.9975	0.89447	0.98157	0.80208
Pat_1-False	0.99476	0.1174	0.8826	0.937	0.96469	0.99476
Pat_1-True	0.8826	0.0052358	0.99476	0.937	0.98123	0.8826
Pat_14-False	0.99868	0.32322	0.67678	0.82212	0.95958	0.99868
Pat_14-True	0.67678	0.0013162	0.99868	0.82212	0.98528	0.67678
Pat_2-False	0.9171	0.1399	0.8601	0.88814	0.56825	0.9171
Pat_2-True	0.8601	0.082901	0.9171	0.88814	0.98102	0.8601
Pat_3-False	0.99725	0.31167	0.68833	0.82852	0.95003	0.99725
Pat_3-True	0.68833	0.002748	0.99725	0.82852	0.97683	0.68833
Pat_5-False	0.98994	0.10485	0.89515	0.94135	0.96886	0.98994
Pat_5-True	0.89515	0.010061	0.98994	0.94135	0.96429	0.89515
Pat_6-False	0.9989	0.41278	0.58722	0.76588	0.95407	0.9989
Pat_6-True	0.58722	0.0010964	0.9989	0.76588	0.98423	0.58722

Table I.17: *hh118.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.99192	0.20715	0.79285	0.88682	0.91847	0.99192
Other_Activity-True	0.79285	0.0080776	0.99192	0.88682	0.97659	0.79285
Pat_0-False	0.99836	0.37298	0.62702	0.7912	0.94888	0.99836
Pat_0-True	0.62702	0.0016406	0.99836	0.7912	0.98218	0.62702
Pat_1-False	0.99831	0.22465	0.77535	0.8798	0.96878	0.99831
Pat_1-True	0.77535	0.0016904	0.99831	0.8798	0.985	0.77535
Pat_14-False	0.99914	0.34976	0.65024	0.80603	0.96707	0.99914
Pat_14-True	0.65024	0.00086042	0.99914	0.80603	0.98658	0.65024
Pat_2-False	0.099828	0.00038355	0.99962	0.31589	0.98305	0.099828
Pat_2-True	0.99962	0.90017	0.099828	0.31589	0.83287	0.99962
Pat_3-False	0.99067	0.24685	0.75315	0.86378	0.931	0.99067
Pat_3-True	0.75315	0.0093309	0.99067	0.86378	0.96001	0.75315
Pat_4-False	0.99831	0.39419	0.60581	0.77768	0.93982	0.99831
Pat_4-True	0.60581	0.0016924	0.99831	0.77768	0.98306	0.60581
Pat_8-False	0.99746	0.23686	0.76314	0.87247	0.96106	0.99746
Pat_8-True	0.76314	0.002544	0.99746	0.87247	0.98084	0.76314

Table I.18: *hh119.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.9757	0.1713	0.8287	0.8992	0.89491	0.9757
Other_Activity-True	0.8287	0.024304	0.9757	0.8992	0.958	0.8287
Pat_0-False	0.98632	0.34807	0.65193	0.80188	0.88535	0.98632
Pat_0-True	0.65193	0.013676	0.98632	0.80188	0.94592	0.65193
Pat_1-False	0.95952	0.13224	0.86776	0.91249	0.82499	0.95952
Pat_1-True	0.86776	0.040477	0.95952	0.91249	0.97059	0.86776
Pat_2-False	0.9991	0.42316	0.57684	0.75916	0.95188	0.9991
Pat_2-True	0.57684	0.00089884	0.9991	0.75916	0.98711	0.57684
Pat_3-False	0.99788	0.26447	0.73553	0.85672	0.97147	0.99788
Pat_3-True	0.73553	0.0021215	0.99788	0.85672	0.97463	0.73553
Pat_4-False	0.99045	0.25703	0.74297	0.85783	0.93592	0.99045
Pat_4-True	0.74297	0.0095454	0.99045	0.85783	0.95357	0.74297
Pat_5-False	0.99601	0.21157	0.78843	0.88616	0.96431	0.99601
Pat_5-True	0.78843	0.0039883	0.99601	0.88616	0.97179	0.78843
Pat_8-False	0.98906	0.11748	0.88252	0.93427	0.98145	0.98906
Pat_8-True	0.88252	0.010943	0.98906	0.93427	0.9277	0.88252

Table I.19: *hh120.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.98674	0.1876	0.8124	0.89534	0.89904	0.98674
Other_Activity-True	0.8124	0.013262	0.98674	0.89534	0.97311	0.8124
Pat_0-False	0.99335	0.11536	0.88464	0.93742	0.96896	0.99335
Pat_0-True	0.88464	0.0066482	0.99335	0.93742	0.97348	0.88464
Pat_1-False	0.84075	0.10569	0.89431	0.86711	0.6946	0.84075
Pat_1-True	0.89431	0.15925	0.84075	0.86711	0.95155	0.89431
Pat_12-False	0.99923	0.35166	0.64834	0.80488	0.97325	0.99923
Pat_12-True	0.64834	0.00077399	0.99923	0.80488	0.98494	0.64834
Pat_13-False	0.99466	0.11748	0.88252	0.93691	0.97967	0.99466
Pat_13-True	0.88252	0.0053365	0.99466	0.93691	0.96672	0.88252
Pat_3-False	0.99647	0.42689	0.57311	0.7557	0.89202	0.99647
Pat_3-True	0.57311	0.0035346	0.99647	0.7557	0.97864	0.57311
Pat_6-False	0.9985	0.30313	0.69687	0.83416	0.95544	0.9985
Pat_6-True	0.69687	0.0014961	0.9985	0.83416	0.98622	0.69687
Pat_8-False	0.9908	0.087302	0.9127	0.95095	0.98237	0.9908
Pat_8-True	0.9127	0.0091994	0.9908	0.95095	0.95286	0.9127

Table I.20: *hh122.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.99153	0.17758	0.82242	0.90303	0.92894	0.99153
Other_Activity-True	0.82242	0.0084738	0.99153	0.90303	0.97645	0.82242
Pat_0-False	0.98969	0.24087	0.75913	0.86678	0.92198	0.98969
Pat_0-True	0.75913	0.010306	0.98969	0.86678	0.96242	0.75913
Pat_1-False	0.96629	0.12595	0.87405	0.91901	0.80805	0.96629
Pat_1-True	0.87405	0.033708	0.96629	0.91901	0.97928	0.87405
Pat_12-False	0.99859	0.31508	0.68492	0.82701	0.95738	0.99859
Pat_12-True	0.68492	0.0014115	0.99859	0.82701	0.9856	0.68492
Pat_2-False	0.99786	0.22115	0.77885	0.88158	0.96585	0.99786
Pat_2-True	0.77885	0.0021385	0.99786	0.88158	0.98308	0.77885
Pat_3-False	0.99827	0.19309	0.80691	0.8975	0.96884	0.99827
Pat_3-True	0.80691	0.0017312	0.99827	0.8975	0.98726	0.80691
Pat_4-False	0.99324	0.17916	0.82084	0.90294	0.9565	0.99324
Pat_4-True	0.82084	0.0067588	0.99324	0.90294	0.96838	0.82084
Pat_6-False	0.99937	0.36509	0.63491	0.79656	0.97366	0.99937
Pat_6-True	0.63491	0.00062806	0.99937	0.79656	0.98682	0.63491

Table I.21: *hh123.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.98725	0.21119	0.78881	0.88247	0.90889	0.98725
Other_Activity-True	0.78881	0.012753	0.98725	0.88247	0.96665	0.78881
Pat_0-False	0.99445	0.21216	0.78784	0.88513	0.95851	0.99445
Pat_0-True	0.78784	0.0055518	0.99445	0.88513	0.96643	0.78784
Pat_10-False	0.99825	0.43587	0.56413	0.75043	0.94592	0.99825
Pat_10-True	0.56413	0.0017528	0.99825	0.75043	0.97682	0.56413
Pat_13-False	0.9955	0.26513	0.73487	0.85531	0.95114	0.9955
Pat_13-True	0.73487	0.0044997	0.9955	0.85531	0.96923	0.73487
Pat_2-False	0.99846	0.3899	0.6101	0.78049	0.95339	0.99846
Pat_2-True	0.6101	0.0015388	0.99846	0.78049	0.98025	0.6101
Pat_3-False	0.98557	0.2599	0.7401	0.85406	0.9156	0.98557
Pat_3-True	0.7401	0.014426	0.98557	0.85406	0.94718	0.7401
Pat_4-False	0.86728	0.067913	0.93209	0.8991	0.84067	0.86728
Pat_4-True	0.93209	0.13272	0.86728	0.8991	0.94444	0.93209
Pat_8-False	0.9981	0.39338	0.60662	0.77812	0.95981	0.9981
Pat_8-True	0.60662	0.0019036	0.9981	0.77812	0.97131	0.60662

Table I.22: *hh125.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.98944	0.19163	0.80837	0.89434	0.9261	0.98944
Other_Activity-True	0.80837	0.010561	0.98944	0.89434	0.96927	0.80837
Pat_0-False	0.96835	0.048843	0.95116	0.95971	0.90385	0.96835
Pat_0-True	0.95116	0.031655	0.96835	0.95971	0.98447	0.95116
Pat_1-False	0.9982	0.29863	0.70137	0.83672	0.94873	0.9982
Pat_1-True	0.70137	0.0017975	0.9982	0.83672	0.98601	0.70137
Pat_11-False	0.99946	0.52015	0.47985	0.69252	0.93764	0.99946
Pat_11-True	0.47985	0.00053657	0.99946	0.69252	0.99133	0.47985
Pat_2-False	0.98953	0.12022	0.87978	0.93304	0.96007	0.98953
Pat_2-True	0.87978	0.010474	0.98953	0.93304	0.96639	0.87978
Pat_3-False	0.99931	0.32948	0.67052	0.81857	0.95685	0.99931
Pat_3-True	0.67052	0.00069228	0.99931	0.81857	0.99251	0.67052
Pat_4-False	0.99049	0.18086	0.81914	0.90075	0.93677	0.99049
Pat_4-True	0.81914	0.0095141	0.99049	0.90075	0.96954	0.81914
Pat_8-False	0.99772	0.38113	0.61887	0.78579	0.92123	0.99772
Pat_8-True	0.61887	0.0022825	0.99772	0.78579	0.98379	0.61887

Table I.23: *hh126.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.98653	0.074987	0.92501	0.95528	0.96204	0.98653
Other_Activity-True	0.92501	0.013466	0.98653	0.95528	0.97272	0.92501
Pat_0-False	0.97787	0.081898	0.9181	0.94751	0.84216	0.97787
Pat_0-True	0.9181	0.022133	0.97787	0.94751	0.98934	0.9181
Pat_1-False	0.99496	0.063085	0.93692	0.9655	0.98321	0.99496
Pat_1-True	0.93692	0.0050381	0.99496	0.9655	0.98042	0.93692
Pat_11-False	0.99911	0.2147	0.7853	0.88578	0.98186	0.99911
Pat_11-True	0.7853	0.00088604	0.99911	0.88578	0.98705	0.7853
Pat_2-False	0.99705	0.15396	0.84604	0.91845	0.9738	0.99705
Pat_2-True	0.84604	0.0029518	0.99705	0.91845	0.98037	0.84604
Pat_4-False	0.99762	0.26659	0.73341	0.85537	0.95912	0.99762
Pat_4-True	0.73341	0.0023778	0.99762	0.85537	0.98008	0.73341
Pat_5-False	0.99751	0.15806	0.84194	0.91643	0.97844	0.99751
Pat_5-True	0.84194	0.0024866	0.99751	0.91643	0.9792	0.84194
Pat_7-False	0.99785	0.18662	0.81338	0.90091	0.97566	0.99785
Pat_7-True	0.81338	0.0021493	0.99785	0.90091	0.98057	0.81338

Table I.24: *hh127.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.9732	0.092048	0.90795	0.94001	0.92236	0.9732
Other_Activity-True	0.90795	0.026796	0.9732	0.94001	0.9679	0.90795
Pat_0-False	0.99114	0.28792	0.71208	0.8401	0.87591	0.99114
Pat_0-True	0.71208	0.0088607	0.99114	0.8401	0.97512	0.71208
Pat_1-False	0.99126	0.086801	0.9132	0.95143	0.97375	0.99126
Pat_1-True	0.9132	0.0087425	0.99126	0.95143	0.96984	0.9132
Pat_12-False	0.98679	0.059185	0.94082	0.96353	0.9813	0.98679
Pat_12-True	0.94082	0.013205	0.98679	0.96353	0.95769	0.94082
Pat_2-False	0.97566	0.045655	0.95435	0.96494	0.97384	0.97566
Pat_2-True	0.95435	0.024342	0.97566	0.96494	0.95745	0.95435
Pat_3-False	0.96322	0.06979	0.93021	0.94657	0.90209	0.96322
Pat_3-True	0.93021	0.036782	0.96322	0.94657	0.97428	0.93021
Pat_6-False	0.97702	0.035982	0.96402	0.9705	0.98289	0.97702
Pat_6-True	0.96402	0.022975	0.97702	0.9705	0.95199	0.96402
Pat_8-False	0.97902	0.057075	0.94293	0.9608	0.9698	0.97902
Pat_8-True	0.94293	0.020983	0.97902	0.9608	0.96001	0.94293

Table I.25: *hh128.AD* activity forecasting accuracies.

Activity	TP Rate	FP Rate	Specificity	G-Mean	Precision	Recall
Other_Activity-False	0.98936	0.18795	0.81205	0.89633	0.92127	0.98936
Other_Activity-True	0.81205	0.010642	0.98936	0.89633	0.97169	0.81205
Pat_0-False	0.9865	0.23352	0.76648	0.86956	0.89559	0.9865
Pat_0-True	0.76648	0.013501	0.9865	0.86956	0.96547	0.76648
Pat_1-False	0.98964	0.15515	0.84485	0.91438	0.93694	0.98964
Pat_1-True	0.84485	0.010363	0.98964	0.91438	0.97222	0.84485
Pat_2-False	0.99548	0.20596	0.79404	0.88908	0.95925	0.99548
Pat_2-True	0.79404	0.0045183	0.99548	0.88908	0.97303	0.79404
Pat_4-False	0.9317	0.079075	0.92093	0.9263	0.86671	0.9317
Pat_4-True	0.92093	0.068295	0.9317	0.9263	0.96068	0.92093
Pat_5-False	0.99844	0.37191	0.62809	0.7919	0.94376	0.99844
Pat_5-True	0.62809	0.0015623	0.99844	0.7919	0.98469	0.62809
Pat_6-False	0.99469	0.1964	0.8036	0.89406	0.95858	0.99469
Pat_6-True	0.8036	0.0053077	0.99469	0.89406	0.9707	0.8036
Pat_7-False	0.99239	0.13814	0.86186	0.92482	0.96567	0.99239
Pat_7-True	0.86186	0.0076084	0.99239	0.92482	0.96659	0.86186

Table I.26: *hh129.AD* activity forecasting accuracies.

.

J DYNAMIC TIME WARPING FORECASTING RESULTS

0	1	←guessed
29352	948	0 = False
2283	31886	1 = True

Table J.1: Results for *navan_2014.DTW* 0 forecasting, with an accuracy of 94.988.

0	1	←guessed
56574	319	0 = False
304	7272	1 = True

Table J.2: Results for *navan_2014.DTW* 1 forecasting, with an accuracy of 99.034.

0	1	←guessed
64220	2	0 = False
44	203	1 = True

Table J.3: Results for *navan_2014.DTW* 10 forecasting, with an accuracy of 99.929.

0	1	←guessed
64385	0	0 = False
77	7	1 = True

Table J.4: Results for *navan_2014.DTW* 11 forecasting, with an accuracy of 99.881.

0	1	←guessed
62086	33	0 = False
220	2130	1 = True

Table J.5: Results for *navan_2014.DTW* 12 forecasting, with an accuracy of 99.608.

0	1	←guessed
64158	0	0 = False
57	254	1 = True

Table J.6: Results for *navan_2014.DTW* 13 forecasting, with an accuracy of 99.912.

0	1	←guessed
59202	11	0 = False
43	5213	1 = True

Table J.7: Results for *navan_2014.DTW* 14 forecasting, with an accuracy of 99.916.

0	1	←guessed
63231	0	0 = False
38	1200	1 = True

Table J.8: Results for *navan_2014.DTW* 15 forecasting, with an accuracy of 99.941.

0	1	←guessed
64271	0	0 = False
34	164	1 = True

Table J.9: Results for *navan_2014.DTW* 16 forecasting, with an accuracy of 99.947.

0	1	←guessed
64419	0	0 = False
40	10	1 = True

Table J.10: Results for *navan_2014.DTW* 17 forecasting, with an accuracy of 99.938.

0	1	←guessed
63622	10	0 = False
62	775	1 = True

Table J.11: Results for *navan_2014.DTW* 18 forecasting, with an accuracy of 99.888.

0	1	←guessed
64411	0	0 = False
21	37	1 = True

Table J.12: Results for *navan_2014.DTW* 19 forecasting, with an accuracy of 99.967.

0	1	←guessed
64076	0	0 = False
33	360	1 = True

Table J.13: Results for *navan_2014.DTW* 2 forecasting, with an accuracy of 99.949.

0	1	←guessed
64384	0	0 = False
34	51	1 = True

Table J.14: Results for *navan_2014.DTW* 20 forecasting, with an accuracy of 99.947.

0	1	←guessed
64390	0	0 = False
15	64	1 = True

Table J.15: Results for *navan_2014.DTW* 21 forecasting, with an accuracy of 99.977.

0	1	←guessed
64426	0	0 = False
43	0	1 = True

Table J.16: Results for *navan_2014.DTW* 22 forecasting, with an accuracy of 99.933.

0	1	←guessed
64271	0	0 = False
3	195	1 = True

Table J.17: Results for *navan_2014.DTW* 23 forecasting, with an accuracy of 99.995.

0	1	←guessed
64440	0	0 = False
2	27	1 = True

Table J.18: Results for *navan_2014.DTW* 24 forecasting, with an accuracy of 99.997.

0	1	←guessed
64413	0	0 = False
55	1	1 = True

Table J.19: Results for *navan_2014.DTW* 25 forecasting, with an accuracy of 99.915.

0	1	←guessed
64417	0	0 = False
28	24	1 = True

Table J.20: Results for *navan_2014.DTW* 26 forecasting, with an accuracy of 99.957.

0	1	←guessed
64039	0	0 = False
28	402	1 = True

Table J.21: Results for *navan_2014.DTW* 27 forecasting, with an accuracy of 99.957.

0	1	←guessed
63727	0	0 = False
40	702	1 = True

Table J.22: Results for *navan_2014.DTW* 28 forecasting, with an accuracy of 99.938.

0	1	←guessed
64414	0	0 = False
21	34	1 = True

Table J.23: Results for *navan_2014.DTW* 29 forecasting, with an accuracy of 99.967.

0	1	←guessed
40284	516	0 = False
20	23649	1 = True

Table J.24: Results for *navan_2014.DTW* 3 forecasting, with an accuracy of 99.169.

0	1	←guessed
64441	0	0 = False
21	7	1 = True

Table J.25: Results for *navan_2014.DTW* 30 forecasting, with an accuracy of 99.967.

0	1	←guessed
64424	0	0 = False
9	36	1 = True

Table J.26: Results for *navan_2014.DTW* 31 forecasting, with an accuracy of 99.986.

0	1	←guessed
64456	0	0 = False
3	10	1 = True

Table J.27: Results for *navan_2014.DTW* 32 forecasting, with an accuracy of 99.995.

0	1	←guessed
64095	0	0 = False
0	374	1 = True

Table J.28: Results for *navan_2014.DTW* 33 forecasting, with an accuracy of 100.

0	1	←guessed
64376	0	0 = False
0	93	1 = True

Table J.29: Results for *navan_2014.DTW* 34 forecasting, with an accuracy of 100.

0	1	←guessed
64085	3	0 = False
63	318	1 = True

Table J.30: Results for *navan_2014.DTW* 4 forecasting, with an accuracy of 99.898.

0	1	←guessed
64399	0	0 = False
37	33	1 = True

Table J.31: Results for *navan_2014.DTW* 5 forecasting, with an accuracy of 99.943.

0	1	←guessed
64373	0	0 = False
20	76	1 = True

Table J.32: Results for *navan_2014.DTW* 6 forecasting, with an accuracy of 99.969.

0	1	←guessed
64295	0	0 = False
115	59	1 = True

Table J.33: Results for *navan_2014.DTW* 7 forecasting, with an accuracy of 99.822.

0	1	←guessed
64388	0	0 = False
33	48	1 = True

Table J.34: Results for *navan_2014.DTW* 8 forecasting, with an accuracy of 99.949.

0	1	←guessed
63943	16	0 = False
66	444	1 = True

Table J.35: Results for *navan_2014.DTW* 9 forecasting, with an accuracy of 99.873.

REFERENCES

[1] B. N. Schilit and M. M. Theimer. Disseminating active map information to mobile hosts. *IEEE Network*, 8(5):22–32, September 1994.

[2] B. N. Schilit, N. Adams, and R. Want. Context-aware computing applications. In *1994 First Workshop on Mobile Computing Systems and Applications*, pages 85–90. Institute of Electrical and Electronics Engineers (IEEE), December 1994.

[3] G. D. Abowd, A. K. Dey, P. J. Brown, N. Davies, M. Smith, and P. Steggles. *Towards a Better Understanding of Context and Context-Awareness*, pages 304–307. Springer Berlin Heidelberg, Berlin, Heidelberg, 1999. Editor: Gellersen, Hans-W.

[4] J. yi Hong, E. ho Suh, and S.-J. Kim. Context-aware systems: A literature review and classification. *Expert Systems with Applications*, 36(4):8509–8522, 2009.

[5] S. Helal, B. Winkler, C. Lee, Y. Kaddoura, L. Ran, C. Giraldo, S. Kuchibhotla, and W. Mann. Enabling location-aware pervasive computing applications for the elderly. In *Proceedings of the First IEEE International Conference on Pervasive Computing and Communications*, pages 531–536, 2003.

[6] S. Mennicken and E. M. Huang. Hacking the natural habitat: an in-the-wild study of smart homes, their development, and the people who live in them. In *Proceedings of the 10th international conference on Pervasive Computing*, Pervasive'12, pages 143–160, Berlin, Heidelberg, 2012. Springer-Verlag.

[7] D. De, S. Tang, W.-Z. Song, D. Cook, and S. K. Das. Actisen: Activity-aware sensor network in smart environments. *Pervasive and Mobile Computing*, 8(5):730–750, 2012.

[8] A. K. Dey. Understanding and using context. *Personal and Ubiquitous Computing*, 5:4–7, 2001.

[9] P. Jaramillo and O. Amft. Improving energy efficiency through activity-aware control of office appliances using proximity sensing - a real-life study. In *IEEE International Conference on Pervasive Computing and Communications Workshops*, pages 664–669, March 2013.

[10] A. Doryab and J. E. Bardram. Designing activity-aware recommender systems for operating rooms. In *Proceedings of the 2011 Workshop on Context-awareness in Retrieval and Recommendation*, CaRR '11, pages 43–46, New York, NY, USA, 2011. ACM.

[11] N. C. Krishnan and D. J. Cook. Activity recognition on streaming sensor data. *Pervasive and Mobile Computing*, 10, Part B(0):138–154, 2014.

[12] S. Lorente. Key issues regarding domotic applications. In *Proceedings. 2004 International Conference on Information and Communication Technologies: From Theory to Applications, 2004.*, pages 121–122, April 2004.

[13] J. K. Aggarwal and M. S. Ryoo. Human activity analysis: A review. *ACM Computing Surveys*, 43(3):1–47, April 2011.

[14] T. Ichinose, K. Shimodozono, and K. Hanaki. Impact of anthropogenic heat on urban climate in tokyo. *Atmospheric Environment*, 33(24):3897–3909, 1999.

[15] C. Wilson and H. Dowlatabadi. Models of decision making and residential energy use. *Annual Review of Environment and Resources*, 32:169–203, 2007.

[16] A. Faruqui and S. Sergici. Household response to dynamic pricing of electricity: a survey of 15 experiments. *Journal of Regulatory Economics*, 38(2):193–225, 2010.

[17] K. Herter, P. McAuliffe, and A. Rosenfeld. An exploratory analysis of california residential customer response to critical peak pricing of electricity. *Energy*, 32(1):25–34, 2007.

[18] D. L. Costa and M. E. Kahn. Energy conservation "nudges" and environmentalist ideology: Evidence from a randomized residential electricity field experiment. *Journal of the European Economic Association*, 11(3):680–702, 2013.

[19] K. Ito. Does conservation targeting work? evidence from a statewide electricity rebate program in california. techreport, Allied Social Science Associations Annual Meeting, 2012.

[20] H. Allcott. Rethinking real-time electricity pricing. *Resource and Energy Economics*, 33(4):820–842, 2011.

[21] K. Jessoe, A. D. Rapson, and E. J. B. Smith. The effect of a mandatory time-of-use pricing reform on residential electricity use. *American Economic Association*, 2012.

[22] K. Ehrhardt-Martinez, K. A. Donnelly, S. Laitner, et al. Advanced metering initiatives and residential feedback programs: a meta-review for household electricity-saving opportunities. In *Report Number E105*, 529 14th Street, Suite 600, Washington, D.C. 20045, June 2010. American Council for an Energy-Efficient Economy Washington, DC.

[23] K. Carrie Armel, A. Gupta, G. Shrimali, and A. Albert. Is disaggregation the holy grail of energy efficiency? the case of electricity. *Energy Policy*, 52:213–234, 2013.

[24] Opower. What is opower? `http://opower.com/what-is-opower`, 2012.

[25] H. Allcott and T. Rogers. The short-run and long-run effects of behavioral interventions: Experimental evidence from energy conservation. Technical report, National Bureau of Economic Research, 2012.

[26] M. Crowley, A. Heitz, A. Matta, K. Mori, and B. Banerjee. Behavioral science-informed technology interventions for change in residential energy consumption. In *CHI '11 Extended Abstracts on Human Factors in Computing Systems*, CHI EA '11, pages 2209–2214, New York, NY, USA, 2011. ACM.

[27] M. Fidler, S. Tan, S. Alqatari, N. Bhansali, A. Chang, M. Davis, E. Kofman, K. Lee, P. Sivilay, M. Cornelius, B. Wypich, and B. Banerjee. Sensor-based physical interactions as interventions for change in residential energy consumption. In *CHI '12 Extended Abstracts on Human Factors in Computing Systems*, CHI EA '12, pages 2129–2134, New York, NY, USA, 2012. ACM.

[28] D. Brounen, N. Kok, and J. M. Quigley. Residential energy literacy and conservation. *Chicago: 47th Annual AREUEA Meeting*, 2012.

[29] S. Darby. Smart metering: What potential for householder engagement? *Building Research & Information*, 38(5):442–457, 2010.

[30] Y. Riche, J. Dodge, and R. A. Metoyer. Studying always-on electricity feedback in the home. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '10, pages 1995–1998, New York, NY, USA, 2010. ACM.

[31] D. Cook and S. Das. *Smart Environments: Technologies, Protocols, and Applications*, volume 43. Wiley-Interscience, 2004.

[32] N. Gyorbiro, A. Fabian, and G. Homanyi. An activity recognition system for mobile phones. *Mobile Networks and Applications*, 14:82–91, 2008.

[33] G. W. Hart. Nonintrusive appliance load monitoring. *Proceedings of the IEEE*, 80(12):1870–1891, 1992.

[34] M. Berges, E. Goldman, H. S. Matthews, and L. Soibelman. Learning systems for electric consumption of buildings. In *ASCE International Workshop on Computing in Civil Engineering, Austin, Texas*, 2009.

[35] S. Gupta, M. S. Reynolds, and S. N. Patel. Electrisense: single-point sensing using EMI for electrical event detection and classification in the home. In *Proceedings of the 12th ACM international conference on Ubiquitous computing*, pages 139–148. ACM, 2010.

[36] Nest. Nest Learning Thermostat. `https://nest.com/`, March 2017.

[37] R. Yang and M. W. Newman. Living with an intelligent thermostat: Advanced control for heating and cooling systems. In *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*, UbiComp '12, pages 1102–1107, New York, NY, USA, 2012. ACM.

[38] R. Yang and M. W. Newman. Learning from a learning thermostat: Lessons for intelligent systems for the home. In *Proceedings of the 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, UbiComp '13, pages 93–102, New York, NY, USA, September 2013. ACM.

[39] J. Z. Kolter and J. Ferreira. A large-scale study on predicting and contextualizing building energy usage. In *AAAI*, 2011.

[40] C. Chen, D. J. Cook, and A. S. Crandall. The user side of sustainability: Modeling behavior and energy usage in the home. *Pervasive and Mobile Computing*, 9(1):161–175, 2013.

[41] M. Gupta, S. S. Intille, and K. Larson. Adding gps-control to traditional thermostats: An exploration of potential energy savings and design challenges. In *Pervasive Computing*, pages 95–114. Springer, 2009.

[42] J. Lu, T. Sookoor, V. Srinivasan, G. Gao, B. Holben, J. Stankovic, E. Field, and K. Whitehouse. The smart thermostat: using occupancy sensors to save energy in homes. In *Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems*, SenSys '10, pages 211–224, New York, NY, USA, 2010. ACM.

[43] J. Scott, A. Bernheim Brush, J. Krumm, B. Meyers, M. Hazas, S. Hodges, and N. Villar. Preheat: controlling home heating using occupancy prediction. In *Proceedings of the 13th international conference on Ubiquitous computing*, UbiComp '11, pages 281–290, New York, NY, USA, 2011. ACM.

[44] J. Page, D. Robinson, N. Morel, and J.-L. Scartezzini. A generalised stochastic model for the simulation of occupant presence. *Energy and Buildings*, 40(2):83–98, 2008.

[45] Energy Star. *Summary of research findings from the programmable thermostat market*. Environmental Protection Agency, Washington, DC: Office of Headquarters, 2004.

[46] H. Sachs, S. Nadel, J. Amann, M. Tuazon, E. Mendelsohn, and L. Rainer. Emerging energy-saving technologies and practices for the buildings sector as of 2004. Technical Report A042, American Council for an Energy-Efficient Economy (ACEEE), 1001 Connecticut Avenue, N.W., Suite 801, Washington, D.C. 20036, October 2004.

[47] United States Environmental Protection Agency (EPA). Programmable thermostats suspension memo, May 2009.

[48] A. Barbato, L. Borsani, A. Capone, and S. Melzi. Home energy saving through a user profiling system based on wireless sensors. In *Proceedings of the First ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings*, BuildSys '09, pages 49–54, New York, NY, USA, 2009. ACM.

[49] L. Hawarah, S. Ploix, and M. Jacomino. User behavior prediction in energy consumption in housing using bayesian networks. In *Proceedings of the 10th International Conference on Artificial Intelligence and Soft Computing: Part I*, ICAISC'10, pages 372–379, Berlin, Heidelberg, 2010. Springer-Verlag.

[50] G. Gao and K. Whitehouse. The self-programming thermostat: optimizing setback schedules based on home occupancy patterns. In *Proceedings of the First ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings*, BuildSys '09, pages 67–72, New York, NY, USA, 2009. ACM.

[51] V. L. Erickson, M. . Carreira-Perpin, and A. E. Cerpa. Observe: Occupancy-based system for efficient reduction of hvac energy. In *Proceedings of the 10th ACM/IEEE International Conference on Information Processing in Sensor Networks*, pages 258–269, April 2011.

[52] B. Dong, K. P. Lam, and C. P. Neuman. Integrated building control based on occupant behavior pattern detection and local weather forecasting. In *Proceedings of Building Simulation 2011*, pages 193–200, Sydney, Austrailia, November 2011. Citeseer.

[53] V. Singhvi, A. Krause, C. Guestrin, J. H. Garrett, Jr., and H. S. Matthews. Intelligent light control using sensor networks. In *Proceedings of the 3rd international conference on Embedded networked sensor systems*, SenSys '05, pages 218–229, New York, NY, USA, 2005. ACM.

[54] H. Chen, P. Chou, S. Duri, H. Lei, and J. Reason. The design and implementation of a smart building control system. In *2009 IEEE International Conference on e-Business Engineering*, pages 255–262, October 2009.

[55] L. Yang, K. Ting, and M. Srivastava. Inferring occupancy from opportunistically available sensor data. In *Pervasive Computing and Communications (PerCom), 2014 IEEE International Conference on*, pages 60–68, March 2014.

[56] M. C. Mozer. The neural network house: An environment that adapts to its inhabitants. In *Proceedings of the AAAI Spring Symposium on Intelligent Environments*, pages 110–114, Menlo Park, CA, 1998. AAAI Press.

[57] A. Marchiori and Q. Han. Distributed wireless control for building energy management. In *Proceedings of the 2Nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Building*, BuildSys '10, pages 37–42, New York, NY, USA, 2010. ACM.

[58] V. Garg and N. Bansal. Smart occupancy sensors to reduce energy consumption. *Energy and Buildings*, 32(1):81–87, 2000.

[59] U.S. Energy Information Administration (EIA). Annual energy review 2011. Technical Report DOE/EIA-0384(2011), Office of Energy Statistics, U.S. Department

of Energy (DOE), September 2012. Forrestal Building, Room 1E-210, 1000 Independence Avenue, S.W., Washington, D.C. 20585.

[60] X-10. Home automation electronics. http://www.x10.com/, 2012.

[61] D. B. Crawley, L. K. Lawrie, C. O. Pedersen, F. C. Winkelmann, M. J. Witte, R. K. Strand, R. J. Liesen, W. F. Buhl, Y. J. Huang, R. H. Henninger, et al. EnergyPlus: an update. *IBPSA-USA Journal*, 1(1), 2004.

[62] T. A. Nguyen and M. Aiello. Energy intelligent buildings based on user activity: A survey. *Energy and buildings*, 56:244–257, 2013.

[63] C. DiLouie. Lighting and productivity: Missing link found? *Architectural Lighting, September/October*, September 2003.

[64] D. T. Delaney, G. M. P. O'Hare, and A. G. Ruzzelli. Evaluation of energy-efficiency in lighting systems using sensor networks. In *Proceedings of the First ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings*, BuildSys '09, pages 61–66, New York, NY, USA, 2009. ACM.

[65] Y.-J. Wen and A. M. Agogino. Wireless networked lighting systems for optimizing energy savings and user satisfaction. In *2008 IEEE Wireless Hive Networks Conference*, pages 1–7, August 2008.

[66] U.S. Energy Information Administration (EIA). April 2016 monthly energy review. Technical Report DOE/EIA-0035(2016/4), U.S. Department of Energy (DOE), April 2016.

[67] U.S. Energy Information Administration (EIA). How much energy is consumed in residential and commercial buildings in the united states? http://www.eia.gov/tools/faqs/faq.cfm?id=86, April 2016.

[68] S. Darby, C. Liddell, D. Hills, and D. Drabble. Smart metering early learning project: Synthesis report. *Department of Energy & Climate Change*, 2015.

[69] S. Szewcyzk, K. Dwan, B. Minor, B. Swedlove, and D. J. Cook. Annotating smart environment sensor data for activity learning. *Technology and Health Care*, 17(3):161–169, August 2009.

[70] D. Brounen, N. Kok, and J. M. Quigley. Residential energy use and conservation: Economics and demographics. *European Economic Review*, 56:931–945, 2012.

[71] C. G. Kim and K. J. Kim. Implementation of a cost-effective home lighting control system on embedded Linux with OpenWrt. *Personal and Ubiquitous Computing*, 18(3):535–542, March 2014.

[72] T. A. Nguyen and M. Aiello. Beyond indoor presence monitoring with simple sensors. In *in Proceedings PECCS, 2012*, pages 5–14, February 2012.

[73] C. Harris and V. Cahill. Exploiting user behaviour for context-aware power management. In *WiMob'2005), IEEE International Conference on Wireless And Mobile Computing, Networking And Communications, 2005.*, volume 4, pages 122–130, August 2005.

[74] G. R. Newsham and B. J. Birt. Building-level occupancy data to improve arima-based electricity use forecasts. In *Proceedings of the 2Nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Building*, BuildSys '10, pages 13–18, New York, NY, USA, 2010. ACM.

[75] R. H. Dodier, G. P. Henze, D. K. Tiller, and X. Guo. Building occupancy detection through sensor belief networks. *Energy and Buildings*, 38(9):1033–1043, 2006.

[76] H. Hagras, V. Callaghan, M. Colley, G. Clarke, A. Pounds-Cornish, and H. Duman. Creating an ambient-intelligence environment using embedded agents. *IEEE Intelligent Systems*, 19(6):12–20, November 2004.

[77] Z. N. Zhen, Q. S. Jia, C. Song, and X. Guan. An indoor localization algorithm for lighting control using rfid. In *2008 IEEE Energy 2030 Conference*, pages 1–6, November 2008.

[78] Department of Health. Speech by the Rt Hon Patricia Hewitt MP, Secretary of State for Health. In *Long-term Conditions Alliance Annual Conference*, 2007.

[79] C. D. Kidd, R. J. Orr, G. D. Abowd, C. G. Atkeson, I. A. Essa, B. MacIntyre, E. Mynatt, T. E. Starner, and W. Newstetter. The aware home: A living laboratory for ubiquitous computing research. In *Proceedings of the Second International Workshop on Cooperative Buildings - CoBuild'99*, pages 191–198. Springer, 1999.

[80] S. Helal, W. Mann, H. El-Zabadani, J. King, Y. Kaddoura, and E. Jansen. The Gator Tech Smart House: a programmable pervasive space. *Computer*, 38(3):50–60, March 2005.

[81] D. J. Cook, M. Youngblood, E. O. Heierman III, K. Gopalratnam, S. Rao, A. Litvin, and F. Khawaja. MavHome: an agent-based smart home. In *Proceedings of the IEEE International Conference on Pervasive Computing and Communications*, PerCom '03, pages 521–524, March 2003.

[82] A. Elfaham, H. Hagras, S. Helal, S. Hossain, J. W. Lee, and D. J. Cook. A fuzzy based verification agent for the Persim human activity simulator in ambient intelligent environments. In *IEEE International Conference on Fuzzy Systems*, FUZZ '10, pages 1–8, July 2010.

[83] D. J. Cook and S. Das. Pervasive computing at scale: Transforming the state of the art. *Pervasive and Mobile Computing*, 8(1):22–35, 2012.

[84] D. J. Cook, A. S. Crandall, B. L. Thomas, and N. C. Krishnan. CASAS: A smart home in a box. *IEEE Computer*, 46(7):62–69, 2013.

[85] D. J. Cook and N. C. Krishnan. *Activity Learning: Discovering, Recognizing, and Predicting Human Behavior from Sensor Data*. Wiley, February 2015.

[86] D. J. Cook, N. Krishnan, and P. Rashidi. Activity discovery and activity recognition: A new partnership. *IEEE Transactions on Systems, Man, and Cybernetics, Part B*, 43(3):820–828, 2013.

[87] D. Cook. Learning setting-generalized activity models for smart spaces. *IEEE Intelligent Systems*, 27(1):32–38, 2012.

[88] A. Crandall and D. J. Cook. *Behaviometrics for multiple residents in a smart environment*, chapter 4, pages 55–71. Atlantis Publishing Corporation, 2013.

[89] L. Chen, J. Hoey, C. D. Nugent, D. J. Cook, and Z. Yu. Sensor-based activity recognition. *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, 42(6):790–808, 2012.

[90] S.-R. Ke, H. L. U. Thuc, Y.-J. Lee, J.-N. Hwang, J.-H. Yoo, and K.-H. Choi. A review on video-based human activity recognition. *Computers*, 2(2):88–131, 2013.

[91] A. Bulling, U. Blanke, and B. Schiele. A tutorial on human activity recognition using body-worn inertial sensors. *ACM Computing Surveys*, 46(3):107–140, 2014.

[92] A. Reiss, D. Stricker, and G. Hendeby. Towards robust activity recognition for everyday life: Methods and evaluation. In *Pervasive Computing Technologies for Healthcare*, pages 25–32, 2013.

[93] S. Vishwakarma and A. Agrawal. A survey on activity recognition and behavior understanding in video surveillance. *The Visual Computer*, 29(10):983–1009, 2013.

[94] O. Lara and M. A. Labrador. A survey on human activity recognition using wearable sensors. *IEEE Communications Surveys and Tutorials*, 15(3):1192–1209, 2013.

[95] L. Chen and I. Khalil. Activity recognition: Approaches, practices and trends. In L. Chen, C. D. Nugent, J. Biswas, and J. Hoey, editors, *Activity Recognition in Pervasive Intelligent Environments*, chapter 1, pages 1–31. Atlantis Ambient and Pervasive Intelligence, 2011.

[96] P. Tuaraga, R. Chellappa, V. S. Subrahmanian, O. Udrea, and P. Turaga. Machine recognition of human activities: A survey. *IEEE Transactions on Circuits and Systems for Video Technology*, 18(11):1473–1488, 2008.

[97] J. Alon, V. Athitsos, Q. Yuan, and S. Sclaroff. A unified framework for gesture recognition and spatiotemporal gesture segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 31:1685–1699, 2008.

[98] J. A. Iglesias, P. Angelov, A. Ledezma, and A. Sanchis. Human activity recognition based on evolving fuzzy systems. *International Journal of Neural Systems*, 20(5):355–364, 2010.

[99] L. Liao, D. Fox, and H. Kautz. Location-based activity recognition using relational markov networks. In *Proceedings of the International Joint Conference on Artificial Intelligence*, IJCAI '05, pages 773–778, San Francisco, CA, USA, 2005. Morgan Kaufmann Publishers Inc.

[100] E. Guenterberg, H. Ghasemzadeh, and R. Jafari. Automatic segmentation and recognition in body sensor networks using a hidden Markov model. *ACM Transactions in Embedded Computing Systems*, 11:S2:1–S2:19, 2012.

[101] J. R. Doppa, A. Fern, and P. Tadepalli. Structured prediction via output space search. *Journal of Machine Learning Research*, 15(1):1317–1350, 2014.

[102] J. R. Doppa, A. Fern, and P. Tadepalli. HC-Search: Learning heuristics and cost functions for structured prediction. *Journal of Artificial Intelligence Research*, 50:369–407, 2014.

[103] H. Hagras, F. Doctor, A. Lopez, and V. Callaghan. An incremental adaptive life long learning approach for type-2 fuzzy embedded agents in ambient intelligent environments. *IEEE Transactions on Fuzzy Systems*, 15(1):41–55, 2007.

[104] E. Munguia-Tapia, S. S. Intille, and K. Larson. Activity recognition in the home using simple and ubiquitous sensors. In *Pervasive*, pages 158–175, 2004.

[105] J. Wan, M. J. O'grady, and G. M. O'hare. Dynamic sensor event segmentation for real-time activity recognition in a smart home context. *Personal Ubiquitous Comput.*, 19(2):287–301, February 2015.

[106] R. Jarafi, S. Sastry, and R. Bajcsy. Distributed recognition of human actions using wearable motion sensor networks. *Journal of Ambient Intelligence and Smart Environments*, 2009.

[107] H. Junker, O. Amft, P. Lukowicz, and G. Tröster. Gesture spotting with body-worn inertial sensors to detect user activities. *Pattern Recognition*, 41(6):2010–2024, 2008.

[108] S. C. Mukhopadhyay. Wearable sensors for human activity monitoring: A review. *IEEE Sensors Journal*, 15(3):1321–1330, March 2014.

[109] T. Gu, S. Chen, X. Tao, and J. Lu. An unsupervised approach to activity recognition and segmentation based on object-use fingerprints. *Data & Knowledge Engineering*, 69(6):533–544, 2010.

[110] M. Philipose, K. P. Fishkin, M. Perkowitz, D. J. Patterson, D. Fox, H. Kautz, and D. Hähnel. Inferring activities from interactions with objects. *IEEE Pervasive Computing*, 3(4):50–57, October–December 2004.

[111] J. R. Kwapisz, G. M. Weiss, and S. A. Moore. Activity recognition using cell phone accelerometers. *SIGKDD Explorer Newsletter*, 12(2):74–82, March 2011.

[112] J. Candamo, M. Shreve, D. Goldgof, D. Sapper, and R. Kasturi. Understanding transit scenes: A survey on human behavior-recognition algorithms. *IEEE Transactions on Intelligent Transportation Systems*, 11(1):206–224, March 2010.

[113] K. Forster, S. Monteleone, A. Calatroni, D. Roggen, and G. Troster. Incremental kNN classifier exploiting correct-error teacher for activity recognition. In *International Conference on Machine Learning and Applications*, pages 445–450, 2010.

[114] O. Amft and G. Troster. On-body sensing solutions for automatic dietary monitoring. *IEEE Pervasive Computing*, 8:62–70, 2009.

[115] M. Zhang and A. A. Sawchuk. Motion primitive-based human activity recognition using a bag-of-features approach. In *ACM SIGHIT International Health Informatics Symposium*, pages 631–640, 2012.

[116] S. Abdullah, N. D. Lane, and T. Choudhury. Towards population scale activity recognition: A framework for handling data diversity. In *National Conference on Artificial Intelligence*, 2012.

[117] T. Hirano and T. Maekawa. A hybrid unsupervised/supervised model for group activity recognition. In *International symposium on wearable computers*, pages 21–24, 2013.

[118] H. Hung, G. Englebienne, and J. Kools. Classifying social actions with a single accelerometer. In *ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pages 207–210, 2013.

[119] J. Petersen, N. Larimer, J. A. Kaye, M. Pavel, and T. L. Hayes. SVM to detect the presence of visitors in a smart home environment. In *International Conference of the IEEE Engineering in Medicine and Biology Society*, pages 5850–5853, 2012.

[120] M. Kjaergaard. Studying sensing-based systems: Scaling to human crowds in the real world. *IEEE Computing*, 17(5):80–84, 2013.

[121] M. Kjaergaard, M. Wirz, D. Roggen, and G. Troster. Detecting pedestrian flocks by fusion of multi-modal sensors in mobile phones. In *ACM Conference on Ubiquitous Computing*, pages 240–249, 2012.

[122] D. Gordon, J.-H. Hanne, M. Berchtold, A. A. N. Shirehjini, and M. Beigl. Towards collaborative group activity recognition using mobile devices. *Mobile Networks and Applications*, 18(3):326–340, 2013.

[123] C.-H. Lu and Y.-T. Chiang. Interaction-enabled multi-user model learning for a home environment using ambient sensors. *IEEE Journal of Biomedical and Health Informatics*, 2015.

[124] L. Wang, T. Gu, X. Tao, H. Chen, and J. Lu. Multi-user activity recognition in a smart home. *Atlantic Ambient and Pervasive Intelligence*, 4:59–81, 2011.

[125] T.-y. Wu, C.-c. Lian, and J. Y.-j. Hsu. Joint recognition of multiple concurrent activities using factorial conditional random fields. In *AAAI Workshop on Plan, Activity, and Intent Recognition*, 2007.

[126] A. Tolstikov, C. Phus, J. Biswas, and W. Huang. Multiple people activity recognition using MHT over DBN. In *International Conference on Smart Homes and Health Telematics*, pages 313–318, 2011.

[127] D. H. Hu and Q. Yang. CIGAR: Concurrent and interleaving goal and activity recognition. In *National Conference on Artificial Intelligence*, pages 1363–1368, 2008.

[128] Y.-T. Chiang, K.-C. Hsu, C.-H. Lu, and L.-C. Fu. Interaction models for multiple-resident activity recognition in a smart home. In *Proceedings of the International Conference on Intelligent Robots and Systems*, pages 3753–3758, 2010.

[129] T. Gu, L. Wang, H. Chen, X. Tao, and J. Lu. Recognizing multiuser activities using wireless body sensor networks. *IEEE Transactions on Mobile Computing*, 10(11):1618–1631, 2011.

[130] U. Blanke, B. Schiele, M. Kreil, P. Lukowicz, B. Sick, and T. Gruber. All for one or one for all? Combining heterogeneous features for activity spotting. In *IEEE International Conference on Pervasive Computing and Communications Workshops*, pages 18–24, 2010.

[131] T. van Kasteren, A. Noulas, G. Englebienne, and B. Krose. Accurate activity recognition in a home setting. In *ACM Conference on Ubiquitous Computing*, pages 1–9, 2008.

[132] A. Bulling, J. A. Ward, and H. Gellersen. Multimodal recognition of reading activity in transit using body-worn sensors. *ACM Transactions on Applied Perception*, 9(1):2:1–2:21, 2012.

[133] S. Wang, W. Pentney, A. M. Popescu, T. Choudhury, and M. Philipose. Common sense based joint training of human activity recognizers. In *International Joint Conference on Artificial Intelligence*, pages 2237–2242, 2007.

[134] J. Lester, T. Choudhury, and G. Borriello. A practical approach to recognizing physical activities. In *International Conference on Pervasive Computing*, pages 1–16, 2006.

[135] J.-H. Hong, J. Ramos, and A. K. Dey. Toward personalized activity recognition systems with a semipopulation approach. *IEEE Transactions on Human-Machine Systems*, 46(1):101–112, February 2016.

[136] M. Lichman and P. Smyth. Modeling human location data with mixtures of kernel densities. In *Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD '14, pages 35–44, New York, NY, USA, 2014. ACM.

[137] L. Breiman. Random forests. *Machine Learning*, 45:5–32, 2001.

[138] T. Luck, M. Luppa, M. C. Angermeyer, A. Villringer, H.-H. Knig, and S. G. Riedel-Heller. Impact of impairment in instrumental activities of daily living and mild cognitive impairment on time to incident dementia: results of the leipzig longitudinal study of the aged. *Psychological Medicine*, 41(5):1087–1097, July 2011.

[139] B. Reisberg, S. Finkel, J. Overall, N. Schmidt-Gollas, S. Kanowski, H. Lehfeld, F. Hulla, S. G. Sclan, H.-U. Wilms, K. Heininger, and et al. The alzheimer's disease activities of daily living international scale (adl-is). *International Psychogeriatrics*, 13(2):163181, 2001.

[140] A. K. Desai, G. T. Grossberg, and D. N. Sheth. Activities of daily living in patients with dementia. *CNS Drugs*, 18(13):853–875, 2004.

[141] C. Graf. The lawton instrumental activities of daily living scale. *AJN, American Journal of Nursing*, 108(4):52–62, April 2008.

[142] E. V. Etten, A. Weakley, M. Schmitter-Edgecombe, and D. Cook. Subjective cognitive complaints and objective memory performance influence prompt preference for instrumental activities of daily living. *Gerontechnology*, 14(3):169–176, March 2016.

[143] D. A. Loewenstein and A. Acevedo. The relationship between instrumental activities of daily living and neuropsychological performance. *Neuropsychology of Everyday Functioning*, pages 93–112, 2009.

[144] K. Gopalratnam and D. J. Cook. Online sequential prediction via incremental parsing: The Active LeZi algorithm. *IEEE Intelligent Systems*, 22(1):52–58, January 2007.

[145] K. P. Hawkins, N. Vo, S. Bansal, and A. Bobick. Probabilistic human action prediction and wait-sensitive planning for responsive human-robot collaboration. In *IEEE-RAS International Conference on Humanoid Robots*, pages 499–506, 2013.

[146] K. M. Kitani, B. D. Ziebart, J. A. Bagnell, and M. Hebert. Activity forecasting. In *Proceedings of the European Conference on Computer Vision*, 2012.

[147] H. S. Koppula and A. Saxena. Anticipating human activities using object affordances for reactive robotic response. In *Robotics: Sciences and Systems*, 2013.

[148] C. Ma, J. R. Doppa, J. W. Orr, P. Mannem, X. Fern, T. G. Dietterich, and P. Tadepalli. Prune-and-score: Learning for greedy coreference resolution. In *Conference on Empirical Methods in Natural Language Processing*, 2014.

[149] J. Xie, C. Ma, J. R. Doppa, P. Mannem, X. Fern, T. G. Dietterich, and P. Tadepalli. Learning greedy policies for the easy-first framework. In *National Conference on Artificial Intelligence*, 2015.

[150] R. Khardon. Learning to take actions. *Machine Learning Journal*, 35(1):57–90, 1999.

[151] S. Ross, G. J. Gordon, and D. Bagnell. A reduction of imitation learning and structured prediction to no-regret online learning. *Journal of Machine Learning Research*, 15(627-635), 2011.

[152] R. Agrawal and R. Srikant. Mining sequential patterns. In *Proceedings of the International Conference on Data Engineering*, pages 3–14, 1995.

[153] T. Gu, S. Chen, X. Tao, and J. Lu. An unsupervised approach to activity recognition and segmentation based on object-use fingerprints. *Data and Knowledge Engineering*, 69(6):533–544, June 2010.

[154] T. Barger, D. Brown, and M. Alwan. Health-status monitoring through analysis of behavioral patterns. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, 35(1):22–27, January 2005.

[155] J. Pei, J. Han, and W. Wang. Constraint-based sequential pattern mining: The pattern-growth methods. *Journal of Intelligent Information Systems*, 28(2):133–160, January 2007.

[156] A. Aztiria, J. C. Augusto, R. Basagoiti, A. Izaguirre, and D. J. Cook. Discovering frequent user–environment interactions in intelligent environments. *Personal Ubiquitous Computing*, 16(1):91–103, January 2012.

[157] E. Heierman and D. Cook. Improving home automation by discovering regularly occurring device usage patterns. In *Proceedings of the IEEE International Conference on Data Mining*, pages 537–540. IEEE Comput. Soc, 2003.

[158] A. Ruotsalainen and T. Ala-Kleemola. Gais: A method for detecting discontinuous sequential patterns from imperfect data. In *Proceedings of the International Conference on Data Mining*, pages 530–534, 2007.

[159] J. Pei, J. Han, B. Mortazavi-Asl, H. Pinto, Q. Chen, U. Dayal, and M.-C. Hsu. PrefixSpan,: mining sequential patterns efficiently by prefix-projected pattern growth. In *Proceedings 17th International Conference on Data Engineering*, pages 215–226. IEEE Comput. Soc, 2001.

[160] M. J. Zaki, N. Lesh, and M. Ogihara. Planmine: Sequence mining for plan failures. In *Proceedings of the International Conference on Knowledge Discovery and Data Mining*, pages 369–373, 1998.

[161] Y.-L. Chen, S.-S. Chen, and P.-Y. Hsu. Mining hybrid sequential patterns and sequential rules. *Information Systems*, 27(5):345–362, July 2002.

[162] P. Rashidi, D. J. Cook, L. B. Holder, and M. Schmitter-Edgecombe. Discovering activities to recognize and track in a smart environment. *IEEE Transactions on Knowledge and Data Engineering*, 23(4):527–539, April 2011.

[163] T. Huynh, M. Fritz, and B. Schiele. Discovery of activity patterns using topic models. In *Proceedings of the 10th international conference on Ubiquitous computing - UbiComp '08*, pages 10–19. ACM Press, 2008.

[164] M. Ester, H.-P. Kriegel, J. Sander, X. Xu, et al. A density-based algorithm for discovering clusters in large spatial databases with noise. In *KDD*, volume 96, pages 226–231, 1996.

[165] H. Ding, G. Trajcevski, P. Scheuermann, X. Wang, and E. Keogh. Querying and mining of time series data: Experimental comparison of representations and distance measures. *Proceedings of the VLDB Endowment*, 1(2):1542–1552, 2008.

[166] E. Keogh and J. Lin. Clustering of time-series subsequences is meaningless: implications for previous and future research. *Knowledge and Information Systems*, 8(2):154–177, 2005.

[167] E. Keogh and A. C. Ratanamahatana. Exact indexing of dynamic time warping. *Knowledge and Information Systems*, 7(3):358–386, 2005.

[168] T. Rakthanmanon, E. J. Keogh, S. Lonardi, and S. Evans. Time series epenthesis: Clustering time series streams requires ignoring some data. In *Data Mining (ICDM), 2011 IEEE 11th International Conference on*, pages 547–556. IEEE, December 2011.

[169] L. Ulanova, N. Begum, and E. Keogh. Scalable clustering of time series with u-shapelets. In *SIAM International Conference on Data Mining (SDM 2015)*, volume 192. SIAM, 2015.

[170] C. Bahlmann and H. Burkhardt. The writer independent online handwriting recognition system frog on hand and cluster generative statistical dynamic time warping. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 26(3):299–310, March 2004.

[171] A. Al-Jawad, M. R. Adame, M. Romanovas, M. Hobert, W. Maetzler, M. Traechtler, K. Moeller, and Y. Manoli. Using multi-dimensional dynamic time warping for tug test instrumentation with inertial sensors. In *2012 IEEE Conference on Multisensor Fusion and Integration for Intelligent Systems (MFI)*, pages 212–218. IEEE, September 2012.

[172] M. Shokoohi-Yekta, J. Wang, and E. Keogh. On the non-trivial generalization of dynamic time warping to the multi-dimensional case. In *Proceedings of the 2015 SIAM International Conference on Data Mining*, pages 39–48. SIAM, 2015.

[173] A. McGovern, D. Rosendahl, R. Brown, and K. Droegemeier. Identifying predictive multi-dimensional time series motifs: An application to severe weather prediction. *Data Mining and Knowledge Discovery*, 22(1-2):232–258, 2011.

[174] M. Shokoohi-Yekta. *Meaningful Rule Discovery and Adaptive Classification of Multi-Dimensional Time Series Data*. phdthesis, University of California Riverside, March 2015.

[175] B. Hu, Y. Chen, and E. Keogh. *Time Series Classification under More Realistic Assumptions*, chapter 63, pages 578–586. SIAM, 2013.

[176] N. Begum, L. Ulanova, J. Wang, and E. Keogh. Accelerating dynamic time warping clustering with a novel admissible pruning strategy. In *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD '15, pages 49–58, New York, NY, USA, 2015. ACM.

[177] F. Petitjean, G. Forestier, G. Webb, A. E. Nicholson, Y. Chen, and E. Keogh. Dynamic time warping averaging of time series allows faster and more accurate classification. In *Data Mining (ICDM), 2014 IEEE International Conference on*, pages 470–479. IEEE, December 2014.

[178] E. J. Keogh and M. J. Pazzani. Scaling up dynamic time warping to massive datasets. In J. M. Żytkow and J. Rauch, editors, *European Conference on Principles of Data Mining and Knowledge Discovery*, pages 1–11. Springer, 1999.

[179] T. Rakthanmanon, B. Campana, A. Mueen, G. Batista, B. Westover, Q. Zhu, J. Zakaria, and E. Keogh. Searching and mining trillions of time series subsequences under dynamic time warping. In *Proceedings of the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD '12, pages 262–270, New York, NY, USA, 2012. ACM.

[180] J. Dahmen, B. L. Thomas, D. J. Cook, and X. Wang. Activity learning as a foundation for security monitoring in smart homes. *Sensors*, 17(4):737, March 2017.