A Model for Energy-Saving in an IoT Smarthome accounting for End-User Convenience

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Abstract

Previously collected sensor data of domestic activities, including activity, start time and end time was evaluated and subsequently cleansed of outliers. Values with an extremely low overall aggregated count were dropped from the dataset, as were values deemed to be highly irrelevant to our analysis. With respect to outlier cleansing, median was found to be a better overall value to fill rather than mean, owing to the extremely large spread of the data. The cleansed dataset was then converted to a boolean-array structure, where each attribute was a domestic activity and the index was a timestamp list. In this structure a '1' was representative of an on state, while a '0' was representative of an off state. This consideration applied equally to activities in the data set that were both energy consuming (e.g., using a lamp) and not energy consuming (e.g., opening a door). A machine learning wrapper method was created to iteratively train and test for each attribute. The method was based on a decision tree model with hyperparameter optimization via grid search over the split criterion ('gini' and 'entropy') maximum depth. Cross validation was performed over five-folds. Using all attributes from the dataset, the model gave varied performance, most likely due to the large imbalance of values in the dataset. The machine learning analysis was repeated using training for only activities requiring energy input. These results were largely similar to the first iteration. Finally, the wrapper method was extended to include consideration of power costs (in kilowatt hours) and appliance energy consumption (in watts) in addition to an antagonistic feature which aimed to reduced the overall period of time an appliance is in an 'on' state. The logic of this model was found to be sound, and improvements to the base machine learning model are recommended to improve the overall performance.

Contents

1 Introduction

1.1 Background

1.1.1 Humankind, Technology & Development

Since the inception of the first home computers in the late 1970s [1], modern society has become dependent on, and - indeed - inexorably bound to digital technology. The rapid and widespread adoption of computational technology has led to the fastest rate of societal and economic development our species has ever experienced, as exemplified in Figure 1 and Figure 2, below. One of the most salient manifestations of progress has been the widespread availability and adoption of Information and Communications Technology (**ICT**), including the rise of the global network of networks known as the Internet.

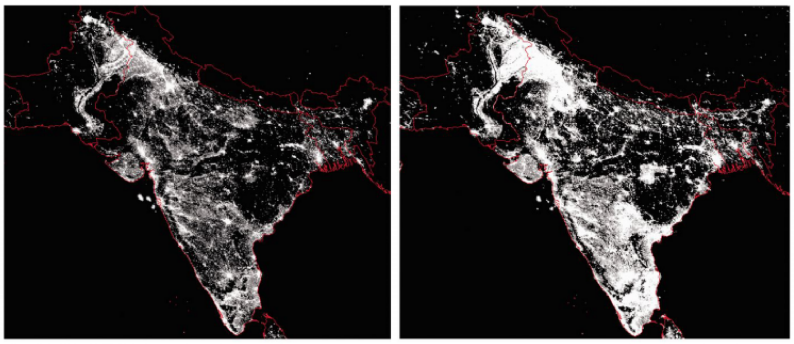


Figure 1: Satellite images of South Asia by night. Left (South Asia in 1994) Right (South Asia in 2010). Images are taken from Maxim Pinkovskiy and Xavier Sala-i-Martin (2016) - Lights, Camera ... Income! Illuminating the National Accounts-Household Surveys Debate. The Quarterly Journal of Economics.

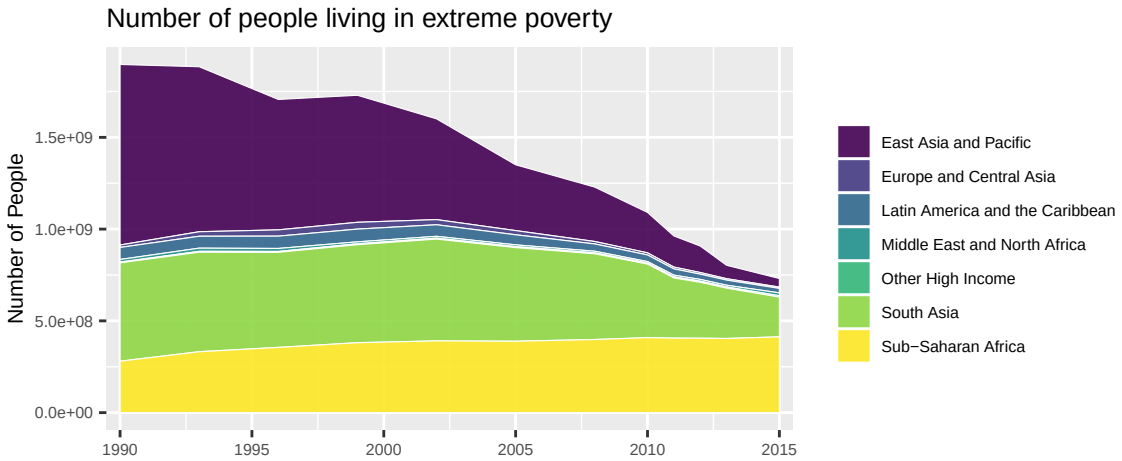


Figure 2: The number of people living in extreme poverty between the years of 1990 till 2015, segmented by region. Source: The World Bank

1.1.2 The Rise and Rise of the World Wide Web

According to the International Telecommunication Unions (**ITU**) 2015 figures, Internet penetration has grown from just over 400 millions users (6 per cent of global population) in 2000 to 3.2 billion users in 2015 (43 per cent of global population). This includes around 2 billion users from developing countries [2]. ICTs bring a broad range of benefits and are recognised as a key to eradicating poverty and unemployment. They enable and facilitate the building of a people-centred, inclusive and development-oriented Information Society, where everyone can create, access, utilise and share information and knowledge. This

enables individuals, communities and peoples to achieve their full potential in promoting their sustainable development and improving their quality of life [3]. In addition to a rapidly growing internet user-base both in the developing and developed world, the nature of internet usage has fundamentally changed. Once the purview of academics, engineers and computer scientists sending tiny packets of information back and forth, there are now some 2.5 quintillion bytes of data created each day by all manner of users, industries and sensors, to name a few [4].

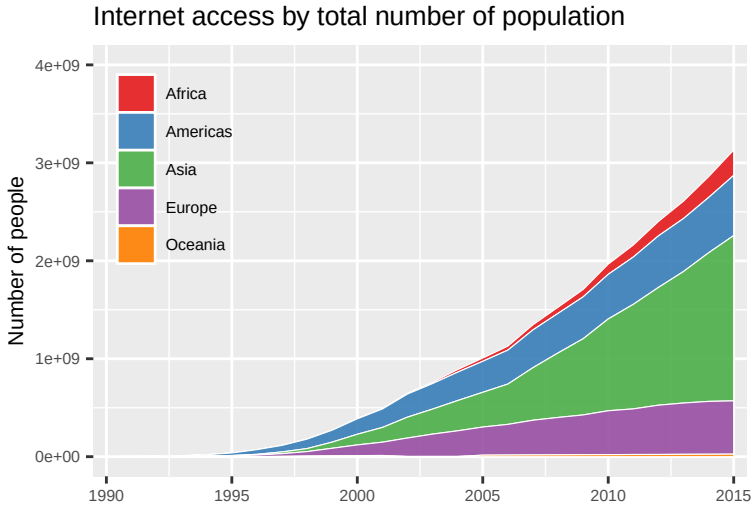


Figure 3: Internet access by total number of population, Source: The World Bank, World Development Indicators

1.1.3 Forging a New Technological Paradigm

Such rapid and widespread internet adoption has created a seemingly insatiable demand for exponentially greater computational power and digital storage capacity. This has led to a new and ubiquitous technological paradigm: Cloud Computing. Cloud Computing is succinctly defined as; the practice of using a network of remote servers hosted on the Internet to store, manage, and process data, rather than a local server or a personal computer [5].

As with the initial rise and widespread implementation of the Internet, Cloud Computing itself acts as a facilitator for new technologies. One such example being the Internet of Things (**IoT**) paradigm. The IoT can be surmised as the extension of the Internet and the Web into the physical realm, by means of the widespread deployment of spatially distributed devices with embedded identification, sensing and/or actuation capabilities, allowing objects to be sensed or controlled remotely through the internet [6], [7], [8]. IoT thus represents a convergence of real-world objects and digital objects into a unified cyber-physical system.

1.1.4 The Bigger Picture

Considering the bigger picture of societal benefit, as seen in Figure 2, from 1990 through 2015 the number of people living in extreme poverty has dropped by more than half. As evidenced by Figure 3, over the same time period, the percentage of people with access to the internet has move from around 1 per cent to an average of around 50 per cent (this trend is now moving exponentially as a function of time). And, Figure 4 shows that over the last 100 years, the human population has experienced unprecedented growth from 1 billion individuals to in excess of 7 billion. Mankind have thus simultaneously increased our population, increased of technological development and decreased poverty (to name but a few, 'key performance indicators').

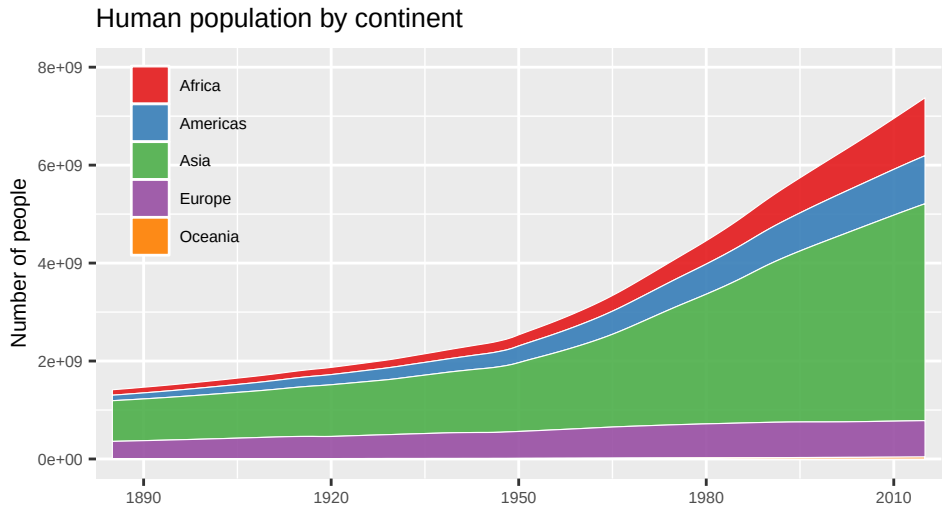


Figure 4: Human population by continent, Source: The World Bank, World Development Indicators

The success of modern human society is not without consequence. All of the benefits our society has enjoyed from the development, production and deployment of technology, has required vast amounts of energy. This energy has, since the industrial revolution, primarily been derived from the burning of fossil fuels, as illustrated by Figure 5.

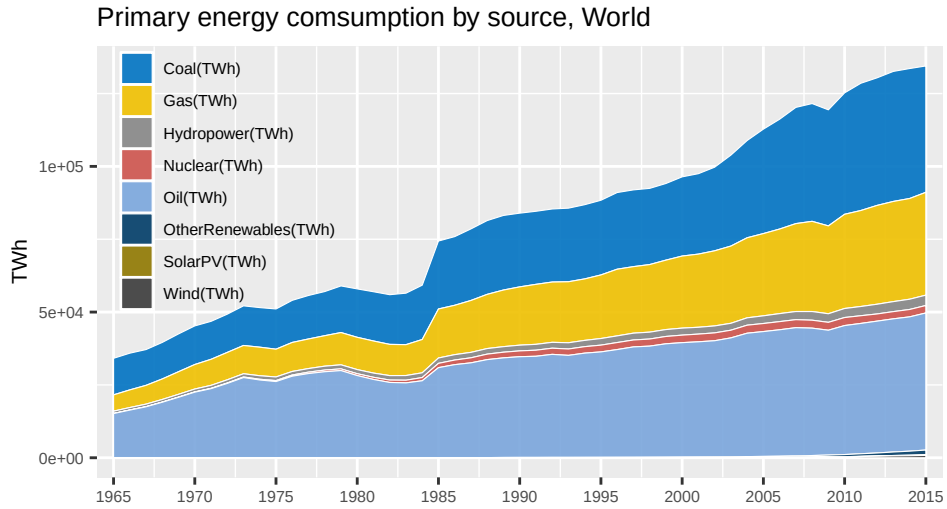


Figure 5: Energy Production and Changing Energy Sources, Source: Our World in Data

The International Panel on Climate Change (IPCC) finds that Human activities are estimated to have caused approximately 1.0°C of global warming above pre-industrial levels, with a likely range of 0.8°C to 1.2°C. Global warming is likely to reach 1.5°C between 2030 and 2052 if it continues to increase at the current rate [9].

Climate change poses an existential threat to modern human civilisation, with warming of between 1.5°C and 2°C predicted to cause increases in mean temperature in most land and ocean regions, hot extremes in most inhabited regions and heavy precipitation changes in some regions. Additionally, increases in ocean temperature as well as associated increases in ocean acidity and decreases in ocean oxygen levels are projected to reduce risks to marine biodiversity, fisheries, and ecosystems, and their functions and services to humans. Taken together, these effects will lead to risks of the health, livelihoods, food security, water supply, human security, and economic growth [9].

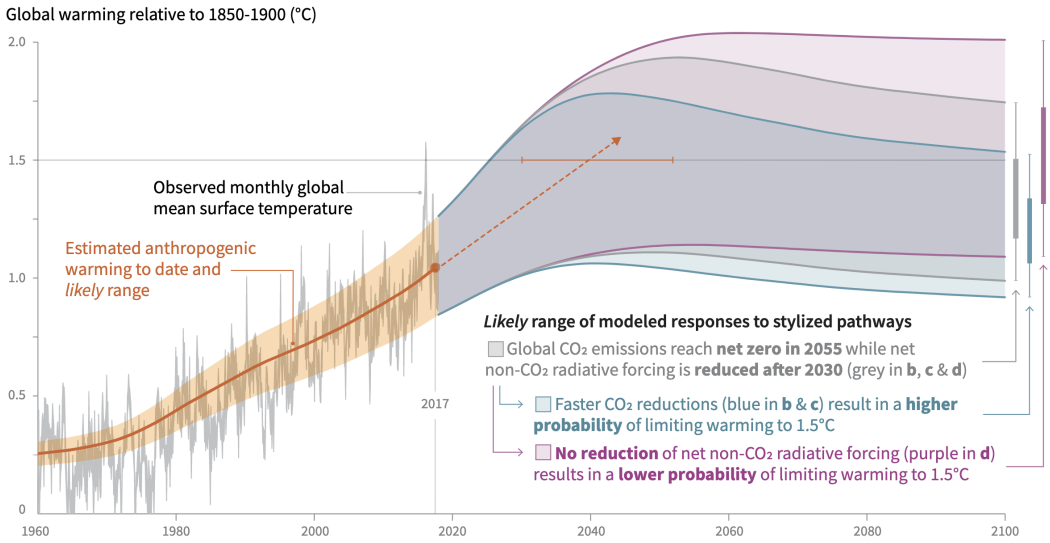


Figure 6: Atmospheric Changes with respect to Carbon Emissions and Global Warming - Observer and Projected. Source: Intergovernmental Panel on Climate Change, 2018

It is therefore imperative moving forward as a species that all steps are be taken to mitigate the emission of greenhouse gases and abate the advance of anthropomorphic climate change. The scale of the challenge is such that technology itself will prove critical in effectively combating this existential threat to civilisation. When considering energy consumption, the industrial sector (including the non-combusted use of fuels) currently consumes around half of all global energy and feedstock fuels, with residential and commercial buildings (29%) and transport (21%) accounting for the remainder [10]

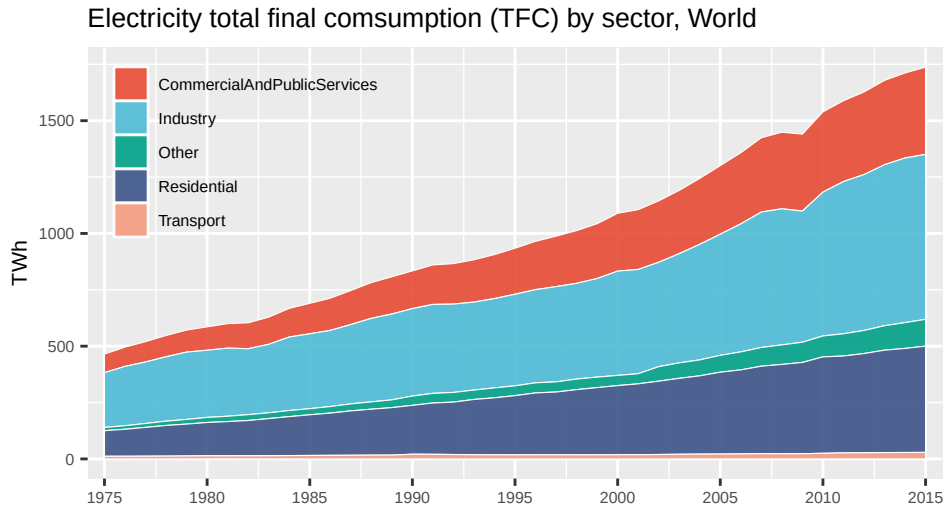


Figure 7: ADD TEXT

1.1.5 Optimising Global Energy Usage

Thus far, our staggering global achievements, including lifting hundreds of millions out of poverty, rapid global technological deployment and strong population growth has been inexorably linked to increased energy consumption. This in turn has led to perturbations in atmospheric chemistry, in the form of anthropogenic climate change (amongst many other environmental challenges), which fundamentally threatens our global achievements. It therefore stands that the key to continued human prosperity is to de-couple growth in energy demand from economic growth. In this work we will explore the possibility of reducing energy consumption via the optimization of services to end users in an IoT Smart Home.

1.1.6 The IoT Smart Home & Service Oriented Computing

As mentioned above, residential and commercial buildings account for 29% of energy demand globally [11]. In this work we propose that an avenue for reduced energy consumption is the optimization of existing services and utilities to end users in an IoT Smart Home. In this proposed smart home, the daily activities of the end user can be performed with the support of a personalised artificial intelligence (AI) system, such that the timing and manner of energy intensive activities is optimised to reduce overall energy consumption, whilst still considering the level of convenience afforded to the end user. This work uses sensor data analogous to what would be expected to be produced from a sensor rich IoT smart home and considers the interplay between end user convenience; predictive analytics; predictive service offering; energy consumption; demand response and smart electricity grids.

1.2 Aim

In this work we aim to use previously captured sensor data of domestic activities to develop a framework for the consideration of convenience with respect to energy savings. We will extrapolate these findings into a proposed hypothetical scenario in which an end user occupying an IoT smart home is able to use a smartphone application to personalise the level of convenience, cost saving or energy saving.

1.2.1 Research Questions

1. Can a generalised methodology for processing data pertaining to end user activity in a smarthome be developed?
2. Can historical sensor data be used to build a meaningful model for the relationship between end user convenience and cost?

2 Preliminaries

Significant growth in digital interconnectivity over the last 20 years has given the internet a pivotal role as an essential element of economic growth [12]. Cloud computing and the IoT paradigm has enabled the association of previously disparate fields into a larger coherent framework. Namely, smart home appliances, demand-response, energy consumption, predictive analytics predictive service offering and end user convenience. This work proposes a framework for the association of sensor data as an into into a machine learning model as a means of predicting energy-intensive appliance usage in a hypothetical IoT smarthome.

2.1 Related Work

2.1.1 Ubiquity of the World Wide Web and Implications for Energy Consumption

The International Telecommunication Union estimated about 3.2 billion people, or almost half of the world's population, would be online by the end of the 2015 [3]. The impact of internet usage and mobile cellular subscriptions (**ICTs**), globalization, electricity consumption, financial development, and economic growth on environmental quality has been examined [12]. By using 1994–2014 panel data of the Brazilian, Russian, Indian, Chinese & South African (**BRICS**) economies, empirical results demonstrate that rise in both internet usage and mobile cellular subscription ICTs likely mitigates CO2 emissions.

2.1.2 Smart Metering

A Smart meter is an electronic device that records consumption of electric energy and communicates the information to the electricity supplier for monitoring and billing. In the Unites States (for example) smart meters are a significant part of the larger Smart Grid infrastructure, and as far back as 2012, had been installed in over 25 million U.S. homes [13]. Smart Meters transmit information about consumer electricity use to utility companies at vastly shorter time intervals than before and this information helps utility companies to coordinate power supply and demand, detect outages, implement time-of-use and dynamic pricing, and in other ways improve system efficiency and reliability. Additionally, these data are also becoming increasingly available, and sought-after, by end-users themselves. Indeed, the main purpose of provisioning smart metering data to end users is to encourage the use of less electricity, by better informing users of their consumption patterns [14]. In the aggregate, these savings can significantly reduce national energy use and curb energy emissions while addressing pressing geopolitical and environmental concerns related to energy security and sustainability [15].

Since the widespread deployment of smart meter technology, there has been huge interest in the capability of these technologies with respect to the technical capacity of utility companies to manage demand (through demand response programs), incorporate renewable sources of electricity into the system, and increase the overall efficiency and reliability of the system [13].

2.1.3 Electricity Demand Response, Smart Electricity Grids and Smart Home Data

Predicting and influencing residential energy use has been the subject to extensive study [16]. Literature indicates that factors such as occupant behaviour and socio-economic status are important. For example Nielsen attributed 36% of variation in energy consumption of homes to lifestyle and occupant behaviour, and 64% to socio-economic influences. This is exemplified by the work of De et al, who show that in developing nations, cooking consumes up to 90% of the overall residential energy consumption and is mainly based on non-renewable energy [17]. Other factors such as climate zone, number of occupants, income level, age of home, and size of home have also been correlated with home energy use [16]. There has been much work both on using smart meter data to evaluate consumer behaviour, and the interplay between smart appliances and shifting households' electricity demand.

Kavousian et al identify the need for developing an analytical method that can leverage 15-minute or 30-minute interval energy consumption data produced via smart metering in order to improve the effectiveness of energy efficiency programs. They note that utilities spend millions of dollars annually to improve appliance energy efficiency. By way of example, in 2013 utilities in California US spent $80 M USD on appliance and plug load efficiency programs, the highest expenditure among all utility energy efficiency programs [18]. A need for analytical methodologies that can process smart meter data and allow energy reduction savings to be identified is demonstrated. Using a smart meter dataset of 4231 households, containing information on electricity consumption at 30-minute intervals, with aggregated local weather data, the authors use smart meter data to rank residential appliance efficiency. Various control methodologies are embedded into the analytical process, taking into account building type, building size (e.g., apartment, detached), household type (e.g., de facto, single, dependents), respondent age and heater type (e.g., electric or gas). The data set included 120+ household variables, many of which were highly correlated, model selection techniques were used to successfully reduce dimensionality. A set of load profiles were compiled based on the results (where normalized load was plotted as a function of hour of day). It was determined that household behaviour and demographic can be used to generate positive and negative energy efficiency coefficients with respect to load profiles. This work has implications for energy grid planning – for example in high-density housing versus suburban housing.

Karjalainen considers the manner in which smart meter data is communicated to end users, with the

principal purpose of the paper being to study what kind of electricity consumption feedback consumers understand and prefer [19]. It is noted that the most effective feedback tools for engaging households in reducing energy consumption are both computerized and interactive. In this work a series of options for feedback is gathered, for example consumption (kHh), power (W), cost ($), environmental impact (e.g., kg CO2), total for household, disaggregation by appliance, real time, hour, day, and so on. Examples of feedback options are shown in Figure 8 and Figure 9, below.

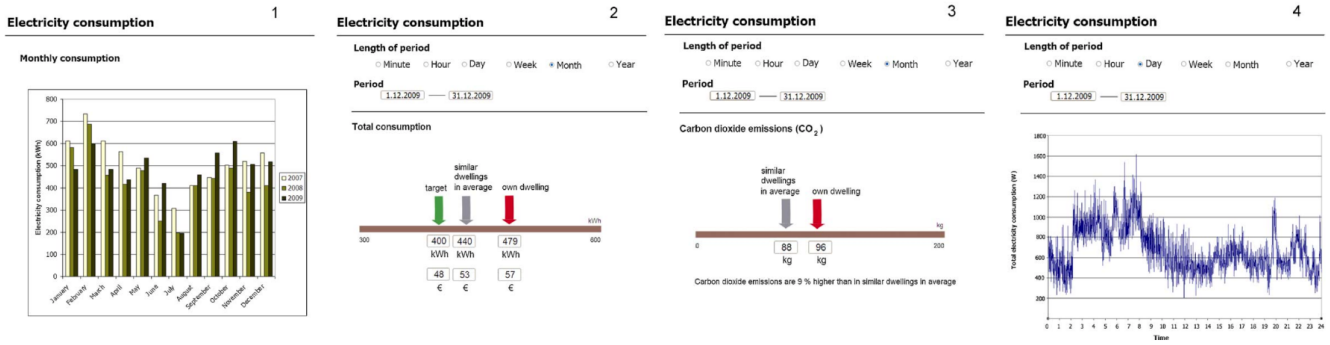


Figure 8: Option One, Two, Three and Four of the smart meter data dashboards proposed by Karjalainen

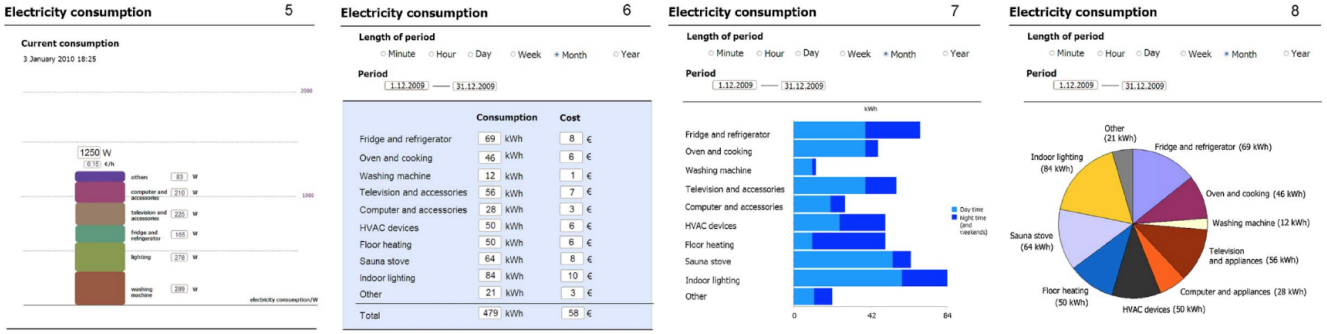


Figure 9: Option Five, Six, Seven and Eight of the smart meter data dashboards proposed by Karjalainen

The results of qualitative participant interviews clearly showed that while some consumers are very interested in saving household electricity, other consumers show only a little interest. When specifically asked to list what measures (if any) were typically taken at home to realize reductions in energy usage, some respondents listed numerous measures, while others just said they turn lights off in rooms that are empty. The author also found some participants were unaware of differences in stand-by versus active modes of operation for electrical appliances, resulting in practising inefficient energy saving measures in the home environment. When trialling feedback prototypes to participants, two main issues were encountered: (1) many people are not familiar with scientific units and do not understand the difference between W and kWh and (2) many people do not understand how carbon dioxide emissions are related to electricity consumption. It is perhaps surprising that the overall most popular prototype was '6', below. Perhaps because unlike the other prototypes, this clearly (the most clearly) articulates cost. The concept of convenience was absent entirely from consideration.

In the domain of supply and demand economics, consumer behaviour and smart appliances Kobus et al investigated if households can shift their electricity demand to times when electricity is abundantly available [20]. Using a household electrical monitoring system (**EMS**) coupled to a smart appliance (smart washing machine), photovoltaic cells and the electricity grid, they were able to show that households can shift 10–77% of the electricity demand of their washing machine. This longitudinal study was conducted via the participation of 50 Dutch households over a period of one year. By utilizing an EMS which shows

appliance status, dynamic tariff information and current status of household electricity usage, participants are able to schedule smart washing machine use in such a way that cost is minimized.

Figure 10: Example dashboards proposed by Kobus et al

Their work is in response to two major challenges to domestic electricity supply and demand. The first being the amount of distributed renewable electricity generation is increasing with time (e.g., as more households install photovoltaic (**PV**) panels), and the second that electricity demand will continue to significantly increase moving into the foreseeable future. These developments pose great challenges to 'traditional' power systems, where supply follows demand entirely. Smart grids are proposed as a potential solution for the affordable introduction of cleaner electricity producing and consuming technologies.

Cetin et al consider electricity usage of appliance, as when aggregated, this accounts for approximately 30 per cent of electricity used in the residential building sector [21]. This, together with small appliances, home electronics and lighting, account for more than 2/3 of total residential electricity use. Cetin et al also highlight that influencing 'time of use' is becoming increasingly important to control the stress on today's electrical grid infrastructure. The authors seek to determine when refrigerators, clothes washers, clothes dryers and dishwashers are predominantly used (and thus consume energy) and what causes variation in their use. Using disaggregated energy data from 40 homes over a period of 1-year, normalized load profiles for the four target appliances were generated, as a percentage of daily electricity load.

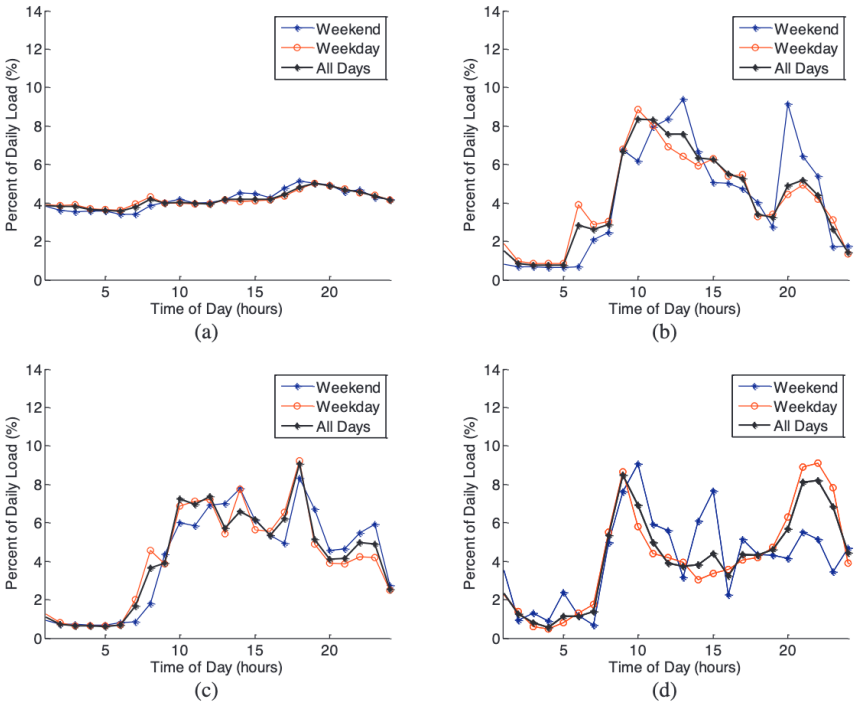


Figure 11: Appliance energy consumption with respect to time of day, A = refrigerators, B = cloths washers, C = Cloths dryers and D = Dishwashers

It was found that the refrigerator had the most consistent consumption profile across all homes surveyed. Influencing factors for the refrigerator were correlated to both indoor and outdoor temperature, however effect was found to be minimal. The clothes washer and dryer were found to have the greatest variation in normalised energy use by hour, with the greatest period of use from 9am until 2pm. The dishwasher had distinct peaks in load profile at 9am and 10pm. The authors found that user-dependent appliance use patterns vary more between homes and between days than automated appliances, weekday and weekend use patterns of appliances are similar, and that electricity use varies more between houses during peak use times of day than during low-use times. Murray et al further explore the topic of home appliance energy consumption using smart meter data, specifically pertaining to residential activities around food storage and preparation [17], with the aim of providing a model that can easily be applied to existing smart meter energy datasets. The authors use real-time energy consumption data from microwaves and ovens, from which user behaviour / desired outcome can be implicitly associated (for example, oven usage on a weekday between the hours of 6pm and 8pm can be associated with the behaviour of preparing dinner). Accurate energy consumption models for major cooking appliances are successfully constructed, further re-enforcing the value and widespread applicability of residential smart meter data.

2.1.4 Predictive Modelling and Forecasting

In the domestic predictive energy consumption space Basu et al consider home automation systems linked via a communication network to enable interaction, data collation and control of appliances remotely by end users [22]. The potential competing priorities of energy savings versus comfort optimization for home occupants is discussed. The objective of this work is to propose a learning system that is able to help the home automation system compute an energetic plan that is also satisfactory to user requests. Taking into account correlation between appliances, a time-series based multi-label classifier is used to predict appliance usage up to one hour into the future.

The attribute construction technique of Knowledge Extraction applied. This process aims to extract novel attributes from underlying substructures in the training instances in the form of sub-events, for example periodicity in data. This Knowledge Extraction process is similar to the implicit associations used by Murray et al, in the analysis of energy consumption for food preparation [17]. The substructures are then fed to a propositional learner. The proposed model is trained in an iterative manner and attempts to take into account all the possible information based on consumption data, time of the event and meteorological information. Time is specifically model time as a periodic variable, segmenting on hour of day and day of week, noting that this takes into account the periodic nature of human behaviour. Using BR1, LP, CC1, CC2 and MLk machine learning algorithms, the precision, recall and accuracy for a variety of electricity-consuming appliances is determined (where each appliance constitutes a target variable over a set of iterations). In the evaluation phase they find that user behaviour toward an appliance is highly variable and the predictability of an appliance is dependent on the regularity of usage patterns of the inhabitants. It is specifically noted that it is therefore very difficult for now to propose a generic methodology of appliance prediction for private houses.

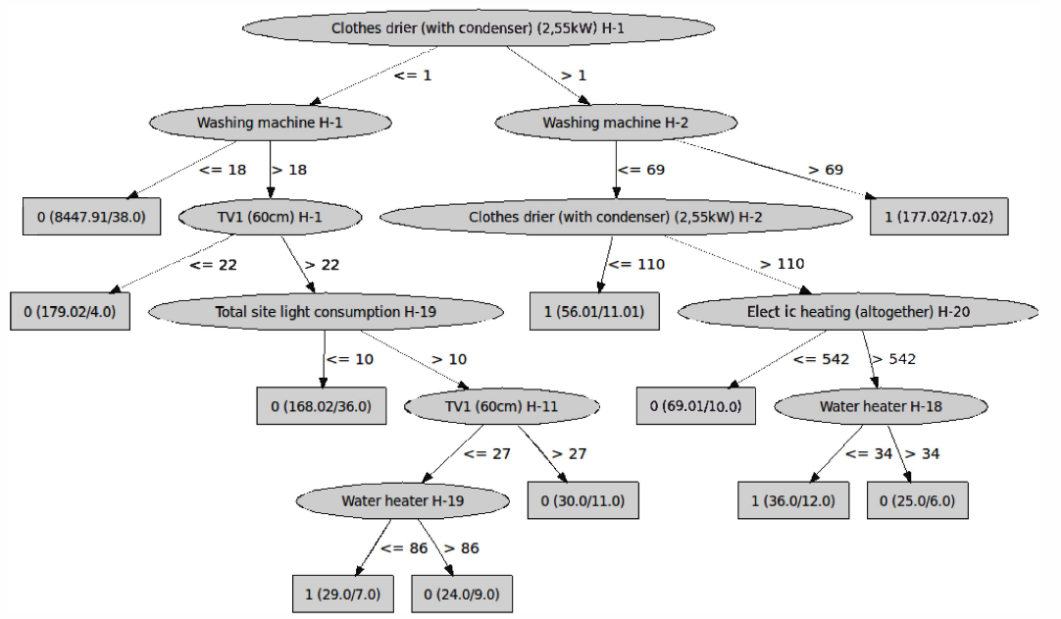


Figure 12: A decision tree from the work of Basu et al

Chou et al consider global energy consumption in the residential housing sector in the context of domestic energy information system (EIS) and smart meter system (smart grids) technologies [14]. They note two influential factors on overall residential energy consumption, the first being the type and number of electrical appliances and the second being the usage of these appliances by occupants. It is proposed that a major challenge for people who are willing to save energy at home is a lack of information about their energy consumption. To test this hypothesis, the authors develop a web-based energy information management system for the power consumption of home appliances that monitors the energy load of a home, analyses its energy consumption based on machine learning, and then sends information to various stakeholders. Interaction with end-users in the home is achieved via energy dashboards and emails. The authors propose that end-users of this system can use forecast information and anomalous data to enhance the efficiency of energy usage in their buildings especially during peak times by adjusting the operating schedule of their appliances and electrical equipment.

During this study, an EIS with 5 main components was installed in an experimental building. The parts were as follows; (1) the internal communication network, (2) the data management infrastructure, (3) the automated prediction system, (4) the web-based system and dashboard and (5) the early warning system. Data from both the smart meter and from sensors was used to compile the model, including timestamps (YYYY-MM-DD hh:mm:ss), outdoor temperature (^{o}C), total building energy consumption (kWh), aggregated energy consumption data (e.g., second floor lighting) and individual appliances. The backend of the application was notably cloud-hosted. They found improve consumer satisfaction by providing real-time services that enable end-users to monitor the energy consumption easily.

2.1.5 IoT and End User Convenience

The term Internet-of-Things (**IoT**) is used as an umbrella keyword for covering various aspects related to the extension of the Internet and the Web into the physical realm, by means of the widespread deployment of spatially distributed devices with embedded identification, sensing and/or actuation capabilities [6]. The IoT paradigm is fundamental to this work, representing the confluence of multiple technological advancements [8] including, ubiquity of internet access, the availability of high-performance internet connectivity, inexpensive consumer electronics with embedded sensing and control systems, automation,

real-time analytics, machine learning, commodity sensors and embedded systems. In the IoT paradigm, digital and physical entities can be linked, by means of appropriate information and communication technologies, to enable a whole new class of applications and services [6]. One consequence resulting from the widespread deployment of consumer electronics with IoT capability is the evolution of the Internet from interconnecting computers to interconnecting things. Figure 13, below, represents the availability of services provisioned by new means facilitated by the internet and cloud computing.

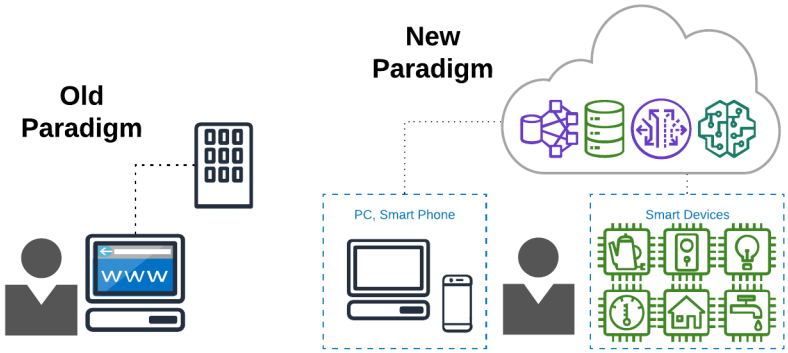


Figure 13: The old and new paradigms of end user interaction with the internet

Huang et al propose a novel service mining framework to personalize services in an IoT-based smart home [7]. This work considers the notion of personal 'convenience' as a driving force behind the provisioning of services to end users. That is, in an IoT smart home, where everything is interconnect, can services (for example, the switching on or off of a light) be automatically served to users such that their level of effort (to interact with their surroundings) will be diminished, and thus their level of convenience will be increased? The input for this work was data from domestic IoT services, with a corresponding timestamp. The end user in this scenario performs daily activities by interacting with IoT services, these interactions are recorded as IoT service event sequences. The output for this work was an IoT service model and a composite IoT service model (based on spatio-temporal features).

2.2 The Data Set

The datasets were created during the thesis *Activity Recognition with End-User Sensor Installation in the Home* by Randy Joseph Rockinson, Submitted to the Program of Media Arts and Sciences, School of Architecture and Planning, in partial fulfilment of the requirement for the degree of Master of Science in Media Arts and Sciences at the Massachusetts Institute of Technology (MIT) February 2008 [23].

The aim of Rockinson was to considered the effect of end user versus professional installation of a sensor array in the home - on the basis that, if installation of sensors is to be considered as a high initial cost, and a barrier to entry for end users wanting this technology, is there a difference if a professional versus an end user performs the installation? Between 80-100 reed switch sensors where installed in two single-person apartments collecting data about human activity for two weeks. The sensors were installed in everyday objects such as drawers, refrigerators, containers, etc to record for example opening-closing events (activation deactivation events) as the subject carried out everyday activities.

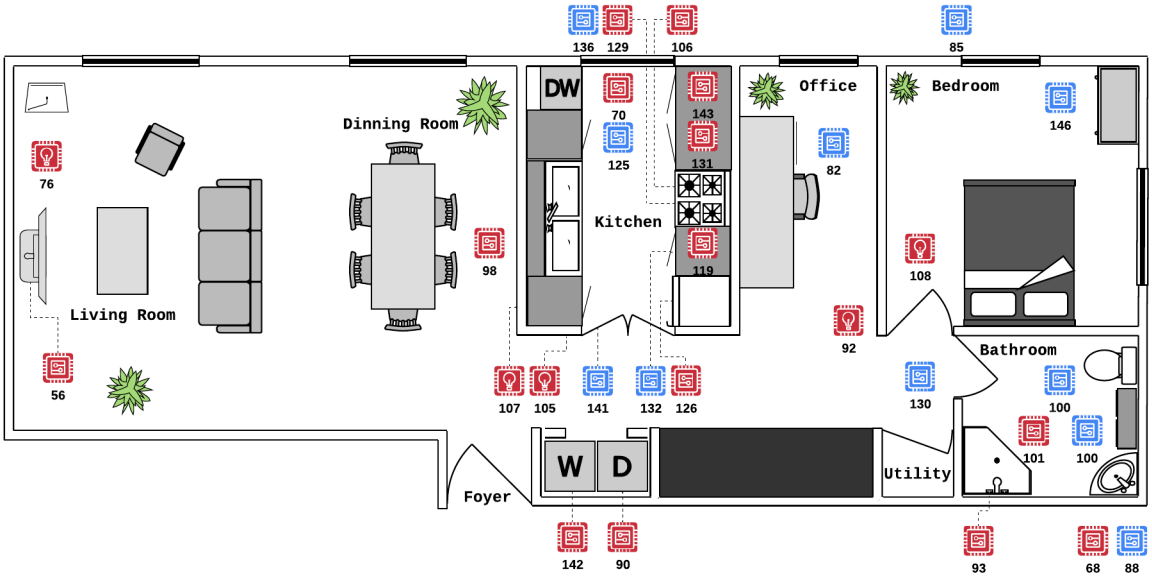


Figure 14: The floor plan of the MIT home lab with a selection of sensors. Sensors in red correspond to those that require an energy source, while blue are activities that require only energy input from the end user, for example opening a door

3 Data Preprocessing & Visualisation

3.1 Importing & Preprocessing the Activities Meta Data

The dataset `S1Activities.csv` was imported into the interactive development environment. These data contains a tabulated summary of Heading, Category, Subcategory and a corresponding unique code. After importation, the dataset has dimensionality of [3, 33], with `Heading`, `Category` & `Subcategory` present as non-null objects, as seen in Table 1 below. The attribute `Code` (which codefies the unique set of Heading, Category & Subcategory) was imported as an index value (n=33). At this time, the activities data will be kept in it's native state and will not be subject to preprocessing.

Table 1: The S1 activities dataset

	Heading	Category	Subcategory
1	Employment related	Employment work at home	Work at home
5	Employment related	Travel employment	Going out to work
10	Personal needs	Eating	Eating
15	Personal needs	Personal hygiene	Toileting
20	Personal needs	Personal hygiene	Bathing

3.2 Importing & Preprocessing the Sensor Meta Data

The dataset `S1sensors.csv` was imported into the interactive development environment. These data contains a tabulated values for Sensor ID, Room and Sensor Descriptor (e.g., light switch), with no header row present in the original dataset. After importation, the dataset has dimensionality of [3, 76], with header 0, 1 & 2 corresponding to SensorID, Room & Sensor Descriptor, respectively, as seen in Table 2. As all attributes are nominal, they were imported as String data types.

Table 2: The S1 sensor meta data

0	1	2
100	Bathroom	Toilet Flush
101	Bathroom	Light switch
104	Foyer	Light switch
105	Kitchen	Light switch
106	Kitchen	Burner

After importation these data were checked for duplicate values. The `Sensor ID` attribute had a 76 unique values, the `Room` attribute had only 7 unique values and the `Activity` attribute had 28 unique values. Examples of the degeneracy in these attributes can be seen in Table 2, e.g., Bathroom & Light Switch. Room[1] and Activity[2] were stripped of whitespace, coerced to lowercase and concatenated using an underscore. The concatenated vector was then bound to the dataframe and the column names updated, resulting in 3, below.

Table 3: The first iteration of processed S1 sensor meta data

subActNum	room	activity	concat
100	Bathroom	Toilet Flush	bathroom_toiletflush
101	Bathroom	Light switch	bathroom_lightswitch
104	Foyer	Light switch	foyer_lightswitch
105	Kitchen	Light switch	kitchen_lightswitch
106	Kitchen	Burner	kitchen_burner
107	Living room	Light switch	livingroom_lightswitch

The number of unique values in `dsS1Sensors.subActNum` is checked once more and found to be n=76, indicating no degeneracy in this attribute. The number of unique values in `dsS1Sensors.concat` is found

to be n=41, indicating the presence of degeneracy. This was investigated by aggregating the duplicate attributes, which are summarised in Table 4, below.

Table 4: Summary of the number of degenerate values (n) for each subactivity, where applicable.

n	concat
3	kitchen_lightswitch
4	kitchen_burner
2	livingroom_lightswitch
7	kitchen_drawer
3	kitchen_refrigerator
15	kitchen_cabinet
2	kitchen_door
5	bedroom_drawer
2	bathroom_medicinecabinet
2	bathroom_cabinet

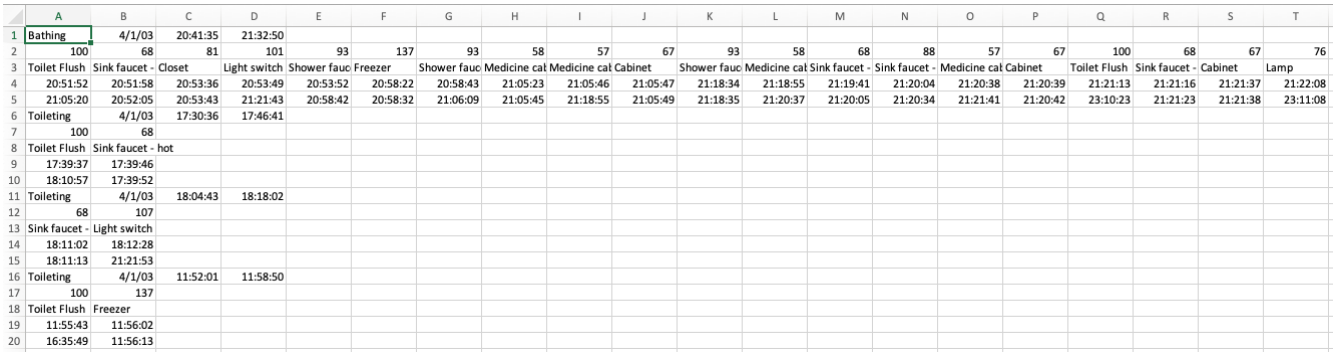
Referering to the work of Rockinson (from where the data originated) it is was determined that these duplicate values are theresult of multiple sensors with extremely similar functionality [23]. For example, kitchen_burner has a value of n=4, accounted for by the presense of one sensor per burner in the original work. While this level of granularity may provide an avenue for further analysis, for the purposes of this research such values serve to significantly increase the dimensionality of the overall dataset, with a low corresponding gain in information. High dimensionality can also lead to difficulties in machine learning models and challenges with data visualisation. The sensor class kitchen_cabinet has a value of n=15, indicating that for the various cabinets in the kitchen, a total of 15 sensors were fitted to monitor activity. This information will be used to inform the pre-processing methodology for the sub activity data in subsequent analysis. The sensor meta data set was inspected and stripped of special characters, and the sub activities requiring an input of energy (e.g., electrical, gas) were flagged with a boolean value, resulting in Table 5. The pre-processed sensor data was exported as `S1Sensors_preprocessed.csv`.

Table 5: Pre-processed sensor data table with addition columns for concatenated value, energy requirement and sub activity number

subActNum	room	activity	concat	reqEnergy	subActNumConcat
100	Bathroom	Toilet Flush	bathroom_toiletflush	FALSE	subActNum_100
101	Bathroom	Light switch	bathroom_lightswitch	TRUE	subActNum_101
104	Foyer	Light switch	foyer_lightswitch	TRUE	subActNum_104
105	Kitchen	Light switch	kitchen_lightswitch	TRUE	subActNum_105
106	Kitchen	Burner	kitchen_burner	TRUE	subActNum_106
107	Living room	Light switch	livingroom_lightswitch	TRUE	subActNum_107

3.3 Importing & Preprocessing the Activities Data

The `S1activities.csv` dataset contains the collated activity and subactivity data from the work of Rockinson [23]. The goal of pre-processing the `S1activities.csv` will be to restructure the dataset into a 'tidy' format, where the attributes are columns, the rows are instances, and each cell contains only one value. Figure 15 shows the data set open in a spreadsheet program and Table 6 shows a sample of the dataset after importation of the dataset into the interactve development environment. Inspection of the original dataset via an interactive development environment shows a structure such that each 5 rows contains is one discrete set of data, for example; row 1) Activity, Date, Start Time, End Time, row 2) Sub-activity (an action that can be executed as part of performing the activity) code-values, row 3) Sub-activity descriptive values, row 4) Sub-activity start time and row 5) Sub-activity end time.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
1	Bathing	4/1/03	20:41:35	21:32:50																
2	100	68	81	101	93	137	93	58	57	67	93	58	68	88	57	67	100	68	67	76
3	Toilet Flush	Sink faucet -	Closet	Light switch	Shower fauc	Freezer	Shower fauc	Medicine cal	Medicine cal	Cabinet	Shower fauc	Medicine cal	Sink faucet -	Sink faucet -	Medicine cal	Cabinet	Toilet Flush	Sink faucet -	Cabinet	Lamp
4	20:51:52	20:51:58	20:53:36	20:53:49	20:53:52	20:58:22	20:58:43	21:05:23	21:05:46	21:05:47	21:18:34	21:18:55	21:19:41	21:20:04	21:20:38	21:20:39	21:21:13	21:21:16	21:21:37	21:22:08
5	21:05:20	20:52:05	20:53:43	21:21:43	20:58:42	20:58:32	21:06:09	21:05:45	21:18:55	21:05:49	21:18:35	21:20:37	21:20:05	21:20:34	21:21:41	21:20:42	23:10:23	21:21:23	21:21:38	23:11:08
6	Toileting	4/1/03	17:30:36	17:46:41																
7	100	68																		
8	Toilet Flush	Sink faucet - hot																		
9	17:39:37	17:39:46																		
10	18:10:57	17:39:52																		
11	Toileting	4/1/03	18:04:43	18:18:02																
12	68	107																		
13	Sink faucet -	Light switch																		
14	18:11:02	18:12:28																		
15	18:11:13	21:21:53																		
16	Toileting	4/1/03	11:52:01	11:58:50																
17	100	137																		
18	Toilet Flush	Freezer																		
19	11:55:43	11:56:02																		
20	16:35:49	11:56:13																		

Figure 15: The S1 Activities dataset shown in a spreadsheet program. The structure of the data, a mixture of tab delimited and comma delimited values with unequal row lengths, presents a variety of challenges with respect to pre-processing

Table 6: A sample of the S1 activities dataset after importation into the interactive development environment

	0
5	Toileting,4/1/2003,17:30:36,17:46:41
6	100,68
7	Toilet Flush,Sink faucet - hot
8	17:39:37,17:39:46
9	18:10:57,17:39:52

Due to the varying number of comma-separated elements in each row (Figure 15) the `S1activities.csv` data was imported as an indexed dataframe, containing only one column, with 1475 rows. In each row, values were comma-separated. After initial imporation the dataframe was converted to a 2D array, using `np.array()`, where each row from the dataframe became an array within the 2D array. The 2D array was flattened to a 1D array using `.flatten()` and each group of observations was then chunked into a list of 5. Using the logic shown in Algorithm 1, below, the activity, date and time data was extracted. During extraction in intermediate activities dataset was generated as seen below in Table 7 followed by the tidy pre-processed activities dataset, as seen in Table 8.

Algorithm 1: Extraction of data from S1 Activities dataset

Result: Intermediate dataframe with 'activity', 'date', 'startTime', 'endTime' as attributes
Input : S1 Activities
Output: S1 Activities Intermediate

```
begin
    array1-8 = [ ]
    i = 0
    while i < length(dataframe) do
        array1.append(dataframe[i][0])
        array2.append([x.strip() for x in array1[i].split(',')])
        array3.append(array2[i][0])
        array4.append(array2[i][1])
        array5.append(array2[i][2])
        array6.append(array2[i][3])
        i = i + 1
    end
    dfIntermediate = pandas.DataFrame(list(zip(array3, array4, array5, array6)))
    start = (dfIntermediate.date + " " + dfIntermediate.startTime)
    end = (dfIntermediate.date + " " + dfIntermediate.endTime)
    i = 0
    while i < length(start) do
        array7.append(datetime.strptime(start[i], mm/dd/yyyy HH:MM:SS))
        array8.append(datetime.strptime(end[i], mm/dd/yyyy HH:MM:SS))
        i = i + 1
    end
    dfFinal = pandas.DataFrame(list(zip(array3, array7, array8)))
    return dfIntermediate
    return dfFinal
end
```

Table 7: The S1 Activities intermediate dataset

activity	date	startTime	endTime
Bathing	4/1/2003	20:41:35	21:32:50
Toileting	4/1/2003	17:30:36	17:46:41
Toileting	4/1/2003	18:4:43	18:18:2
Toileting	4/1/2003	11:52:1	11:58:50

Table 8: The S1 activities tidy dataset

activity	start	end
Bathing	2003-04-01 20:41:35	2003-04-01 21:32:50
Toileting	2003-04-01 17:30:36	2003-04-01 17:46:41
Toileting	2003-04-01 18:04:43	2003-04-01 18:18:02
Toileting	2003-04-01 11:52:01	2003-04-01 11:58:50

3.4 Importing, Visualizing and Preprocessing the SubActivities Data

As mentioned above, the `S1Activities_data.csv` dataset contains the collated activity and subactivity data from the work of Rockinson [23]. As with the activities data extraction, the dataframe was converted to a 2D array, using `np.array()`, where each row from the dataframe became an array within the 2D array. The 2D array was flattened to a 1D array using `.flatten()` and each group of observations was then chunked into a list of 5. The sub-activity, date and time data was then extracted from the dataset, by employing the logic shown in Algorithm 2, below.An intermediate sub-activities dataset was generated as seen below in Table 9 followed by the tidy pre-processed sub-activities dataset, as seen in Table 10. This dataset was exported as `S1SubActivities_ds.csv`.

Algorithm 2: Extraction of sub-activity data from S1 activities dataset

Result: Intermediate dataframe with 'activity', 'date', 'startTime', 'endTime' as attributes
Input : S1 Activities
Output: S1 Activities Intermediate

```
begin
    array1-21 = [ ]
    while i < length(dataframe) do
        array1.append(dataframe[i][0])
        array2.append([x.strip() for x in array1[i].split(',')])
        array3.append(array2[i][0])
        array4.append(array2[i][1])
        array5.append(array2[i][2])
        array6.append(array2[i][3])
        i = i + 1
    end
    while i < length(dataframe) do
        array7.append(dataframe[i][1])
        array8.append([x.strip() for x in array7[i].split(',')])
        array9.append(dataframe[i][2])
        array10.append([x.strip() for x in array9[i].split(',')])
        array11.append(dataframe[i][3])
        array12.append([x.strip() for x in array11[i].split(',')])
        array13.append(dataframe[i][4])
        array14.append([x.strip() for x in array13[i].split(',')])
        i = i + 1
    end
    while i < length(dataframe) do
        for x in range(len(array8[i])) : array15.append(array4[i])
        i = i + 1
    end
    for sublist in array8: for item in sublist: array16.append(item)
    for sublist in array10: for item in sublist: array17.append(item)
    for sublist in array12: for item in sublist: array18.append(item)
    for sublist in array13: for item in sublist: array19.append(item)
    dfIntermediate = pandas.DataFrame(list(zip(array16, array17, array15, array18, array19)))
    start = (dfIntermediate.date + " " + dfIntermediate.startTime)
    end = (dfIntermediate.date + " " + dfIntermediate.endTime)
    while i < length(start) do
        array20.append(datetime.strptime(start[i], mm/dd/yyyy HH:MM:SS))
        array21.append(datetime.strptime(end[i], mm/dd/yyyy HH:MM:SS))
        i = i + 1
    end
    dfFinal = pandas.DataFrame(list(zip(array16, array17, array20, array21)))
    return dfIntermediate
    return dfFinal
end
```

Table 9: The S1 sub-activities intermediate dataset

subActNum	subAct	date	startTime	endTime
100	Toilet Flush	4/1/2003	20:51:52	21:5:20
68	Sink faucet - hot	4/1/2003	20:51:58	20:52:5
81	Closet	4/1/2003	20:53:36	20:53:43
101	Light switch	4/1/2003	20:53:49	21:21:43

Table 10: The S1 sub-activities tidy dataset

subActNum	subAct	start	end
67	Cabinet	2003-03-27 06:43:40	2003-03-27 06:43:43
100	Toilet Flush	2003-03-27 06:44:06	2003-03-27 07:12:41
101	Light switch	2003-03-27 06:44:20	2003-03-27 07:46:34
57	Medicine cabinet	2003-03-27 06:44:35	2003-03-27 06:44:48

3.4.1 Amalgamating 'duplicate' sub-activity instances

As mentioned in above, 10 of the sensors have duplicated values, owing to the presence of more than one sensor for certain activities. The sub-activity `kitchen_refrigerator`, for example, has the numbers [91, 126, 144] associated with it, as seen in Table 11, below. These values are subsequently replaced with [126]. As is the case with all sub-activities with degenerate numbers, the end value is chosen based on the first appearance in the S1 Sensors dataset. All duplicated values, as seen in Table 4 were aggregated to have the same sensor ID / subAct number, thus giving a value of n=1 with respect to duplication.The first occurence of each degenerate subactivity provided the subAct number to be used for all subsequent instances. This dataset was exported as `S1SubActivities_preprocessed.csv`.

Table 11: Example of duplicate sub-activity number removal

Prior to duplicate removal				Post to duplicate removal			
subActNum_pr	subAct_pr	start_pr	end_pr	subActNum_po	subAct_po	start_po	end_po
91	kitchen_refrigerator	27/3/03 7:41	27/3/03 7:41	126	kitchen_refrigerator	27/3/03 7:41	27/3/03 7:41
91	kitchen_refrigerator	27/3/03 11:38	27/3/03 11:38	126	kitchen_refrigerator	27/3/03 11:38	27/3/03 11:38
126	kitchen_refrigerator	29/3/03 14:42	29/3/03 14:42	126	kitchen_refrigerator	29/3/03 14:42	29/3/03 14:42
144	kitchen_refrigerator	29/3/03 14:42	29/3/03 14:42	126	kitchen_refrigerator	29/3/03 14:42	29/3/03 14:42
126	kitchen_refrigerator	29/3/03 14:43	29/3/03 14:43	126	kitchen_refrigerator	29/3/03 14:43	29/3/03 14:43

3.4.2 Addition of Temporal Features to the pre-processed sub-activities data

As noted by Basu et al, human behavior with respect to home appliance interaction and activity, is typically periodic in nature [22], that is, certain activities occur at specific times of day or in a particular sequence. It is helpful therefore to add categorical temporal features to our dataset, in order to inform further analysis. Using the Python `pandas` and `datetime` packages, the following features were added to all instances of the pre-processed S1 sub activities dataset; `dayNumeric`, `DAY`, `WDWE` (where WD is weekday and WE is weekend), `HOUR` (based on 24-hour time) and `durationSec` (the delta seconds value between `start` and `end`). This dataset was exported as `S1SubActivities_preprocessedWfeatures.csv`.

Table 12: A sample of n=1 of each sub-activity from the pre-processed dataset

subActNum	subAct	start	end	dayNumeric	DAY	WDWE	HOUR	durationSec
67	bathroom_cabinet	2003-03-27 06:43:40	2003-03-27 06:43:43	3	Thu	WD	6	4
100	bathroom_toiletflush	2003-03-27 06:44:06	2003-03-27 07:12:41	3	Thu	WD	6	1716
101	bathroom_lightswitch	2003-03-27 06:44:20	2003-03-27 07:46:34	3	Thu	WD	6	3735
57	bathroom_medicinecabinet	2003-03-27 06:44:35	2003-03-27 06:44:48	3	Thu	WD	6	14
82	study_drawer	2003-03-27 06:45:45	2003-03-27 06:45:48	3	Thu	WD	6	4
146	bedroom_drawer	2003-03-27 06:46:12	2003-03-27 06:46:20	3	Thu	WD	6	9
132	kitchen_cabinet	2003-03-27 06:51:43	2003-03-27 06:51:46	3	Thu	WD	6	4
143	kitchen_microwave	2003-03-27 06:54:09	2003-03-27 13:07:43	3	Thu	WD	6	22415
141	kitchen_door	2003-03-27 06:57:05	2003-03-27 06:57:08	3	Thu	WD	6	4
93	bathroom_showerfaucet	2003-03-27 07:05:22	2003-03-27 07:05:24	3	Thu	WD	7	3
125	kitchen_drawer	2003-03-27 07:38:48	2003-03-27 07:38:51	3	Thu	WD	7	4
70	kitchen_dishwasher	2003-03-27 07:40:32	2003-03-27 07:40:34	3	Thu	WD	7	3
126	kitchen_refrigerator	2003-03-27 07:41:08	2003-03-27 07:41:16	3	Thu	WD	7	9
88	bathroom_sinkfaucet-cold	2003-03-27 07:43:22	2003-03-27 07:43:48	3	Thu	WD	7	27
68	bathroom_sinkfaucet-hot	2003-03-27 07:43:23	2003-03-27 07:43:48	3	Thu	WD	7	26
140	foyer_door	2003-03-27 07:48:49	2003-03-27 07:48:53	3	Thu	WD	7	5
137	kitchen_freezer	2003-03-27 11:36:15	2003-03-27 11:36:21	3	Thu	WD	11	7
106	kitchen_burner	2003-03-27 11:37:13	2003-03-27 11:42:24	3	Thu	WD	11	312
105	kitchen_lightswitch	2003-03-27 11:38:54	2003-03-27 12:31:05	3	Thu	WD	11	3132
92	study_lightwitch	2003-03-27 16:28:23	2003-03-27 18:44:14	3	Thu	WD	16	8152
130	bathroom_door	2003-03-27 17:43:10	2003-03-27 17:43:12	3	Thu	WD	17	3
104	foyer_lightswitch	2003-03-27 19:36:32	2003-03-27 19:50:07	3	Thu	WD	19	816
131	kitchen_toaster	2003-03-28 12:32:00	2003-03-28 15:10:16	4	Fri	WD	12	9497
96	bathroom_exhaustfan	2003-03-28 17:43:17	2003-03-28 18:25:19	4	Fri	WD	17	2523
108	bedroom_lightswitch	2003-03-28 18:24:48	2003-03-28 19:55:44	4	Fri	WD	18	5457
129	kitchen_oven	2003-03-28 19:09:26	2003-03-28 19:09:30	4	Fri	WD	19	5
56	livingroom_dvd	2003-03-28 19:55:24	2003-03-28 19:55:29	4	Fri	WD	19	6
76	livingroom_lamp	2003-03-29 13:30:51	2003-03-29 18:50:13	5	Sat	WE	13	19163
139	bedroom_jewelrybox	2003-03-29 15:12:44	2003-03-29 15:12:45	5	Sat	WE	15	2
142	kitchen_washingmachine	2003-03-29 15:44:24	2003-03-29 15:44:26	5	Sat	WE	15	3
90	kitchen_laundrydryer	2003-03-29 15:48:18	2003-03-29 15:48:54	5	Sat	WE	15	37
98	kitchen_garbagedisposal	2003-03-29 15:54:50	2003-03-29 15:54:51	5	Sat	WE	15	2
107	livingroom_lightswitch	2003-03-29 18:50:43	2003-03-29 18:51:09	5	Sat	WE	18	27
81	foyer_closet	2003-04-01 06:13:26	2003-04-01 06:13:34	1	Tue	WD	6	9
145	kitchen_cereal	2003-04-01 06:37:18	2003-04-01 06:37:59	1	Tue	WD	6	42
60	kitchen_containers	2003-04-01 06:38:14	2003-04-01 06:38:48	1	Tue	WD	6	35
119	kitchen_coffeemachine	2003-04-09 08:46:07	2003-04-09 08:46:35	2	Wed	WD	8	29
64	bedroom_lamp	2003-04-09 20:16:36	2003-04-09 21:13:19	2	Wed	WD	20	3404

3.4.3 SubActivity Visualisation and Outlier Inspection

3.4.3.1 Aggregated Line Chart

The `S1SubActivities_preprocessedWfeatures.csv` dataset was analysed using data visualisation techniques. A plot of aggregated sub-activity count versus sub-activity was generated, as seen in Figure 16, below. The chart shows that there is a high level of consistency with respect to the overall aggregated count of each sub-activity, when compared to the feature `Day of the Week`.

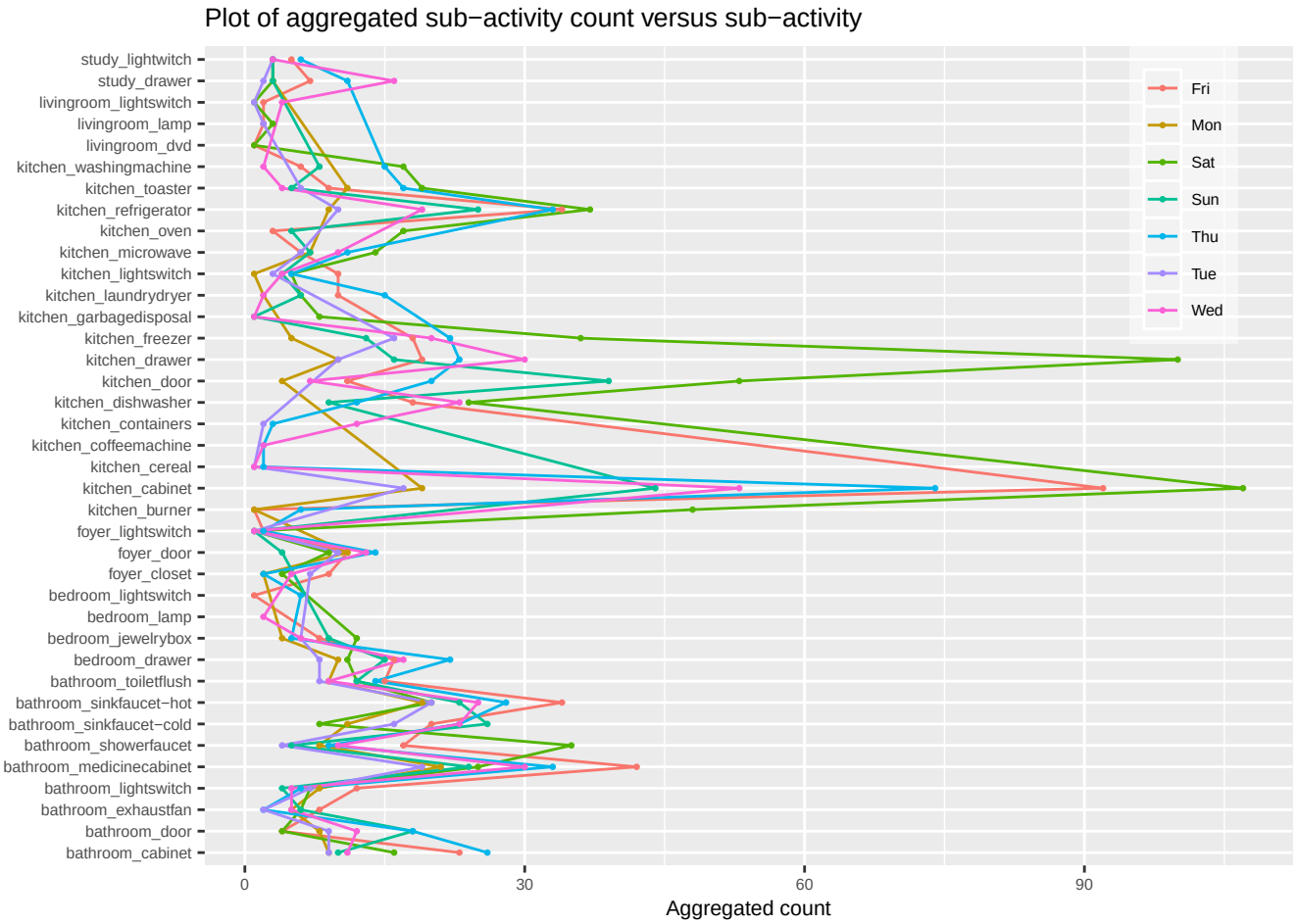


Figure 16: Aggregated line chart

3.4.3.2 Aggregated Box Plot of Sub-Activities

Figure 17, below, shows boxplots of all sub-activities versus their duration values. In this plot, we can see many outliers, which will inform further analysis. We also note that many of the outliers are extremely unrealistic. Of particular concern Kitchen_Toaster with a duration of almost 30,000 seconds, Bathroom_toiletflush distributed up to the range of 20,000 seconds. This potentially indicates challenges with the initial data collection methodology or experimental conditions / setup. Each sub-activity will be individually considered with respect to it's outliers.

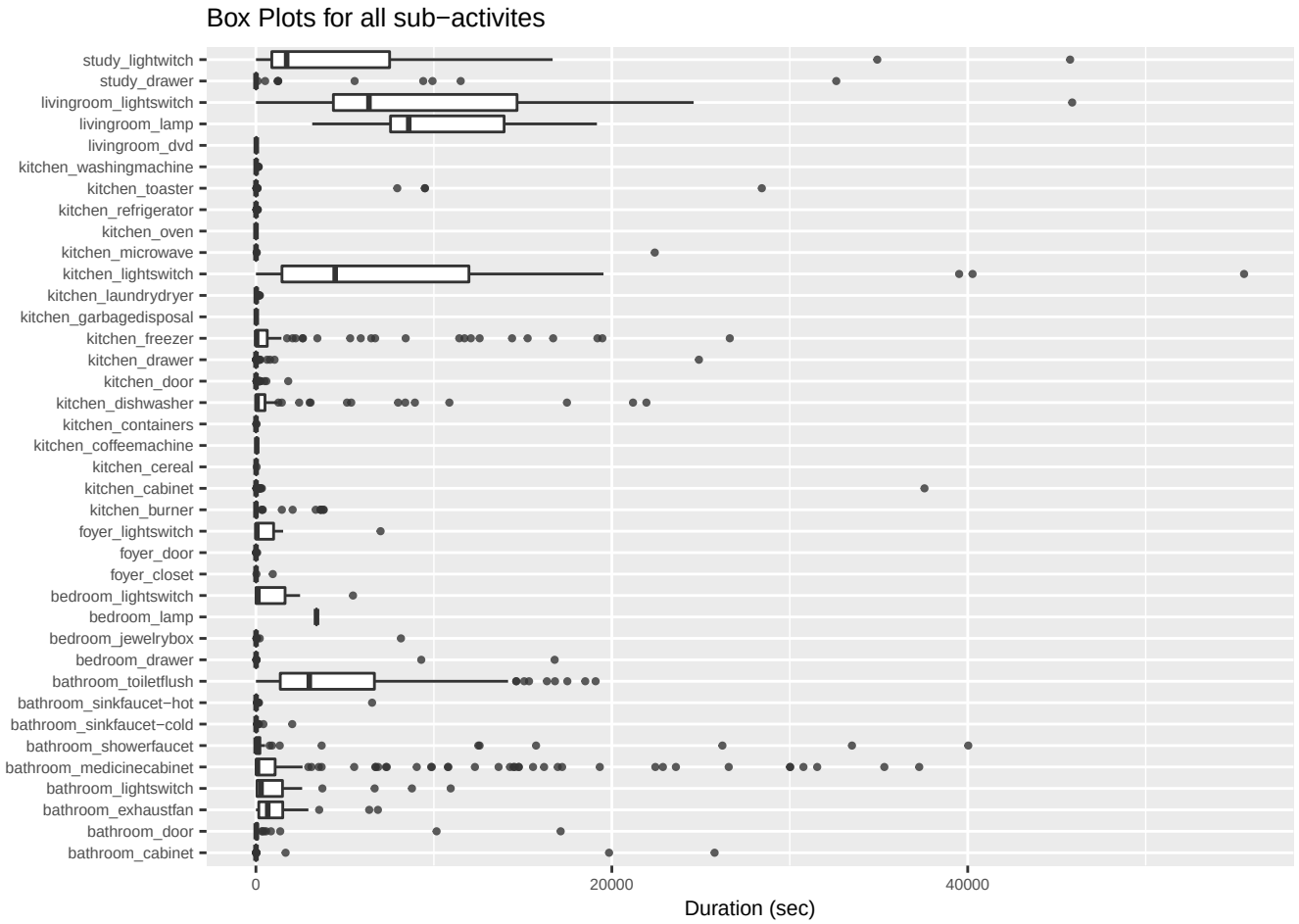


Figure 17: Box plots for all sub-activites

3.4.4 Sub-Activity Data Cleansing

Via the inspection of each sub-activity the following set of instances were identified, as seen in Table 13. In all cases the standard deviation of each aggregated instance (n=Count) is found to be greater than the mean, indicating that the data points are not even distributed with respect to total duration of the sub-activity, additionally, the median in all cases is found to be vastly different from the mean. The bathroom medicine cabinet, for example, has a mean value of 3188 seconds (53 minutes) and a median value of 88 seconds. Accross all sub-activities seen in Table 13, the median gives more reasonable values. Therefore the median value for each sub-activity below will be used to fill the outlier values. There were in total 4 pre-processing methodologies used. 1. Filling outliers with median 2. All values replaced with one value 3. No further processing required 4. Sub-activity dropped

Table 13: Summary table of outliers with respect to sub-activity duration over all instances

SubAct	Count	Median	Mean	Std
bathroom_cabinet	104	4.0	460.22115	3176.1633
bathroom_medicinecabinet	194	88.0	3188.97423	7354.1424
study_drawer	45	6.0	1634.48889	5432.4063
bedroom_drawer	99	10.0	273.47475	1918.7262
kitchen_cabinet	406	7.0	112.82020	1864.0122
kitchen_microwave	61	6.0	377.40984	2868.6679
kitchen_door	134	4.0	46.11194	174.1857
bathroom_showerfaucet	88	15.0	1754.35227	6540.7295
kitchen_drawer	208	4.0	145.06250	1727.5767
bathroom_sinkfaucet-hot	169	11.0	57.90533	501.2729
kitchen_freezer	130	39.0	1738.10769	4512.5738
bathroom_door	73	17.0	461.61644	2310.8116
kitchen_toaster	71	5.0	790.36620	3793.6744
kitchen_lightswitch	32	4454.0	9318.71875	13081.3404
study_lightwitch	26	1728.5	6430.73077	11002.3025
kitchen_dishwasher	86	63.5	1518.40698	4146.6375
livingroom_lightswitch	8	6352.5	12545.12500	15556.6628
foyer_closet	29	8.0	42.44828	174.4286

3.4.5 Sub-Activity Cleansing - 1) Filling outliers with median

This methodology was also applied to all of the other sub-activities in Table 13.

3.4.5.1 Bathroom Cabinet - Sub-Activity 67

As per Table 13, above, the bathroom cabinet has an overall count of n=104 in the dataset. In Figure 18 the boxplot (A) in row one shows several outliers, most notably around the 20,000 second mark for Friday and the 25,000 mark for Sunday. When considering all weekday and weekend values together, the mean is found to be 460.22 seconds, while the standard deviation is found to be 3176.16. As the SD in this case greatly overwhelms the mean, and the values of 20,000 seconds and 25,000 seconds are highly unrealistic for the sub-activity in question, the outliers will be filled with the median (4.0 seconds). The resultant plots can be seen in the second row.

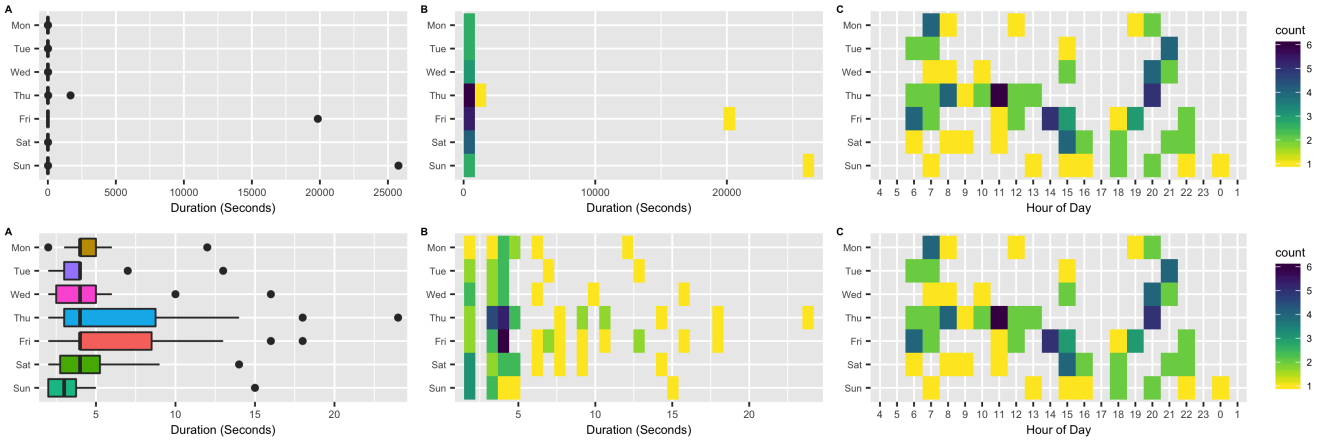


Figure 18: Initial and processed data box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the bathroom cabinet sub-activity.

3.4.5.2 Bathroom Medicine Cabinet - Sub-Activity 57

The bathroom medicine cabinet has an overall count of n=194 in the dataset. In Figure 19 boxplot (A) in row one shows a large amount of outliers, ranging all the way to nearly 40,000 seconds (over 11 hours). This is clearly outside the expected range for this sub-activity, with a median of 88.0 seconds, a mean of 460.22 seconds, and a standard deviation of 7354.14 seconds. These outliers will be filled with the median (88.0 seconds). The resultant plots can be seen in the second row.

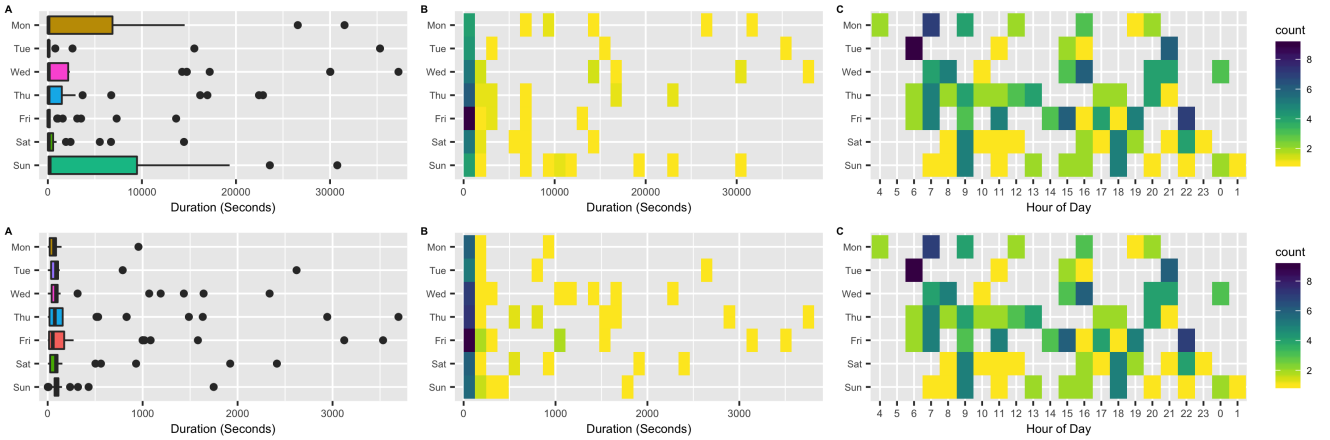


Figure 19: Initial and processed data box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Bathroom Medicine Cabinet sub activity.

3.4.5.3 Study Drawer - Sub-Activity 82

The study drawer has an overall count of n=45 in the dataset. In Figure 20 boxplot (A) in row one shows some abnormal results for Monday, Friday and Saturday. While the median is 6.0 seconds, there are results for Saturday that stretch beyond 30,000 seconds, clearly indicating sensor or measurement error. It is also outside the expected range for this sub-activity, causing the mean to be 1634.49 seconds with a standard deviation of 5432.41 seconds. These outliers will be filled with the median (6.0 seconds). The resultant plots can be seen in the second row.

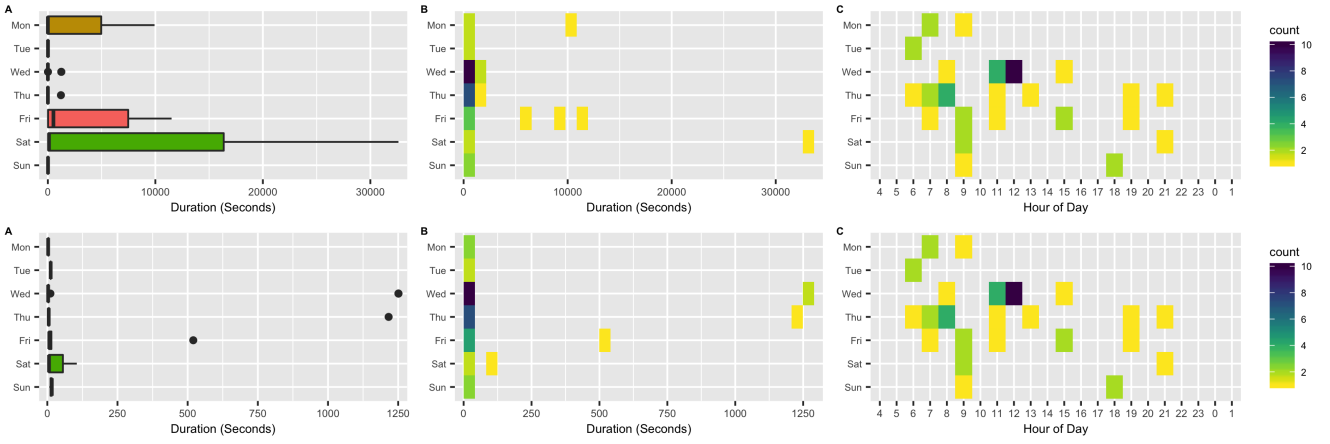


Figure 20: Initial and processed data box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Study Drawer sub activity.

3.4.5.4 Bedroom Drawer - Sub-Activity 146

The bedroom drawer has an overall count of n=99. In Figure 21 boxplot (A) in row one shows two main outliers, one on Friday at just under 10,000 seconds, and one on Wednesday at around 17,000 seconds. The median for this sub-activity is 10.0 seconds, and such outliers are clearly outside the expected range

for this sub-activity, causing the mean to be 273.47 seconds with a standard deviation of 1918.73 seconds. These outliers will be filled with the median (10.0 seconds). The resultant plots can be seen in the second row.

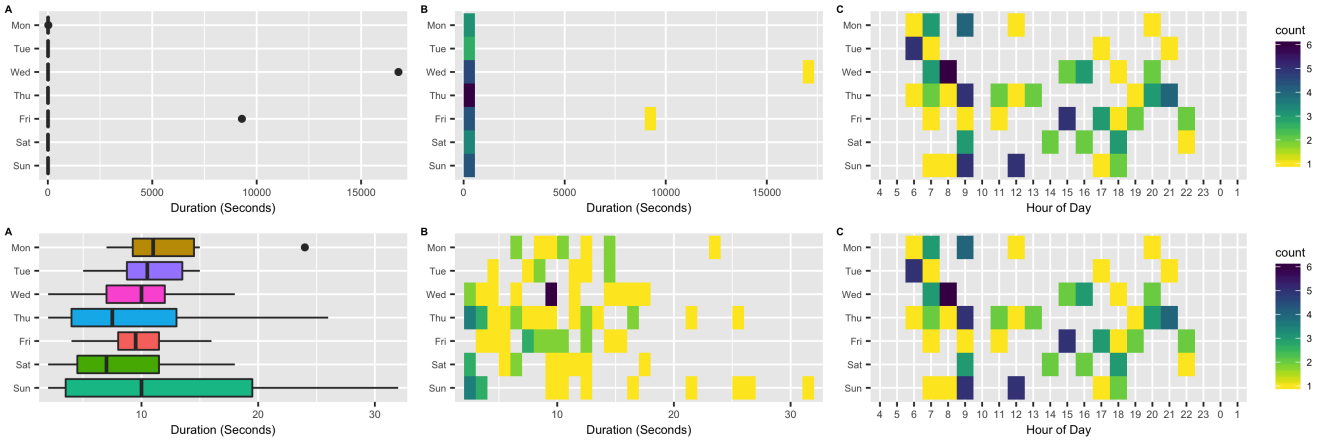


Figure 21: Initial and processed data box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Bedroom Drawer sub activity.

3.4.5.5 Kitchen Cabinet - Sub-Activity 132

The kitchen cabinet has an overall count of n=406. Figure 22 boxplot (A) in row one shows one main outlier on Tuesday, at nearly 40,000 seconds. The median for this sub-activity is 7.0 seconds, and this outlier is clearly outside the expected range for this sub-activity, causing the mean to be 112.82 seconds with a standard deviation of 1864.01 seconds. This outlier will be filled with the median (7.0 seconds). The resultant plots can be seen in the second row.

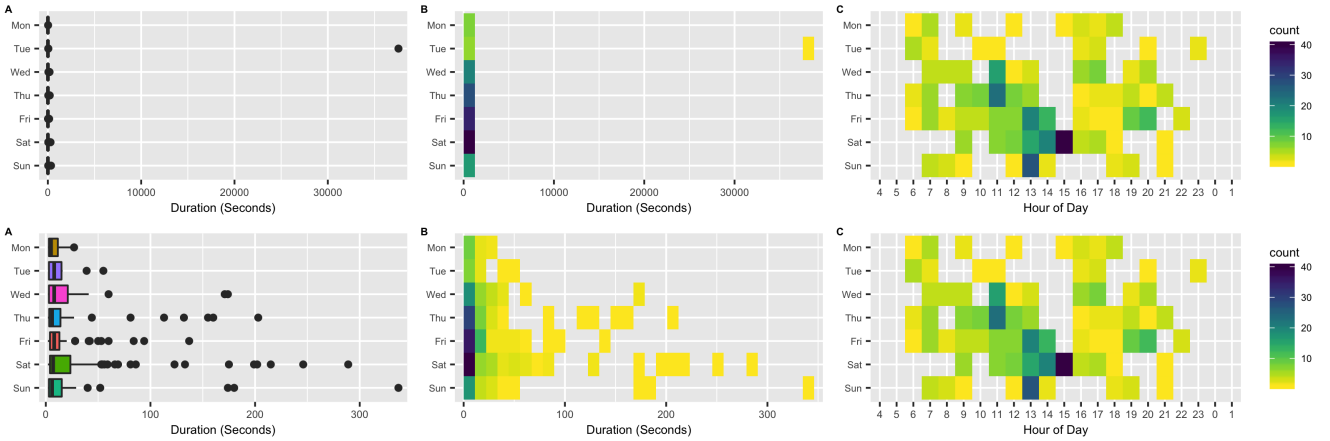


Figure 22: Initial and processed data box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Kitchen Cabinet sub activity.

3.4.5.6 Kitchen Microwave - Sub-Activity 143

The kitchen microwave has an overall count of n=61.Figure 23 boxplot (A) in row one shows one main outlier on Thursday, at nearly 22,500 seconds. The median for this sub-activity is 6.0 seconds, and this outlier is clearly outside the expected range for this sub-activity, causing the mean to be 377.41 seconds with a standard deviation of 2868.67 seconds. This outlier will be filled with the median (6.0 seconds). The resultant plots can be seen in the second row.

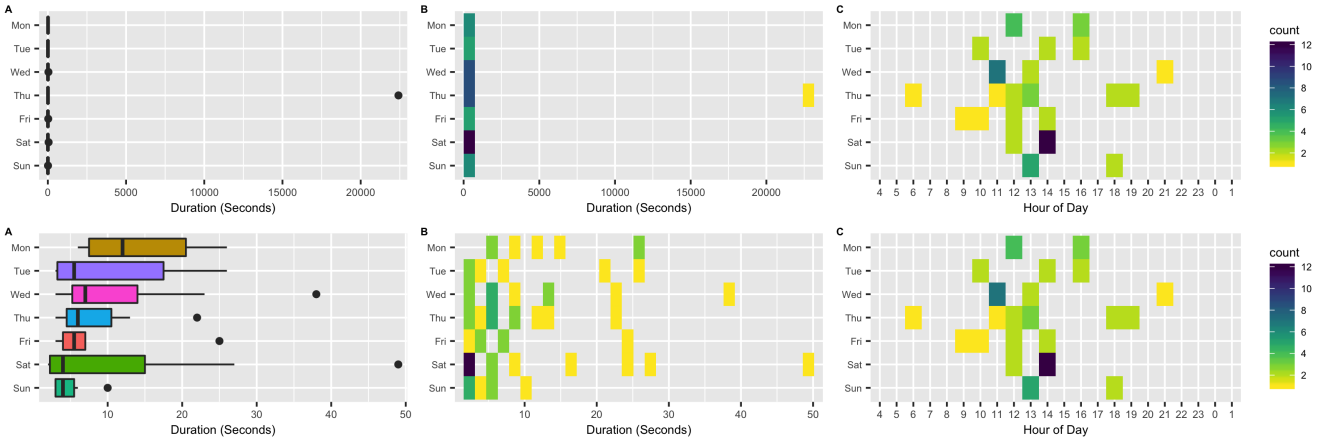


Figure 23: Initial and processed data box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Kitchen Microwave sub activity.

3.4.5.7 Kitchen Door - Sub-Activity 141

The kitchen door has an overall count of n=134. Figure 24 boxplot (A) in row one shows several key outliers, notably one on Friday at over 1,750 seconds. The median for this sub-activity is 4.0 seconds, and these outliers are clearly outside the expected range for this sub-activity, causing the mean to be 46.11 seconds with a standard deviation of 174.19 seconds. These outliers will be filled with the median (4.0 seconds). The resultant plots can be seen in the second row.

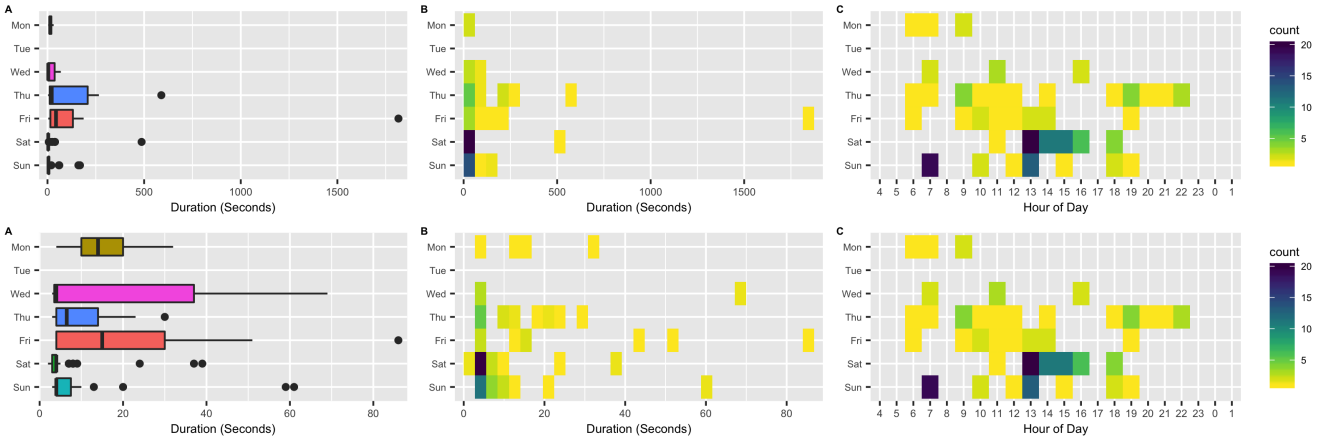


Figure 24: Initial and processed data box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Kitchen Door sub activity.

3.4.5.8 Bathroom Shower Faucet - Sub-Activity 93

The bathroom shower faucet has an overall count of n=88. Figure 25 boxplot (A) in row one shows several outliers, with six of particular concern that range from over 10,000 seconds to 40,000 seconds. The median for this sub-activity is 15.0 seconds, and these extreme outliers are clearly outside the expected range for this sub-activity, causing the mean to be 1754.35 seconds with a standard deviation of 6540.73 seconds. The outliers will be filled with the median (15.0 seconds). The resultant plots can be seen in the second row.

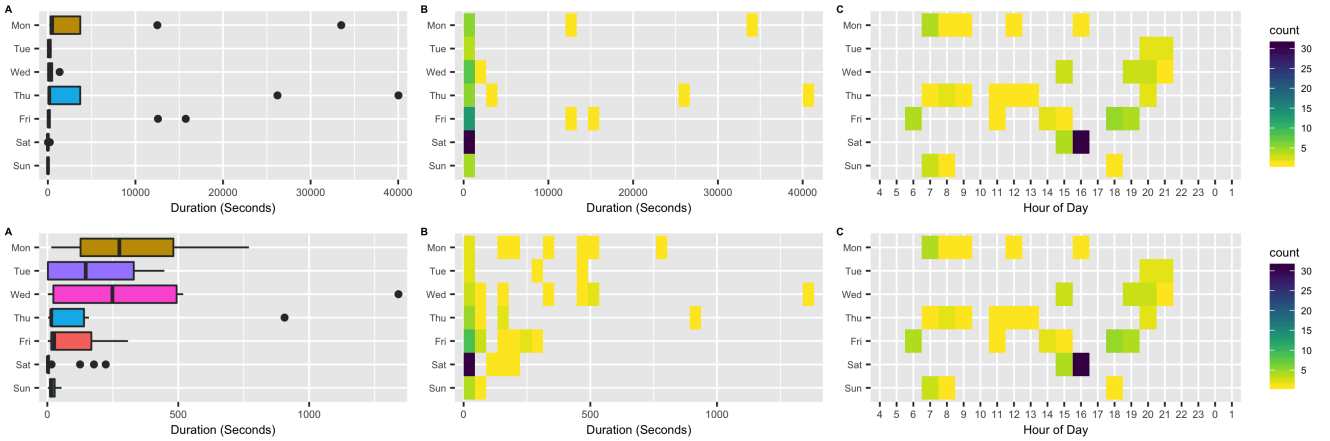


Figure 25: Initial and processed data box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Bathroom Shower Faucet sub activity.

3.4.5.9 Kitchen Drawer - Sub-Activity 125

The kitchen drawer has an overall count of n=208. Figure 26 boxplot (A) in row one shows one main outlier on Sunday, at nearly 25,000 seconds. The median for this sub-activity is 4.0 seconds, and this outlier is clearly outside the expected range for this sub-activity, causing the mean to be 145.06 seconds with a standard deviation of 1727.58 seconds. This outlier will be filled with the median (4.0 seconds). The resultant plots can be seen in the second row.

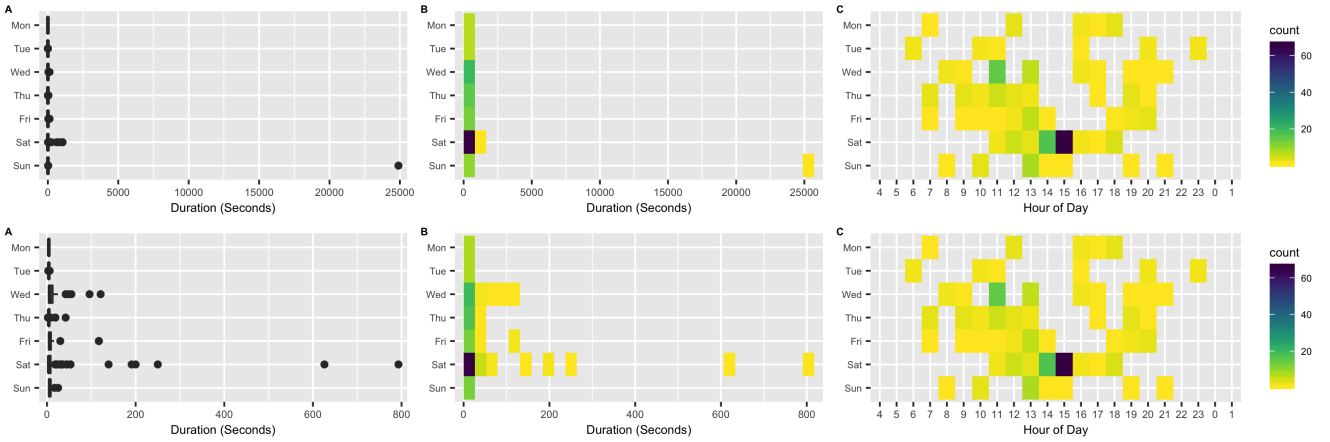


Figure 26: Initial and processed data box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Kitchen Drawer sub activity.

3.4.5.10 Kitchen Dishwasher - Sub-Activity 70

The kitchen dishwasher has an overall count of n=86. Figure 27 boxplot (A) in row one shows several outliers, particularly six in the range of 7500 seconds to nearly 25,000 seconds. The observations for Thursdays are also much higher on average than the observations for the other days. The median for this sub-activity is 63.5 seconds, and these outliers and abnormal results are clearly outside the expected range for this sub-activity, causing the mean to be 1518.41 seconds with a standard deviation of 4146.64 seconds. These outliers will be filled with the median (63.5 seconds). The resultant plots can be seen in the second row.

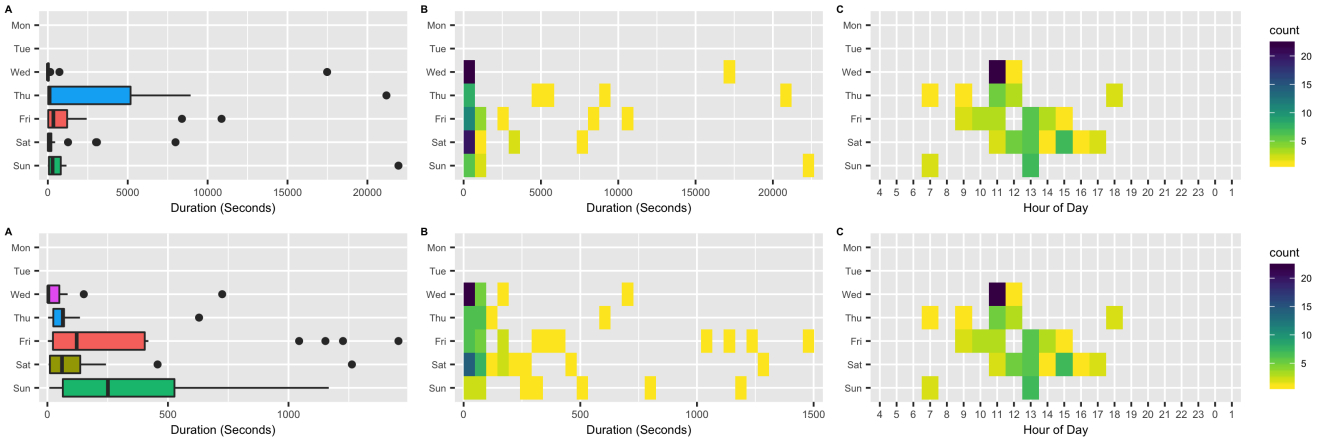


Figure 27: Initial and processed data box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Kitchen Dishwasher sub activity.

3.4.5.11 Bathroom Sink Faucet (Hot) - Sub-Activity 68

The bathroom sink faucet has an overall count of n=169. Figure 28 boxplot (A) in row one shows one main outlier on Saturday, at over 6000 seconds. The median for this sub-activity is 11.0 seconds, and this outlier is clearly outside the expected range for this sub-activity, causing the mean to be 57.91 seconds with a standard deviation of 501.27 seconds. This outlier will be filled with the median (11.0 seconds). The resultant plots can be seen in the second row.

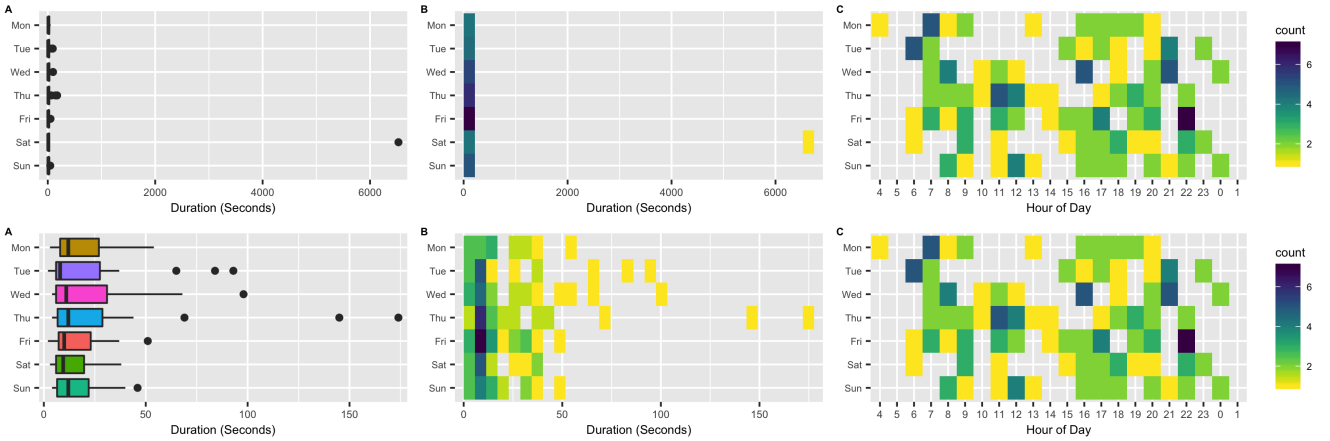


Figure 28: Initial and processed data box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Bathroom Sink Faucet sub activity.

3.4.5.12 Kitchen Freezer - Sub-Activity 137

The kitchen freezer has an overall count of n=130. Figure 29 boxplot (A) in row one shows many outliers on all days but Monday, and abnormal results on Monday compared to the other days. The median for this sub-activity is 39.0 seconds, and these outliers are clearly outside the expected range for this sub-activity, causing the mean to be 1738.11 seconds with a standard deviation of 4512.57 seconds. These outliers will be filled with the median (39.0 seconds). The resultant plots can be seen in the second row.

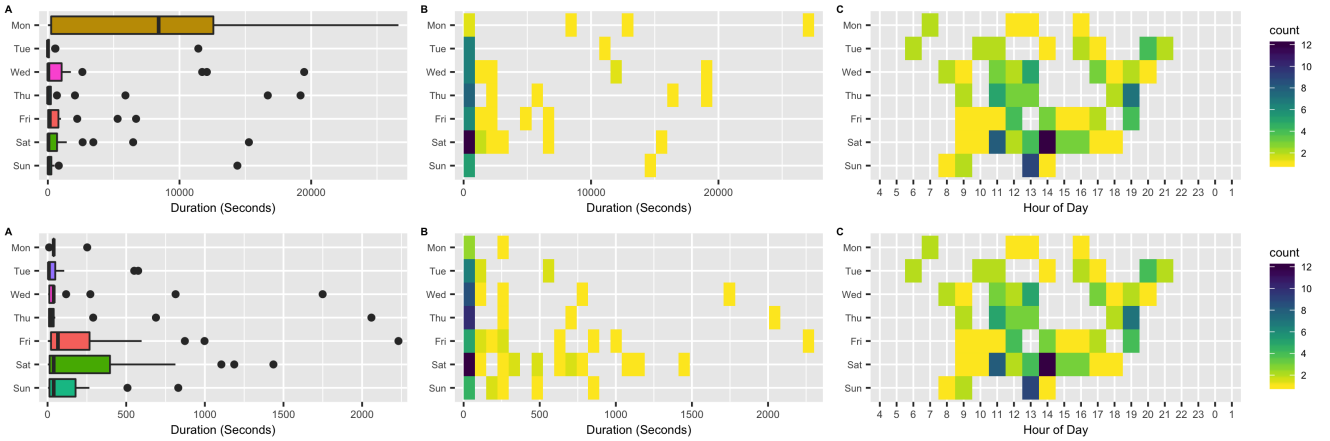


Figure 29: Initial and processed data box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Kitchen Freezer sub activity.

3.4.5.13 Kitchen Lightswitch - Sub-Activity 105

The kitchen lightswitch has an overall count of n=32. Figure 30 boxplot (A) in row one shows many abnormal results, including one observation on Sunday at nearly 55,000 seconds, and abnormally high results for Saturday when compared to the other days. The median for this sub-activity is 4454.0 seconds, and many of these results and outliers are clearly outside the expected range for this sub-activity, causing the mean to be 9318.72 seconds with a standard deviation of 13,081.34 seconds. The outliers will be filled with the median (4454.0 seconds). The resultant plots can be seen in the second row.

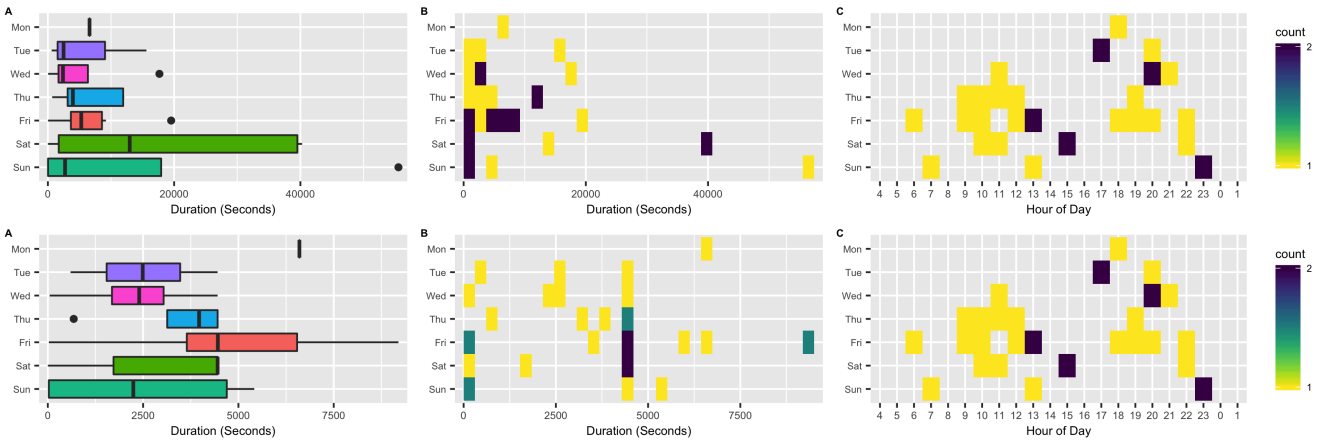


Figure 30: Initial and processed data box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Kitchen Lightswitch sub activity.

3.4.5.14 Study Lightswitch - Sub-Activity 92

The study lightswitch has an overall count of n=26. Figure 31 boxplot (A) in row one shows abnormal results for Saturday and Sunday as compared to the other days. The median for this sub-activity is 1728.5 seconds, and these abnormal results are clearly outside the expected range for this sub-activity, causing the mean to be 6430.73 seconds with a standard deviation of 11,002.30 seconds. These outliers will be filled with the median (1728.50 seconds). The resultant plots can be seen in the second row.

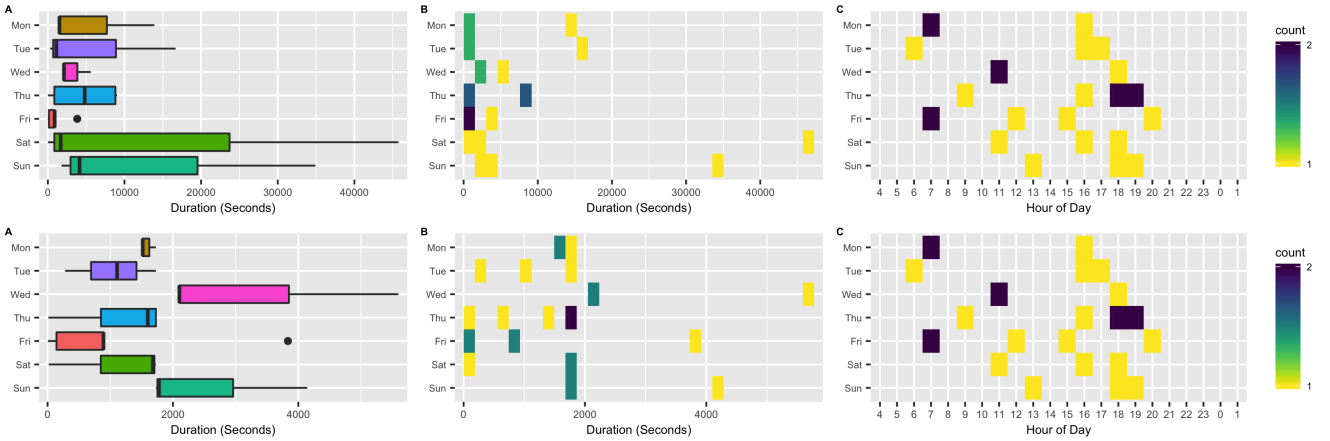


Figure 31: Initial and processed data box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Study Lightswitch sub-activity.

3.4.5.15 Bathroom Door - Sub-Activity 130

The bathroom door has an overall count of n=73. Figure 32 boxplot (A) in row one shows six extreme outliers, with two of particular concern – one on Thursday at around 10,000 seconds and one on Sunday at around 17,500 seconds. The median for this sub-activity is 17.0 seconds, and these outliers are clearly outside the expected range for this sub-activity, causing the mean to be 461.62 seconds with a standard deviation of 2310.81 seconds. These outliers will be filled with the median (17.0 seconds). The resultant plots can be seen in the second row.

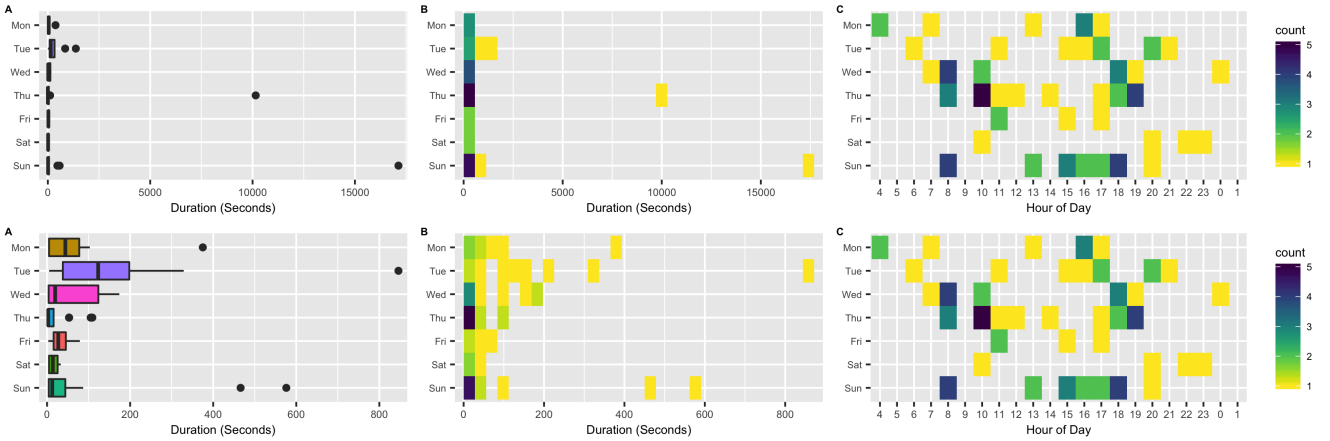


Figure 32: Initial and processed data box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Bathroom Door sub-activity.

3.4.5.16 Kitchen Toaster - Sub-Activity 131

The kitchen toaster has an overall count of n=71. Figure 33 boxplot (A) in row one shows two main extreme outliers, one on Thursday at nearly 10,000 seconds and one on Friday at nearly 30,000 seconds. There are also general abnormal results on Friday as compared to the other days. The median for this sub-activity is 5.0 seconds, and these outliers and abnormal results are clearly outside the expected range for this sub-activity, causing the mean to be 790.37 seconds with a standard deviation of 3793.67 seconds. These outliers and abnormal results will be filled with the median (5.0 seconds). The resultant plots can be seen in the second row.

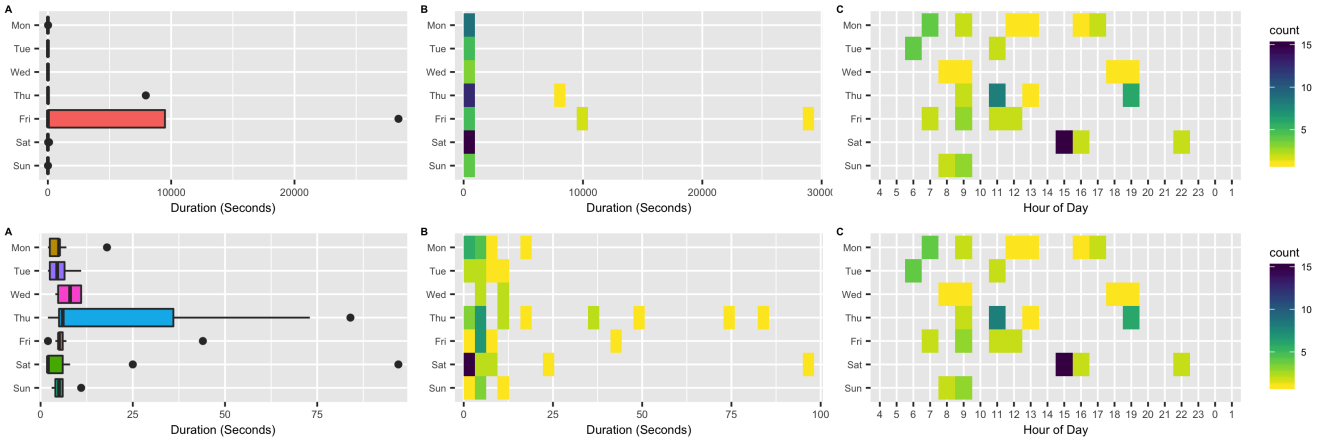


Figure 33: Initial and processed data box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Kitchen Toaster sub-activity.

3.4.5.17 Livingroom Lightswitch - Sub-Activity 107

The livingroom lightswitch has an overall count of n=8. Figure 34 boxplot (A) in row one shows variable results due to the low count, with abnormally high results for Friday as compared to the other days. The median for this sub-activity is 6352.5 seconds, with a mean of 12,545.13 seconds and a standard deviation of 15,556.66 seconds. The abnormal values will be filled with the median (6352.50 seconds). The resultant plots can be seen in the second row.

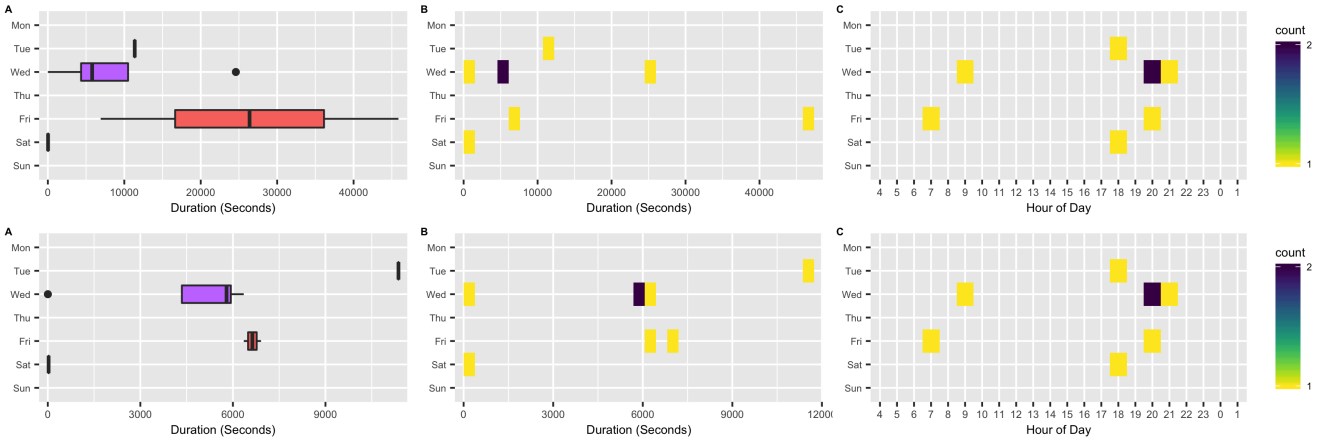


Figure 34: Initial and processed data box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Livingroom Lightswitch sub-activity.

3.4.5.18 Foyer Closet - Sub-Activity 81

The foyer closer has an overall count of n=29 in the dataset. In Figure 35 boxplot (A) in row one shows one key outlier just under 1000 seconds. When considering all values together, the mean is found to be 42.45 seconds, while the standard deviation is found to be 174.43 second. As the observation is so far from the median, it is clearly having a large impact on the mean and standard deviation, and the value of nearly 1000 seconds is unrealistic for the sub-activity in question, the outlier will be filled with the median (8.0 seconds). The resultant plots can be seen in the second row.

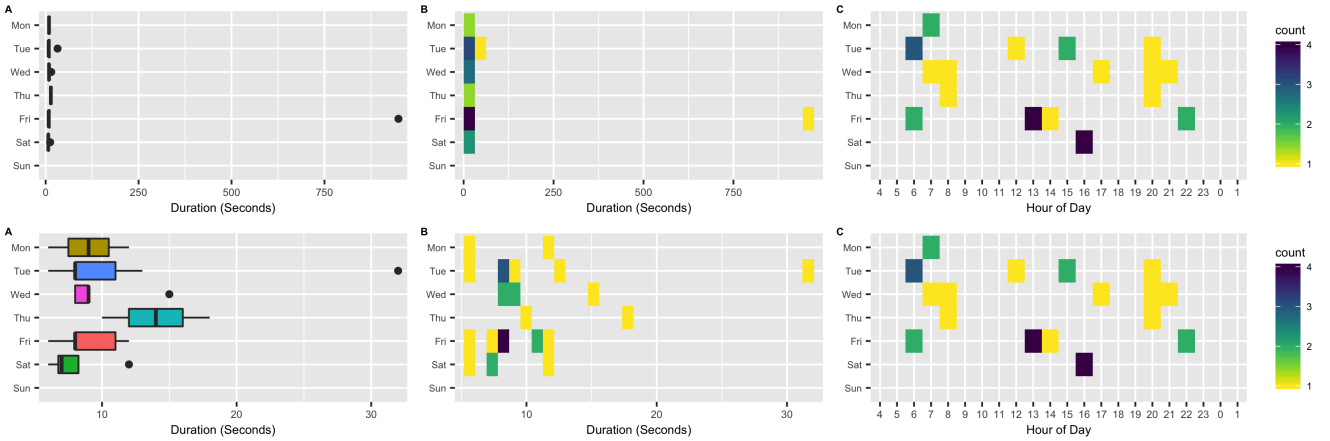


Figure 35: Initial and processed data box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Foyer Closet sub activity.

3.4.6 SubActivity Cleansing - 2) All values replaced with one value

This methodology was applied only to the bathroom toiletflush, with all values being set to 1 second.

3.4.6.1 Bathroom Toiletflush - Sub-Activity 100

Given the domain knowledge that it is unrealistic for a toilet flush to last for thousands of seconds, and the lack of variability of the length of toilet flushes, it was appropriate in this circumstance to presume sensor or measurement error, and to replace the values instead with one value – 1 second. The initial (row one) and resultant (row two) plots can be seen in Figure 36

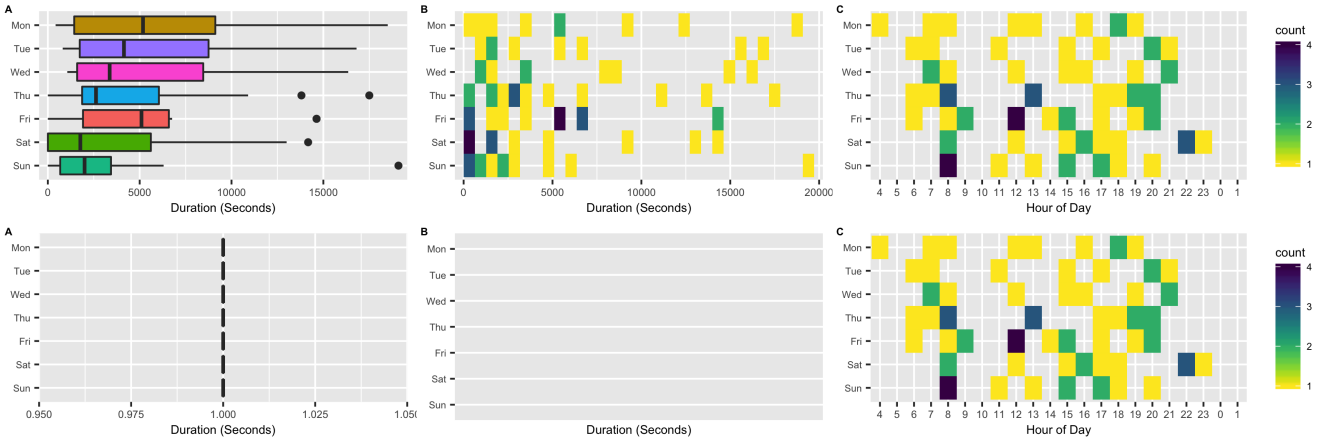


Figure 36: Initial and processed data box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the bathroom toiletflush sub-activity.

3.4.7 SubActivity Cleansing Review - 3) No futher processing required

Based on the investigation of the box plots (A in all sub activity plots), heat maps of day of week versus duration in seconds mapped by count (B in all subactivity plots) and heat maps of day of week versus hour of day mapped by count (C in all subactivity plots) the following sub activities were left in their native state; `bathroom_lightswitch` (Figure 37, below), `kitchen_refrigerator` (Figure 38, below), `bathroom_sinkfaucet-cold` (Figure 39, below), `foyer_door` (Figure 40, below), `kitchen_burner` (Figure 40, below), `foyer_lightswitch` (Figure 42, below), `bathroom_exhaustfan` (Figure 43, below),

`bedroom_lightswitch` (Figure 44, below), `kitchen_oven` (Figure 45, below), `livingroom_lamp` (Figure 46, below), `kitchen_washingmachine` (Figure 47, below), `kitchen_laundrydryer` (Figure 48, below), `kitchen_garbagedisposal` (Figure 49, below) and `kitchen_coffeemachine` (Figure 50, below).

3.4.7.1 Bathroom Lightswitch - Sub-Activity 101

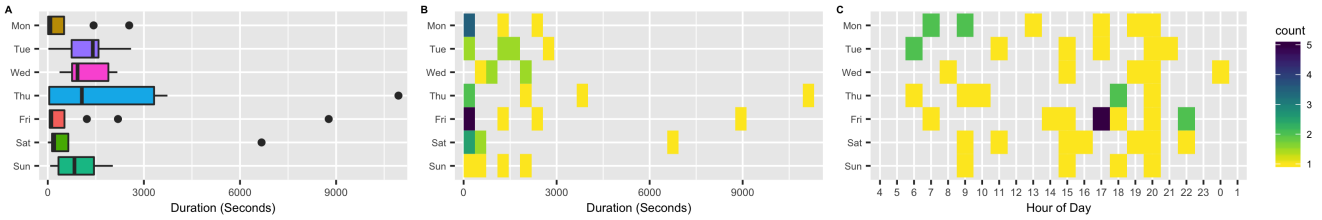


Figure 37: A caption

3.4.7.2 Kitchen Refrigerator - Sub-Activity 126

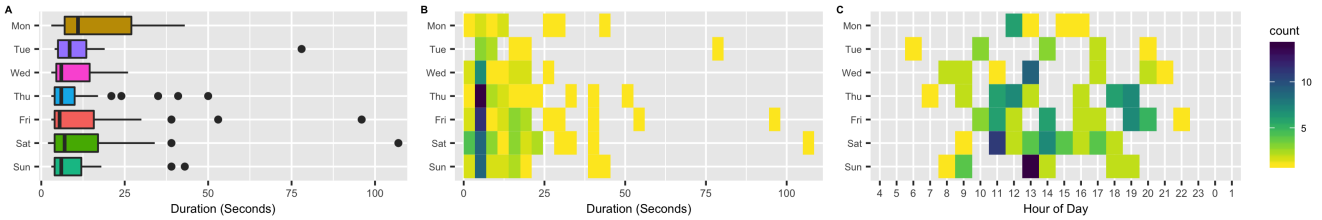


Figure 38: Box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Kitchen Refrigerator sub activity.

3.4.7.3 Bathroom Sink Faucet (Cold) - Sub-Activity 88

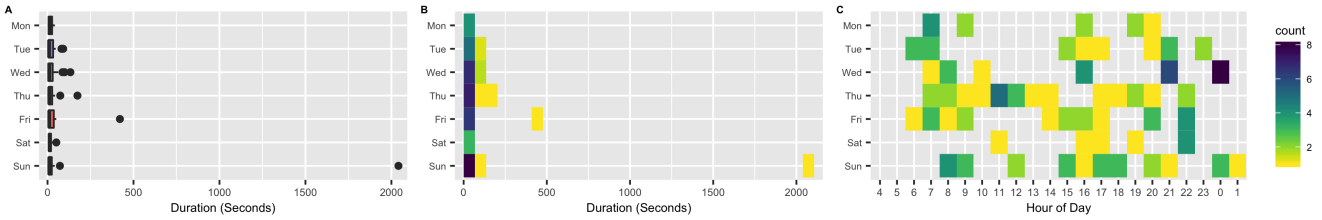


Figure 39: Box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Bathroom sick faucted - cold sub-activity.

3.4.7.4 Foyer Door - Sub-Activity 140

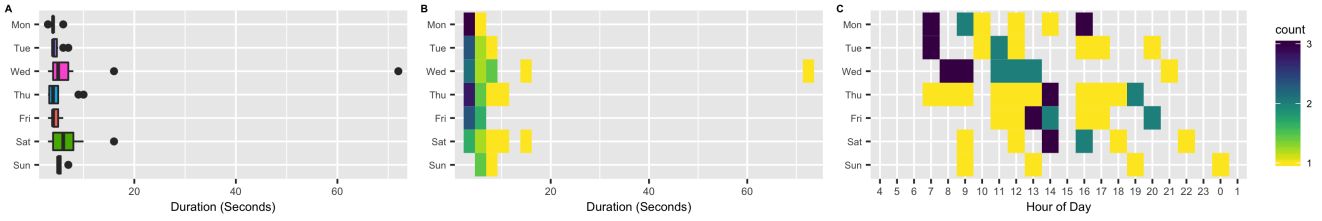


Figure 40: Box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Foyer Door sub-activity.

3.4.7.5 Kitchen Burner - Sub-Activity 140

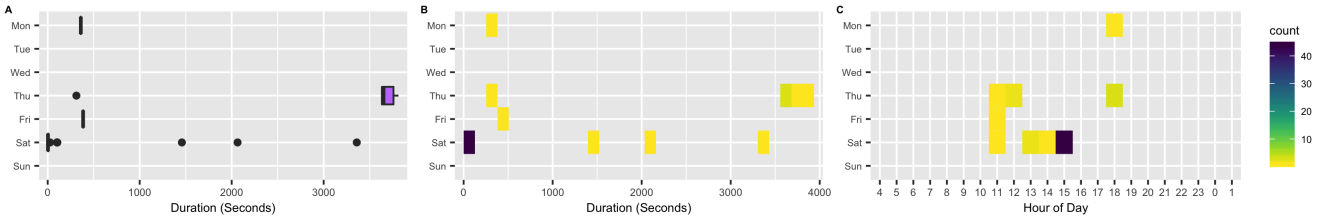


Figure 41: Box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Kitchen Burner sub-activity.

3.4.7.6 Foyer Lightswitch - Sub-Activity 104

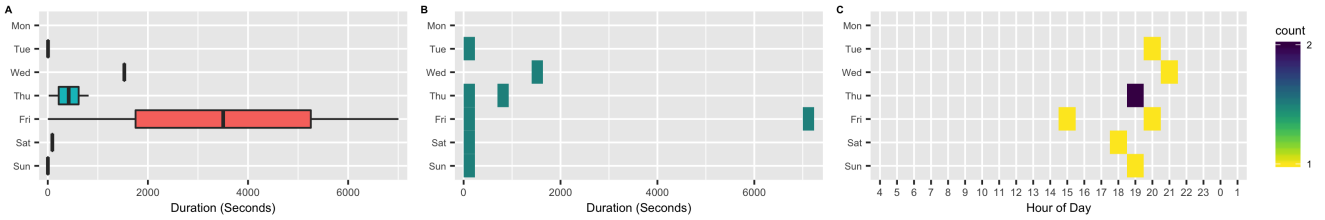


Figure 42: Box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Foyer Lightswitch sub-activity.

3.4.7.7 Bathroom Exhaust Fan - Sub-Activity 96

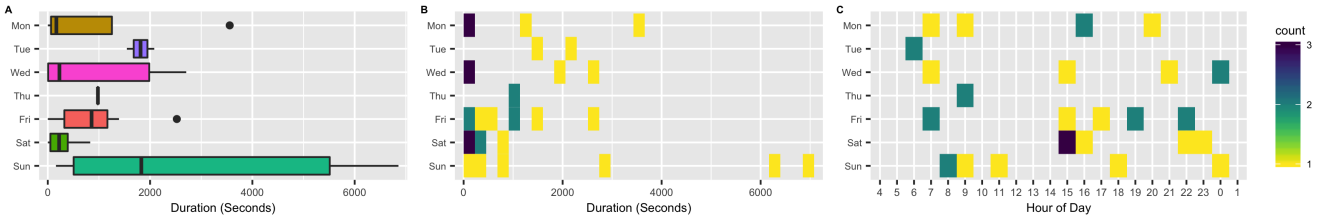


Figure 43: Box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Bathroom Exhaust Fan sub-activity.

3.4.7.8 Bedroom Lightswitch - Sub-Activity 108

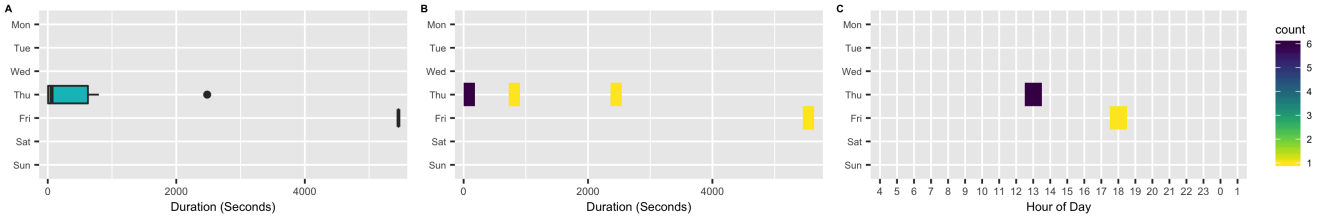


Figure 44: Box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Bedroom Lightswitch sub-activity.

3.4.7.9 Kitchen Oven - Sub-Activity 129

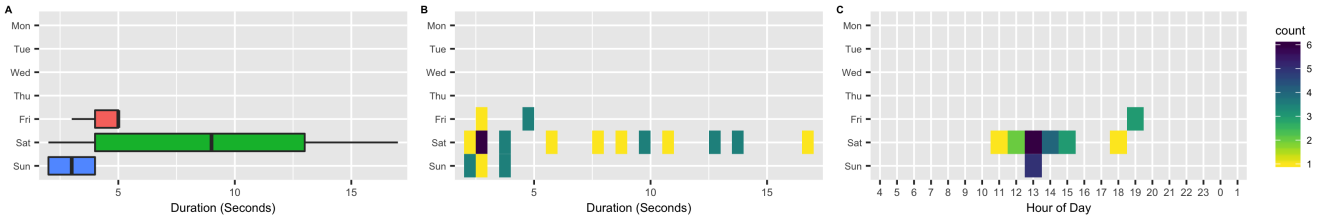


Figure 45: Box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Kitchen Oven sub-activity.

3.4.7.10 Livingroom Lamp - Sub-Activity 76

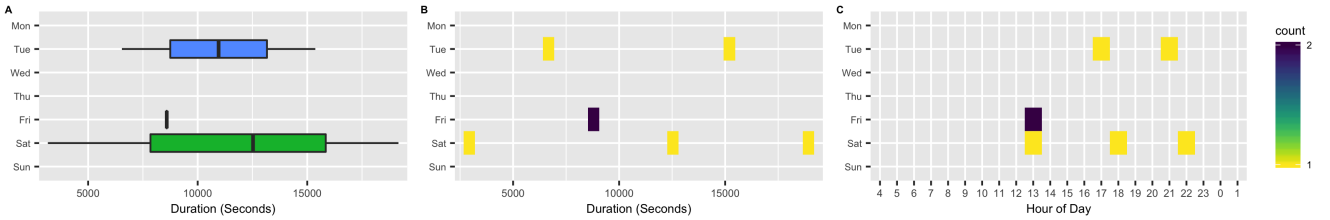


Figure 46: Box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Livingroom Lamp sub-activity.

3.4.7.11 Kitchen Washingmachine - Sub-Activity 142

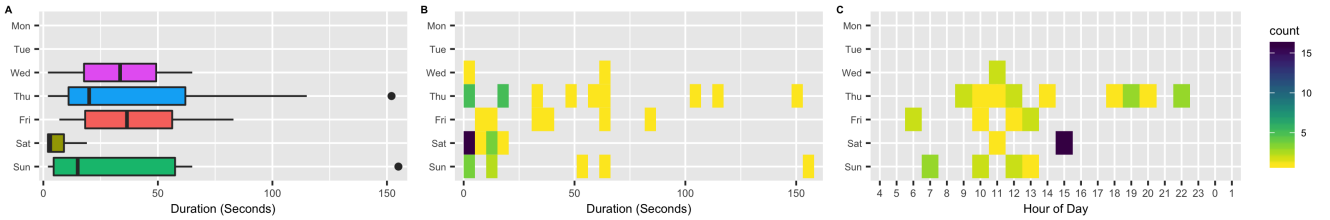


Figure 47: Box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Kitchen Washingmachine sub-activity.

3.4.7.12 Kitchen Laundry Dryer - Sub-Activity 90

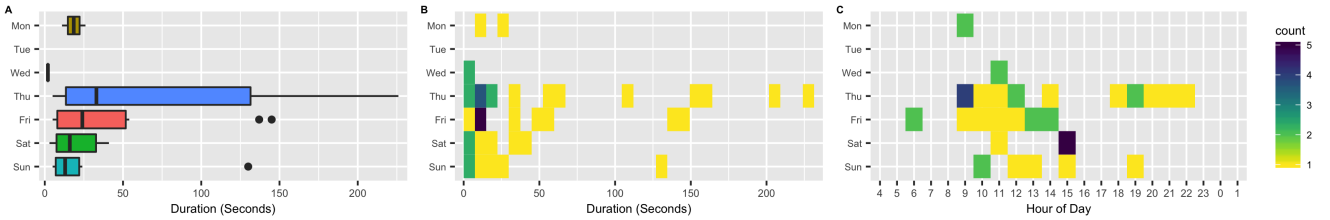


Figure 48: Box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Kitchen Laundry Dryer sub-activity.

3.4.7.13 Kitchen Garbage Disposal - Sub-Activity 98

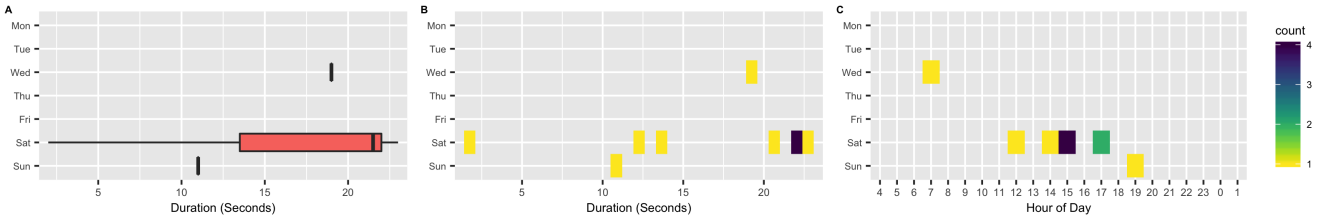


Figure 49: Box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Kitchen Garbage Disposal sub-activity.

3.4.7.14 Kitchen Coffee Machine - Sub-Activity 119

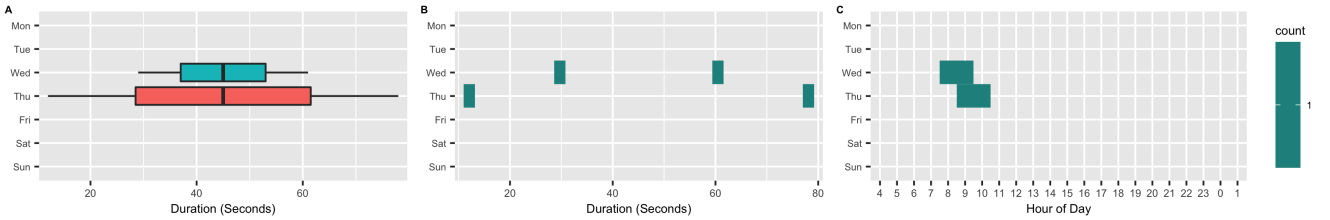


Figure 50: Box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Kitchen Coffee Machine sub-activity.

3.4.8 SubActivity Cleansing - 4) Sub-activity dropped

Based on the investigation of the box plots (A in all sub activity plots), heat maps of day of week versus duration in seconds mapped by count (B in all subactivity plots) and heat maps of day of week versus hour of day mapped by count (C in all subactivity plots) the following sub activities were dropped from the dataset. This livingroom DVD sub activity, as plotted below in Figure 51 was dropped from the dataset due to it's sparsity (only two instances in the dataset). Similarly, the bedroom lamp sub-activity, as plotted below in Figure 52 also had only two instances in the dataset and was dropped. The bedroom jewelrybox subactivity, as seen in Figure 53 was dropped due to the extremely specific nature of this subactivity. In building a generalized model, we do not wish to have such datapoints present for our analysis. Likewise with the bedroom jewelry box, the kitchen cereal subactivity, Figure 54 below, were dropped for the same reason.

3.4.8.1 Livingroom DVD - Sub-Activity 56

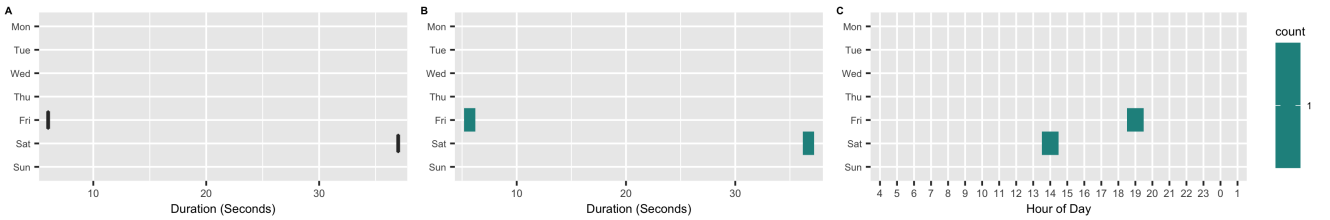


Figure 51: Box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Livingroom DVD sub activity.

3.4.8.2 Bedroom Lamp - Sub-Activity 64

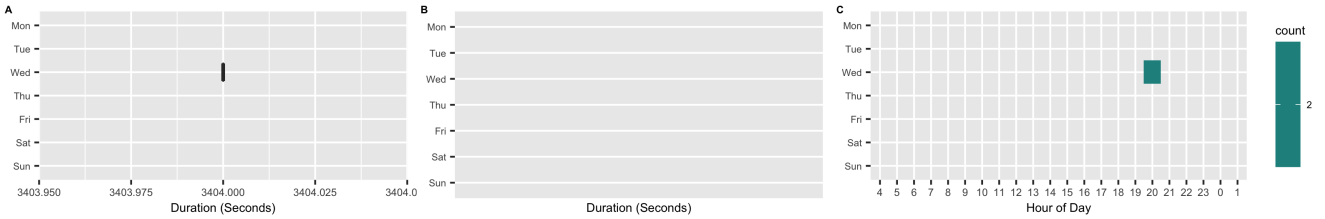


Figure 52: Box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Bedroom Lamp sub-activity.

3.4.8.3 Bedroom Jewelrybox - Sub-Activity 139

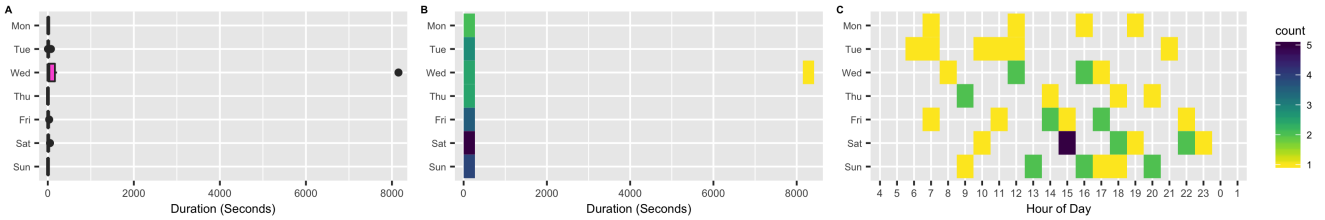


Figure 53: Box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Bedroom Jewelrybox sub activity.

3.4.8.4 Kitchen Cereal - Sub-Activity 145

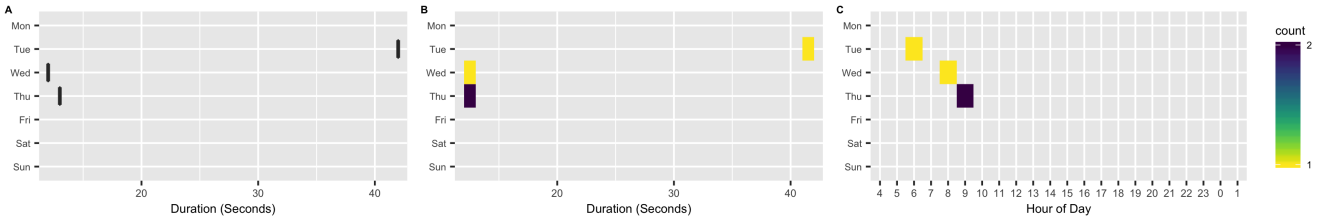


Figure 54: Box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Kitchen Cereal sub-activity.

3.4.8.5 Kitchen Containers - Sub-Activity 60

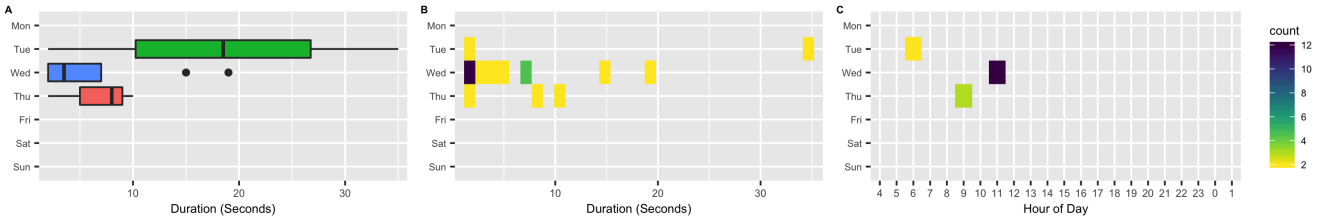


Figure 55: Box plot (A) and heat maps (B = day of week versus duration in seconds mapped by count, C = day of week versus hour of day mapped by count) for the Kitchen Containers sub-activity.

3.4.9 The Final pre-processed dataset

The final pre-processed dataset had the following attributes; `subActNum` (the aub-activity number from the original `S1 Activities` dataset), `subAct` (the aub-activity descriptor from the original `S1 Activities` dataset), `start` (the start datetime for this specific instance of the sub-activity), `end` (the end datetime for this specific instance of the aub-activity), `dayNumeric` (a categorical variable to indiate day), `DAY`

(e.g., 'Fri', 'Sat'), `WDWE` (WD signifies 'weekday' and WE signifies 'weekend'), `HOUR` (a categorical value to indicate time of the day, by the hour).

3.5 Data Analysis and Manipulation

The primary focus of this section will be qualitative and quantitative analysis of the pre-processed data. This includes casting the data into a structure for sequential analysis via Sankey diagrams, and into a Boolean Array structure for subsequent machine learning.

3.5.1 Sequential Analysis Algorithm

An algorithm was created to capture the amount of time between the start of one event (`Event A`) and the start of another event (`Event B`). In is worth noting that as the target dataset (Table **??**) is row-wise event data on a continuous scale, without correct bounds, this algorithm would consider the start of every `Event B` after each `Event A`, subsequently creating an extremely noisy and large dataset via a combinatorial explosion. In this scenario, we would have meaningless associations with delta values in the order of hundreds of thousands of seconds.

The algorithm `id_delta` was created to perform sequential analysis without combinatorial explosion and to capture the amount of time between the start of `Event A` and the start of event `Event B`, as the value `Delta` in seconds. The algorithm does this by taking three arguments. The first argument, `events`, is the dataset with each event occuring as a row instance. The second argument, `n`, is the total number of subsequent `Event B` for any one `Event A`. The final argument, `delta_threshold` takes interger quantities representative of the number of seconds into the future to consider.

By way of an example `id_delta(ds, 10, dt.timedelta(0,-60))` for each event row instance in `ds`, `10` neighbouring subevents will be captured, as long as they occur within a range of `0` till `60` seconds forward. In this scenario, if only four `Event B` occur within sixty seconds of `EventA` then only these four will be captured. Likewise, if thirteen `EventB` occur within sixty seconds of `EventA`, then only ten will be captured.

```
def id_delta(events, n=1, delta_threshold=dt.timedelta(-99)): # D
    nns = [] # Create an empty array
    for row in events.itertuples():
        start_time = getattr(row, 'start') # Extract `start` from data set
        end_time = getattr(row, 'end') # Extract `end` from data set
        subActNum = getattr(row, 'subActNum') # Extract `subActNum` from data set
        row_index = getattr(row, 'Index') # Extract `index` from data set

        nn = events[(events.start >= start_time) & #
                    (events.index != row_index) & #
                    ((start_time - events.start) > delta_threshold)][:n]
        ordered = pd.DataFrame()
        ordered['Dummy'] = nn['subActNum'] # Created for indexing purposes
        ordered['EventA'] = subActNum
        ordered['EventB'] = nn['subActNum']
        ordered['EvA_Start'] = start_time
        ordered['EvB_Start'] = nn['start']
        ordered['EvA_End'] = end_time
        ordered['EvB_End'] = nn['end']
```

```
        del ordered['Dummy'] # Dropped
        nns.append(ordered)

    result = pd.concat(nns)
    result['Delta'] = np.where(result['EvA_Start'] == result['EvB_Start'], 0,
                               (result['EvB_Start'] - result['EvA_Start']))
    result['Delta'] = result['Delta'].dt.total_seconds()
    return result
```

A shotgun analysis of the combinatorics associated with varying input arguments resulted in the following observations; * One neighbour for 10 seconds gave a dataset of 1063 instances (`id_delta(ds, 1, dt.timedelta(0,-10))`) * One neighbour for 60 seconds gave a dataset of 1989 instances (`id_delta(ds, 1, dt.timedelta(0,-60))`) * Ten neighbours for 10 seconds gave a dataset of 1536 instances (`id_delta(ds, 10, dt.timedelta(0,-10))`) * Ten neighbours for 60 seconds gave a dataset of 5385 instances (`id_delta(ds, 10, dt.timedelta(0,-60))`)

We are focussing our analysis on the sequential analysis algorithm run with the parameters of one neighbouring sub-activity over a sixty second period (`id_delta(ds, 1, dt.timedelta(0,-60))`), the head of the resultant dataset (`ds_1n_60s.csv`) can be Table 14, below. The reasoning behind chosing this dataset being 1) It is best practise to start with the most 'simple' form of a problem in order to develop understanding, in this case being that one neighbour only is considered for each row and 2) For further analysis these data may be collapsed from a seconds time scale to a minute time scale, so it is useful to know the variety of activities that can occur within one minute (60 seconds of each other).

Table 14: Sequential analysis result: one neighbouring sub-activity over a sixty second period

EventA	EventB	EvA_Start	EvB_Start	EvA_End	EvB_End	Delta	DAY	WDWE	Hour
67	100	2003-03-27 06:43:40	2003-03-27 06:44:06	2003-03-27 06:43:44	2003-03-27 06:44:07	26	Thu	WD	6
100	101	2003-03-27 06:44:06	2003-03-27 06:44:20	2003-03-27 06:44:07	2003-03-27 07:46:35	14	Thu	WD	6
101	57	2003-03-27 06:44:20	2003-03-27 06:44:35	2003-03-27 07:46:35	2003-03-27 06:44:49	15	Thu	WD	6
57	57	2003-03-27 06:44:35	2003-03-27 06:44:36	2003-03-27 06:44:49	2003-03-27 06:44:49	1	Thu	WD	6
57	67	2003-03-27 06:44:36	2003-03-27 06:44:49	2003-03-27 06:44:49	2003-03-27 06:44:57	13	Thu	WD	6
67	82	2003-03-27 06:44:49	2003-03-27 06:45:45	2003-03-27 06:44:57	2003-03-27 06:45:49	56	Thu	WD	6

3.5.2 Qualitative Sequential Analysis via Sankey Diagram

In order to develop understanding of the interrelaterness of the sub-activites, the data from the sequential analysis `ds_1n_60s.csv` were plotted as Sankey diagrams using a bespoke wrapper method written in Python. Using the previously mentioned features of `HOUR` and `WDWE` in the dataset, the resultant diagrams were segmented over 6 time periods, namely:

1. Figure 56 - Weekday Morning, initial morning sub-activity until 11.59 am
2. Figure 57 - Weekday Afternoon, 12 noon until 17.59 pm
3. Figure 58 - Weekday Evening, 18:00 pm until mid-night
4. Figure 59 - Weekend Morning, initial morning sub-activity until 11.59 am
5. Figure 60 - Weekend Afternoon, 12 noon until 17.59pm
6. Figure 61 - Weekend Evening, 18:00pm untill mid-night

Sankey diagrams are used to visualise flows of energy, materials or other resources in a variety of applications (Lupton, 2017).In our case, the Sankey diagrams will allow us to visualise the flow of end-user interaction with each sub-activity over the time-boxes 1 through 6, as described above. Our Sankey

diagrams (derived from the 1 neighbour over 60 seconds sequential analysis) have the following features i) The each represent a specific aggregated time period from the dataset, ii) In each Sankey, the sub-acitivity nodes that require energy input only from the end user (e.g., Kitchen Door) are blue, while the sub-activity nodes that require external energy to function (e.g., Kitchen Toaster), iii) The width of each sub-activity in the Sankey diagram is indicative to the number of times interaction occured, a thicker node means more interaction, iv) The lines between each node indicate the event of one sub-activity proceeding or preceeding another and v) Some events nodes are centralised, with at least one activity 'flowing in' and at least one 'flowing out' while other nodes a terminal, with only activities 'flowing in' or 'flowing out' (but not both).

Each Sankey diagram, as seen below, shows a high level of interactivity between the various sub-acitivities. We observer that of all the 'no external energy' sub-activities, only the foyer closet (as seen in Figure 57 and Figure 58) acts as a terminal node. In comparision, numerous sub-activities that require energy (as seen in Figure 58 and Figure 61) act as terminal nodes. We also observe that there is a very level of interactivity between the sub-activities that do and do no require an external energy source (red and blue nodes, respectively) to function. This will provide direction for further analyis.

3.5.2.1 Weekday Morning, initial morning sub-activity until 11.59 am

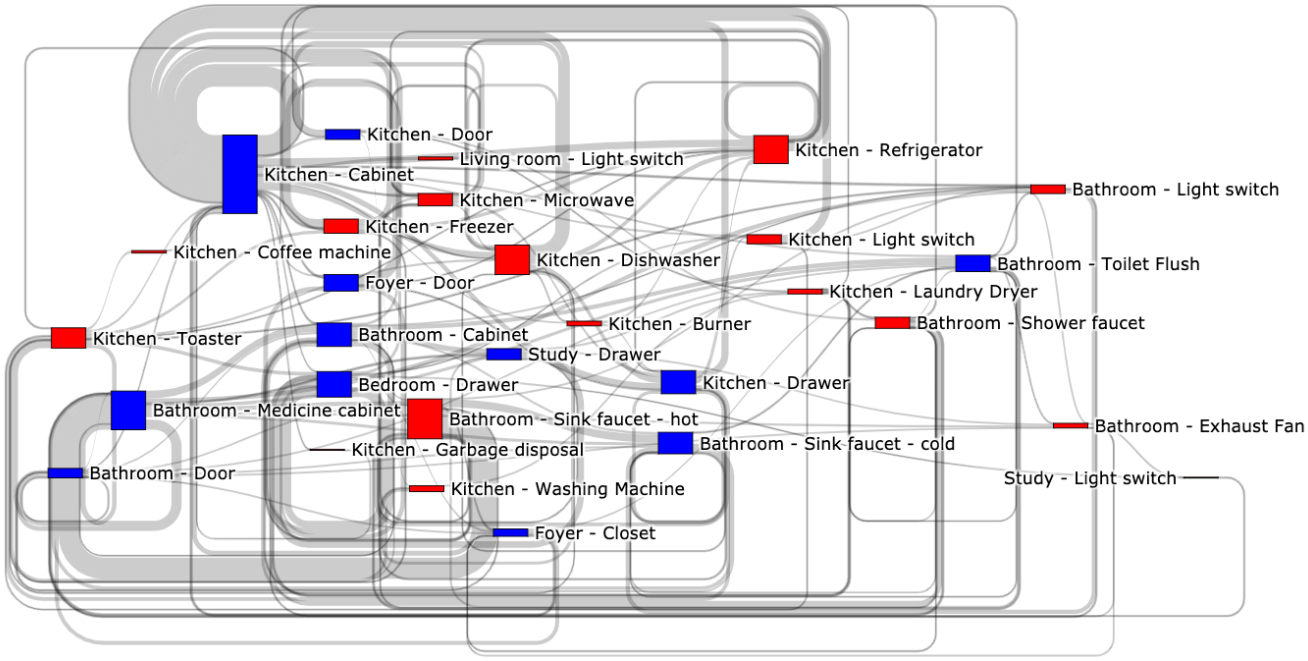


Figure 56: Sankey Diagram of Weekday Mornings, considering all one neighbour per instance within a 60 second period

3.5.2.2 Weekday Afternoon, 12 noon until 17.59 pm

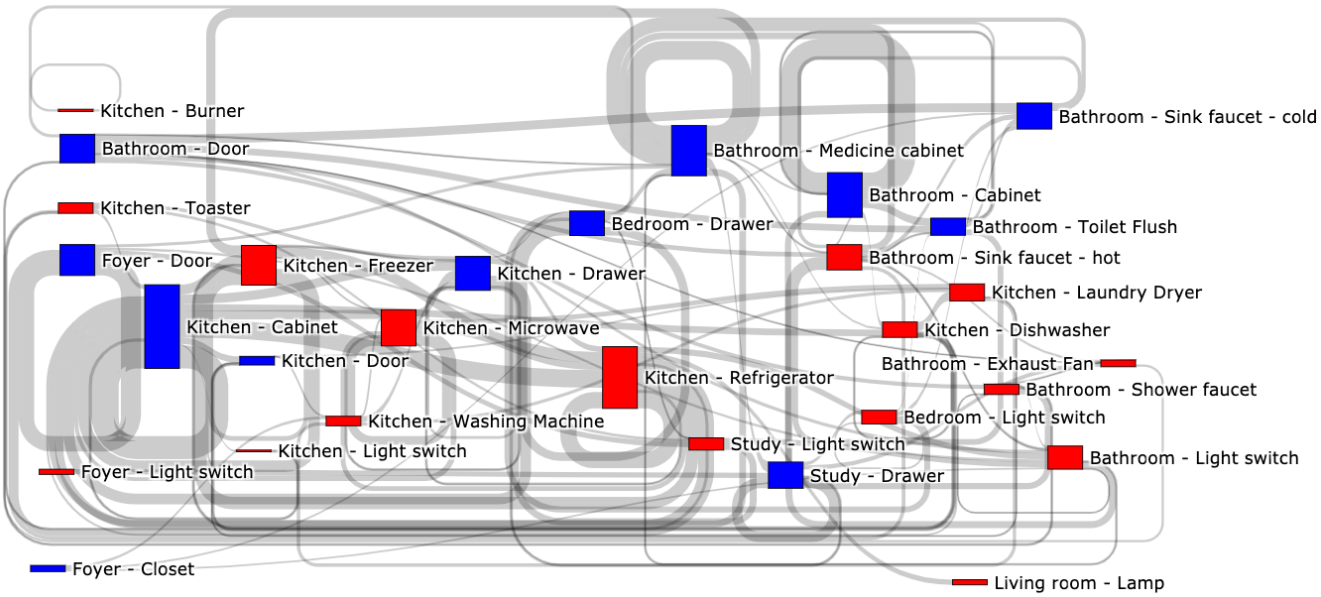


Figure 57: Sankey Diagram of Weekday Afternoons, considering all one neighbour per instance within a 60 second period

3.5.2.3 Weekday Evening, 18:00 pm until mid-night

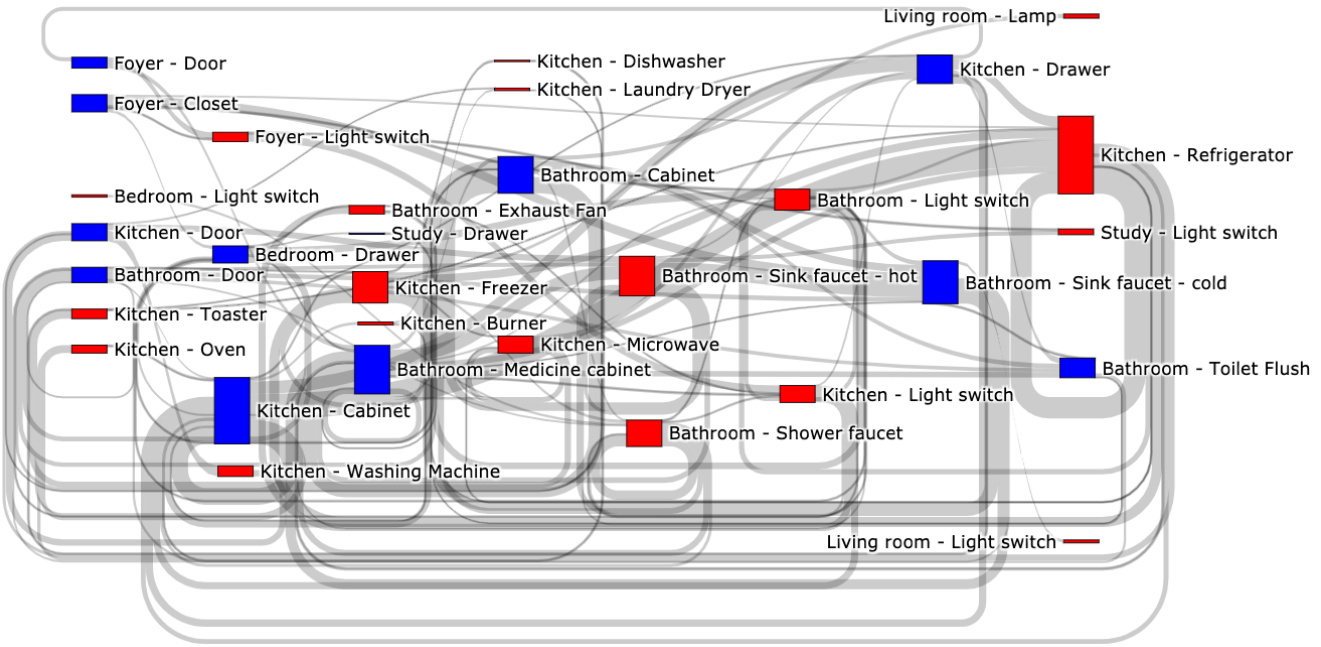


Figure 58: Sankey Diagram of Weekday Evenings, considering all one neighbour per instance within a 60 second period

3.5.2.4 Weekend Morning, initial morning sub-activity until 11.59 am

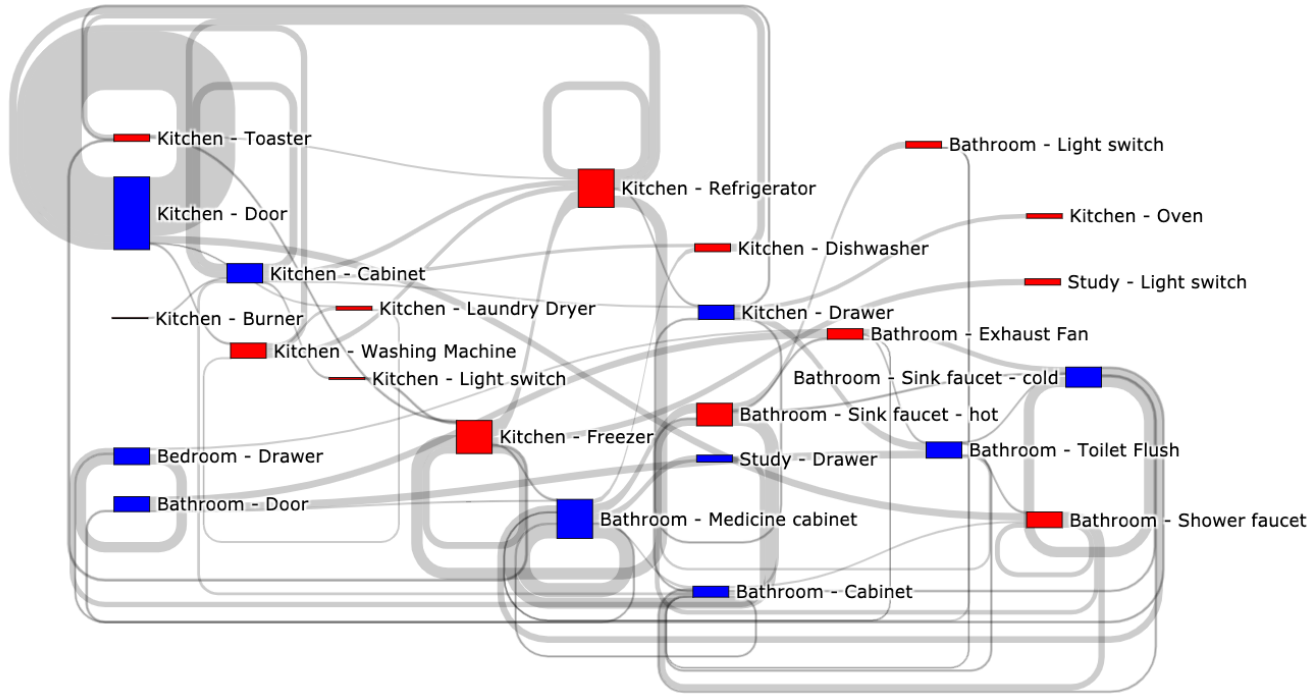


Figure 59: Sankey Diagram of Weekend Mornings, considering all one neighbour per instance within a 60 second period

3.5.2.5 Weekend Afternoon, 12 noon until 17.59pm

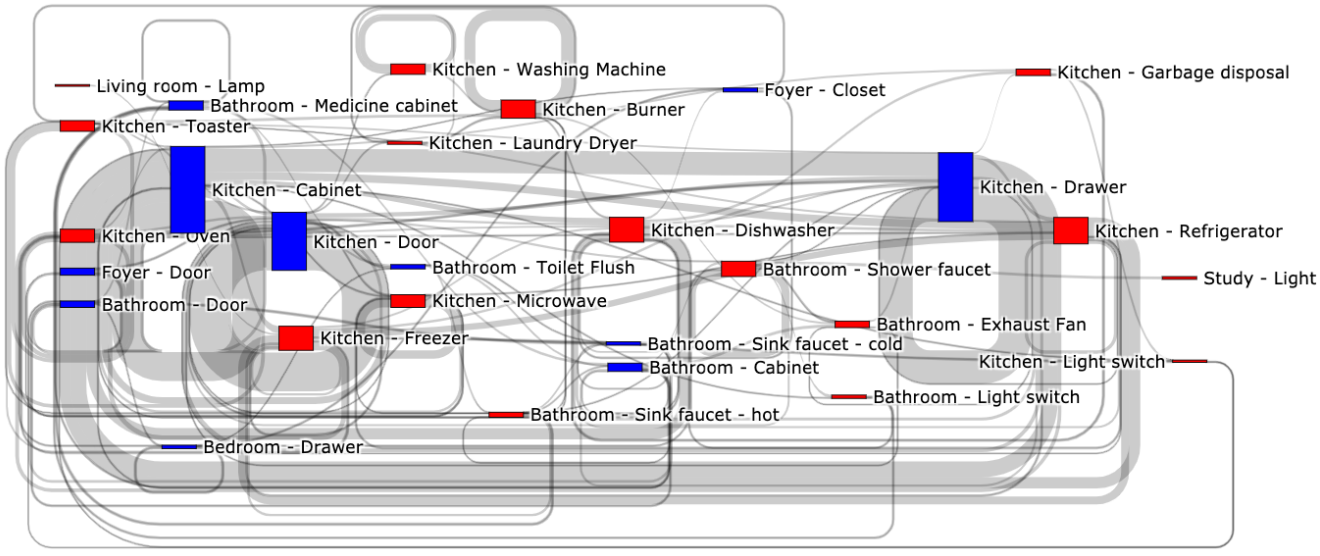


Figure 60: Sankey Diagram of Weekend Afternoons, considering all one neighbour per instance within a 60 second period

3.5.2.6 Weekend Evening, 18:00pm untill mid-night

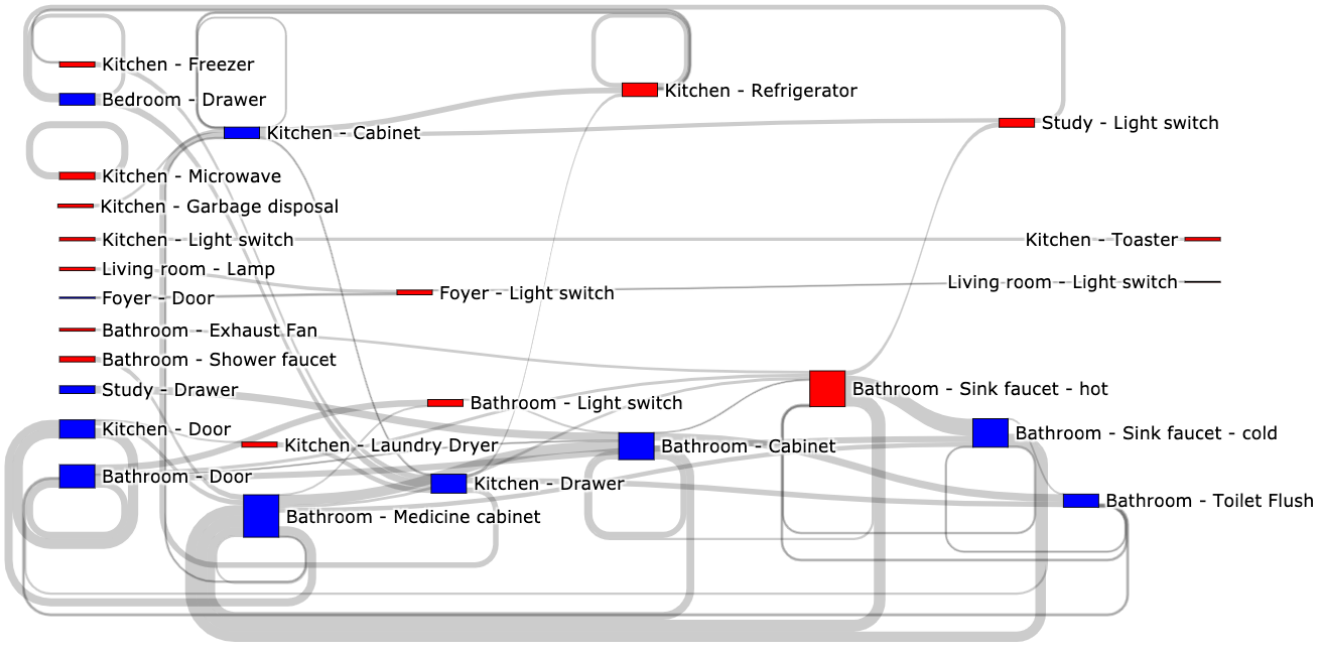


Figure 61: Sankey Diagram of Weekend Evenings, considering all one neighbour per instance within a 60 second period

3.5.3 Re-casting the Dataset as a Boolean Array

Based on the analysis above, we sought a data structure whereby every simultaneous subactivity occuring at one point in time could potentially be evaluated. In order to acheive this without having to place a large emphasis on complex combinatorics, it was decided to cast the data structure into a Boolean Array. In this structure, each sub-activity will become an attribute, with every row is a timestamp index. This structure will span the duration of the dataset - in other words, every second that was accounted for in the original dataset will have a row instance (a row).

The required transformations were for performed on the pre-processed dataset, with an initial index occuring at 27/03/2003 6:43:40 am, and the final index occuring at 11/4/2003 10:24:18 pm. In some regions of the dataset there were no results, so it is not an uninterrupted timescale from the first to last index. This will not affect our analysis as we are considering sequences of events as they occur with respect to concurrency.

A sample of the processed boolean array data (with omitted attributes) can be seen below in Table 15. Here we can see the following sub-activities in an 'active' state; 57 (bathroom medicine cabinet), 101 (bathroom lightswitch) and 96 (bathroom exhaustfan). All other sub-activities are inactive. At 01/04/2003 6:54:56 am sub-activity 88 (bathroom sinkfaucet - hot) becomes active, followed by one second later at 01/04/2003 6:54:57 am sub-activity 68 (bathroom sinkfaucet - cold) becoming active. Sub-activity 57, 101, 68, 88 and 96 all remain active at 01/04/2003 6:55:01 am.

This data structure thus offers the following benefits; i) Simultaneous consideration of the state of multiple sub-activities,ii) Present in a format that is still readily human interprettable and iii) Present in a format that can be easily consumed by a machine.

And the following challenges; i) The dataset is overall very large, potentially requiring large amounts of computational power for downstream analysis, ii) The dataset is potentially highly homogeneous in certain temporal regions and iii) A second-by-second analysis is most likely to granular for the purposes of this work

Table 15: Add text

IDX	57	67	100	101	104	68	93	88	90	96	130
01/04/2003 6:54:50 am	1	0	0	1	0	0	0	0	0	1	0
01/04/2003 6:54:51 am	1	0	0	1	0	0	0	0	0	1	0
01/04/2003 6:54:52 am	1	0	0	1	0	0	0	0	0	1	0
01/04/2003 6:54:53 am	1	0	0	1	0	0	0	0	0	1	0
01/04/2003 6:54:54 am	1	0	0	1	0	0	0	0	0	1	0
01/04/2003 6:54:55 am	1	0	0	1	0	0	0	0	0	1	0
01/04/2003 6:54:56 am	1	0	0	1	0	0	0	1	0	1	0
01/04/2003 6:54:57 am	1	0	0	1	0	1	0	1	0	1	0
01/04/2003 6:54:58 am	1	0	0	1	0	1	0	1	0	1	0
01/04/2003 6:54:59 am	1	0	0	1	0	1	0	1	0	1	0
01/04/2003 6:55:00 am	1	0	0	1	0	1	0	1	0	1	0
01/04/2003 6:55:01 am	1	0	0	1	0	1	0	1	0	1	0

In order to remedy this, we converted the Boolean Array structure into the minute-scale, by aggregating all the second values for each attribute for each minute. For example, if a sub-activity had occured for 30 seconds during one minute, it will not be represented as a '1' for that minute in the dataframe.

Table 16: Add text

IDX	57	67	100	101	104	68	93	88	90	96	130
01/04/2003 6:45:00 am	1	0	0	1	0	0	0	0	0	1	0
01/04/2003 6:46:00 am	1	0	0	1	0	0	0	0	0	1	0
01/04/2003 6:47:00 am	1	0	0	1	0	0	0	0	0	1	0
01/04/2003 6:48:00 am	1	0	0	1	0	0	0	0	0	1	0
01/04/2003 6:49:00 am	1	0	0	1	0	0	0	0	0	1	0
01/04/2003 6:51:00 am	1	0	0	1	0	0	0	0	0	1	0
01/04/2003 6:52:00 am	1	0	0	1	0	0	0	0	0	1	0
01/04/2003 6:53:00 am	1	0	0	1	0	0	0	0	0	1	0
01/04/2003 6:54:00 am	1	0	0	1	0	1	0	0	0	1	0
01/04/2003 6:55:00 am	1	0	0	1	0	1	0	1	0	1	0
01/04/2003 6:56:00 am	1	0	0	1	0	1	0	1	0	1	0
01/04/2003 6:57:00 am	1	0	0	1	0	0	0	0	0	1	0

4 Machine Learning Analysis

Using the pre-processed boolean array data (minute-scale) we will now attempt to create a predictive model with the aim of identifying patterns of co-occurrence between the sub-activities. As we are attempting to predict the on or off state of activities, this is a binary classification problem. As discussed during the Sankey analysis, the sub-activities can be broadly categorised as requiring energy input only from the end user (e.g., Kitchen Door) or requiring external energy to function (e.g., Kitchen Toaster). Note that for the purposes of further discussion such appliances will be referred to as energy-intensive (e.g., light switch, fridge and so on). Our model we will only attempt to predict the state of energy-intensive appliances, for reasons outlined in the discussion section.

4.1 The Machine Learning Algorithm

A wrapper method will be created centered around the the sklearn Decision Tree Classifier. This method will use a decision tree model and optimize its hyperparameters using a grid search. The grid search will be performed over split criterion ('gini' and 'entropy') and maximum depth. Feature selection will be performed using the entropy-based method of mutual information, for the top five features. Cross-validation will be performed using 5-folds. The wrapper method will enable the model to perform the

functions described above in an iterative fashion for each of the energy-intensive sub-activity features in the dataset. The processed sub-activities meta data will also be parsed to provide the data on which sub-activity is energy intensive and which is not. Throughout the iterations, key data will be parsed to *.csv format for later analysis.

4.1.1 Data

The dataset used will be the boolean array on the minute scale. In preparation for the analysis, the datetime index is removed, as will be discussed below. Important to note that these data currently contain no categorical features (e.g, day of week, weekend / weekday, hour of day, room of house, e.t.c,).

4.1.2 The Wrapper Method

The following python script was used to perform the desired machine learning analysis.

```
for subAct in poweredSubActs:
    row = {"Target":subAct}
    Data = ds.drop(columns = subAct).values
    target = ds[subAct]
    D_train, D_test, t_train, t_test = train_test_split(Data, target, test_size = 0.3,
                                        random_state=999)
    cv_method = RepeatedStratifiedKFold(n_splits = 5, n_repeats = 3, random_state = 999)
    dt_classifier = DecisionTreeClassifier(random_state=999)
    params_DT = {'criterion': ['gini', 'entropy'],
                'max_depth': [2, 3, 4, 5, 6, 7, 8, 9, 10]}
    gs = GridSearchCV(estimator=dt_classifier, param_grid=params_DT, cv=cv_method,
                      verbose=1, scoring='accuracy')
    gs.fit(Data, target)
    row['Original_Fit'] = gs.best_score_
    num_features = 5

    fs_fit_mutual_info = fs.SelectKBest(fs.mutual_info_classif, k=num_features)
    fs_fit_mutual_info.fit_transform(Data, target)
    fs_indices_mutual_info = np.argsort(fs_fit_mutual_info.scores_)[::-1][0:num_features]
    best_features_mutual_info = ds.columns[fs_indices_mutual_info].values
    feature_importances_mutual_info = fs_fit_mutual_info.scores_[fs_indices_mutual_info]
    results_DT = pd.DataFrame(gs.cv_results_['params'])
    results_DT['test_score'] = gs.cv_results_['mean_test_score']
    results_DT.to_csv(subAct + "_dt.csv", index=False)

    t_pred = gs.predict(D_test)
    t_prob = gs.predict_proba(D_test)
    metrics.roc_auc_score(t_test, t_pred)
    fpr, tpr, _ = metrics.roc_curve(t_test, t_prob[:, 1])
    roc_auc = metrics.auc(fpr, tpr)
    df = pd.DataFrame({'fpr': fpr, 'tpr': tpr})
    df.to_csv(subAct + "_roc.csv", index = False)

    report = metrics.classification_report(t_test, t_pred, output_dict=True)
```

```
rep = pd.DataFrame(report).transpose()
rep.to_csv(subAct + "_rep.csv", index=True)

report = metrics.confusion_matrix(t_test, t_pred)
rep = pd.DataFrame(report).transpose()
rep.to_csv(subAct + "_confusion.csv", index=True)
```

4.1.3 Machine Learning Model Results

The following section provides an evaluation of the machine learning model results.

4.1.3.1 Bedroom Lightswitch - Sub-Activity 108

The top five most important features for predicting this sub-activity (as shown in tile 'A' of the plot below) are: bathroom light switch, kitchen cabinet, kitchen dishwasher, kitchen laundry dryer and livingroom light switch. The bathroom light switch is significantly more important than the other four. For the analysis of the bedroom light switch feature it was determined that the best parameters were 'entropy' with a maximum tree depth of 4. The plot of Mean CV Score versus Maximum depth shows that 'gini' is the better parameter at certain tree depths. The shape of the ROC curve and the corresponding ROC_AUC value of 0.9016 are indicative of a good fit. The extremely high precision (0.98) and recall (1.00) values for 0 as compared to the relatively low recall (0.36) value for 1 are due to the unbalanced data set, where of the 1588 instances, 1543 are 0, while 45 are 1.

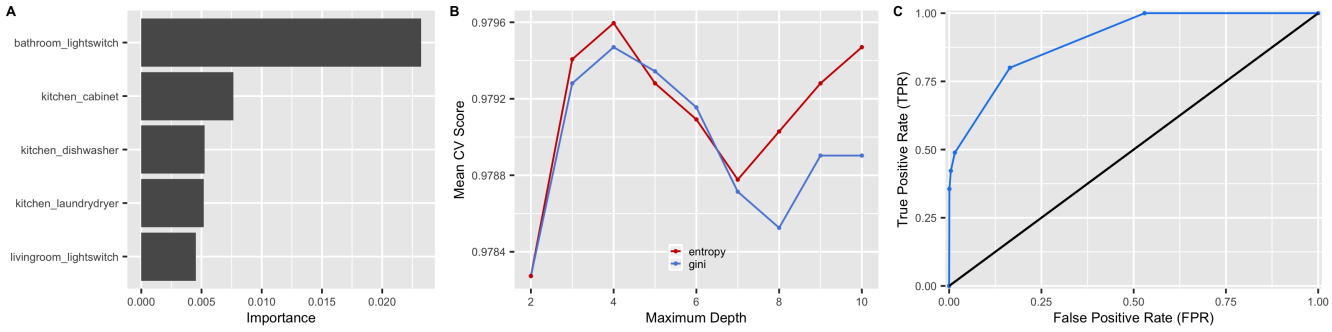


Figure 62: Plot of Mutual Information Feature Importance (A), DT Performance Comparison (B) and ROC Curve of DT (C)

4.1.3.2 Kitchen Laundry Dryer - Sub-Activity 90

The top five most important features for predicting this sub-activity (as shown in tile 'A' of the plot below) are: kitchen door, kitchen washing machine, bathroom medicine cabinet, kitchen dishwasher and bedroom drawer. The kitchen door and kitchen washing machine are significantly more important than the other three. For the analysis of the kitchen laundry dryer feature it was determined that the best parameter¬s were 'gini' with a maximum tree depth of 5. The plot of Mean CV Score versus Maximum depth shows that 'gini' is the better parameter at all tree depths up to 10. The shape of the ROC curve and the corresponding ROC_AUC value of 0.9551 are indicative of a good fit. The extremely high precision (0.99) and recall (1.00) values for 0 as compared to the relatively low recall (0.30) value for 1 are due to the unbalanced data set, where of the 1588 instances, 1565 are 0, while 23 are 1.

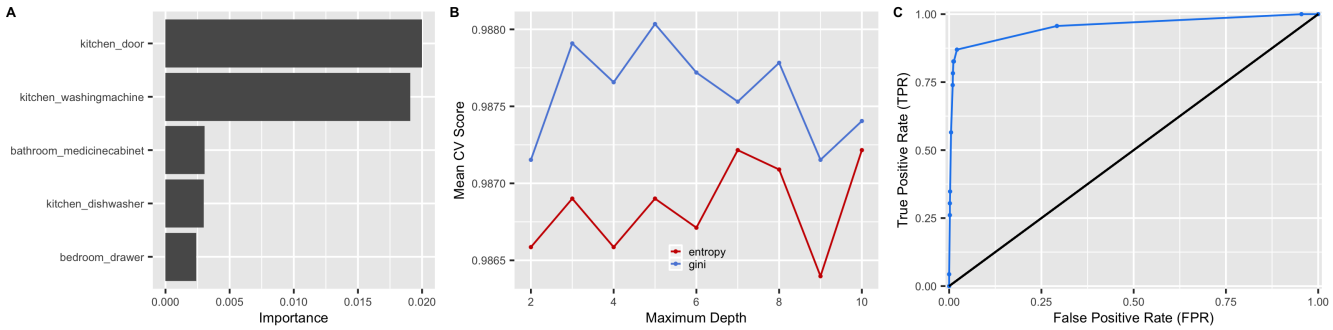


Figure 63: Plot of Mutual Information Feature Importance (A), DT Performance Comparison (B) and ROC Curve of DT (C)

4.1.3.3 Kitchen Freezer - Sub-Activity 137

The top five most important features for predicting this sub-activity (as shown in tile 'A' of the plot below) are: kitchen refrigerator, livingroom light switch, foyer closet, bathroom door and bathroom toilet flush. The kitchen refrigerator is significantly more important than the other four. For the analysis of the kitchen freezer feature it was determined that the best parameters were 'gini' with a maximum tree depth of 9. The plot of Mean CV Score versus Maximum depth shows that 'gini' is the better parameter at all tree depths from 3 up to 10. The shape of the ROC curve and the corresponding ROC_AUC value of 0.8639 are indicative of a good fit. The extremely high precision (0.94) and recall (0.98) values for 0 as compared to the relatively low recall (0.44) value for 1 are due to the unbalanced data set, where of the 1588 instances, 1423 are 0, while 165 are 1. The model has successfully categorised 73 of the 165 instances of 1, and in these circumstances has performed adequately.

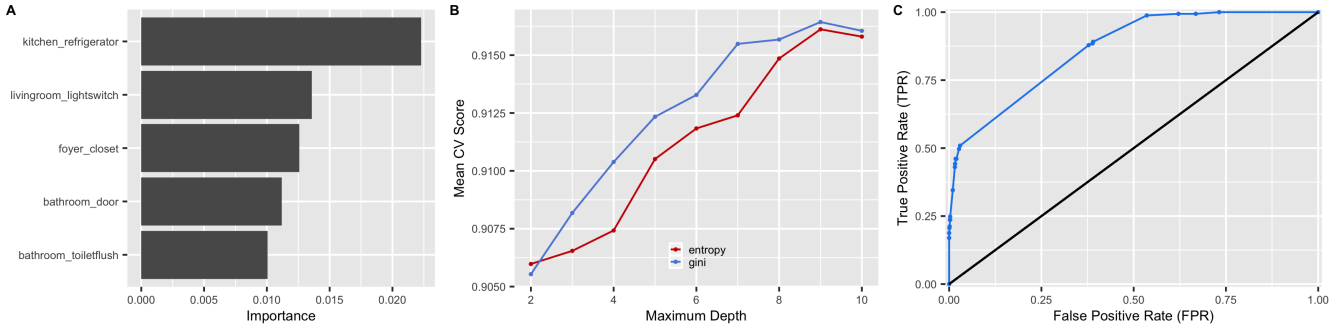


Figure 64: Plot of Mutual Information Feature Importance (A), DT Performance Comparison (B) and ROC Curve of DT (C)

4.1.3.4 Kitchen Toaster - Sub-Activity 131

The top five most important features for predicting this sub-activity (as shown in tile 'A' of the plot below) are: kitchen cabinet, bathroom exhaust fan, study light switch, kitchen toaster and livingroom light switch. The kitchen cabinet is significantly more important than the other four. For the analysis of the kitchen toaster feature it was determined that the best parameters were 'gini' with a maximum tree depth of 3. The plot of Mean CV Score versus Maximum depth shows that 'gini' is the better parameter at all tree depths up to 6, and then 'entropy' is the better parameter from 7 to 10. The shape of the ROC curve and the corresponding ROC_AUC value of 0.7782 are indicative of an adequate fit. The extremely high precision (0.99) and recall (1.00) values for 0 as compared to the relatively low recall (0.23) value for 1 are due to the unbalanced data set, where of the 1588 instances, 1566 are 0, while 22 are 1.

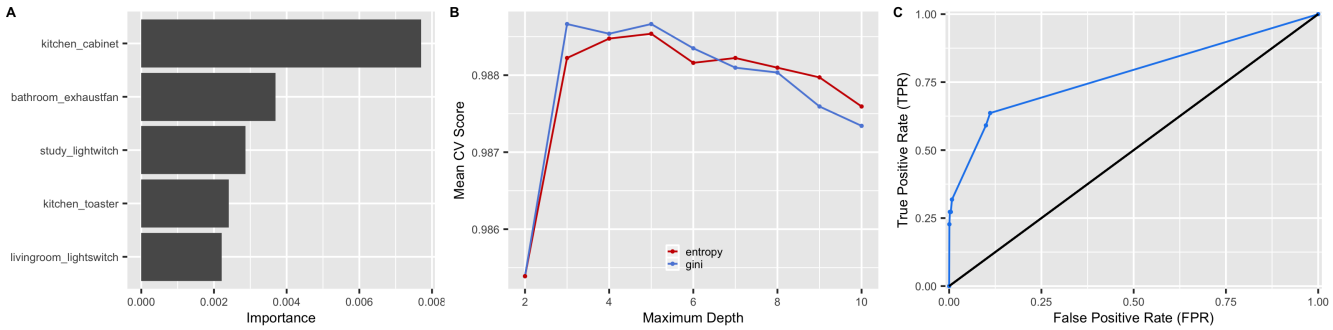


Figure 65: Plot of Mutual Information Feature Importance (A), DT Performance Comparison (B) and ROC Curve of DT (C)

4.1.3.5 Bathroom Exhaust Fan - Sub-Activity 96

The top five most important features for predicting this sub-activity (as shown in tile 'A' of the plot below) are: livingroom light switch, bathroom sink faucet hot, livingroom lamp, bathroom medicine cabinet and foyer door. The livingroom light switch, bathroom sink faucet hot and livingroom lamp are noticeably more important than the other two. For the analysis of the bathroom exhaust fan feature it was determined that the best parameters were 'gini' with a maximum tree depth of 8. The plot of Mean CV Score versus Maximum depth shows that 'gini' is the better parameter at all tree depths up to 10. The shape of the ROC curve and the corresponding ROC_AUC value of 0.9054 are indicative of a good fit. The extremely high precision (0.90) and recall (0.99) values for 0 as compared to the relatively low recall (0.25) value for 1 are due to the unbalanced data set, where of the 1588 instances, 1384 are 0, while 204 are 1.

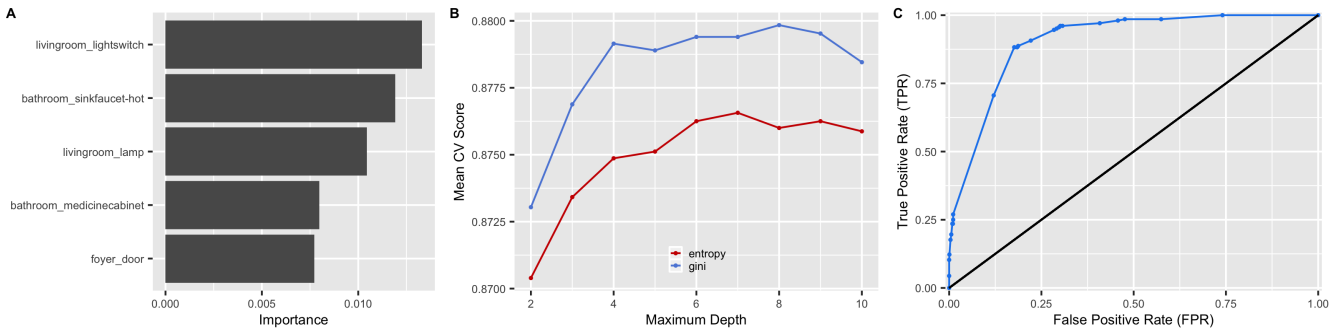


Figure 66: Plot of Mutual Information Feature Importance (A), DT Performance Comparison (B) and ROC Curve of DT (C)

4.1.3.6 Bathroom Shower Faucet - Sub-Activity 93

The top five most important features for predicting this sub-activity (as shown in tile 'A' of the plot below) are: bathroom light switch, kitchen refrigerator, kitchen dishwasher, foyer door and kitchen microwave. The bathroom light switch, kitchen refrigerator and kitchen dishwasher are significantly more important than the other two. For the analysis of the bathroom shower faucet feature it was determined that the best parameters were 'entropy' with a maximum tree depth of 8. The plot of Mean CV Score versus Maximum depth shows that 'entropy' is the better parameter at all tree depths up to 10. The shape of the ROC curve and the corresponding ROC_AUC value of 0.9280 are indicative of a good fit. The extremely high precision (0.97) and recall (1.00) values for 0 as compared to the relatively low recall (0.40) value for 1 are due to the unbalanced data set, where of the 1588 instances, 1520 are 0, while 68 are 1. The model has successfully categorised 27 of the 68 instances of 1, and in these circumstances has performed adequately.

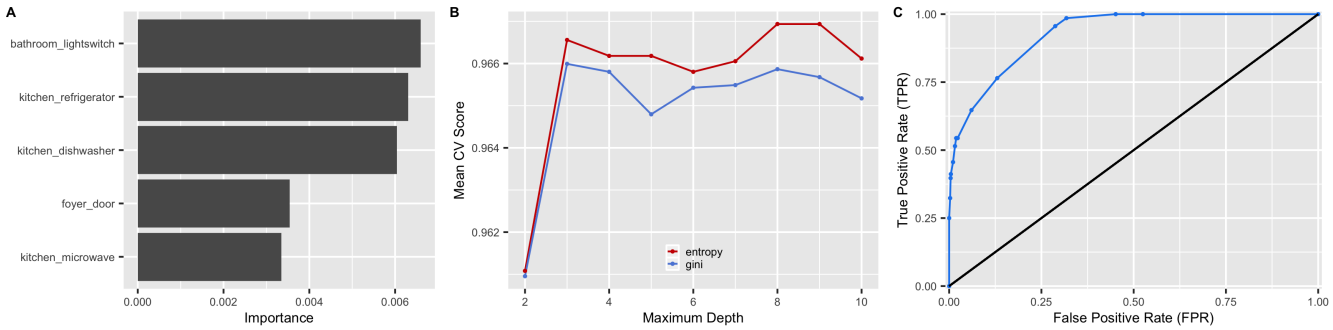


Figure 67: Plot of Mutual Information Feature Importance (A), DT Performance Comparison (B) and ROC Curve of DT (C)

4.1.3.7 Bathroom Lightswitch - Sub-Activity 101

The top five most important features for predicting this sub-activity (as shown in tile 'A' of the plot below) are: kitchen dishwasher, bedroom drawer, livingroom light switch, bathroom cabinet and foyer light switch. The kitchen dishwasher, bedroom drawer and livingroom light switch are significantly more important than the other two. For the analysis of the bathroom light switch feature it was determined that the best parameters were 'gini' with a maximum tree depth of 10. The plot of Mean CV Score versus Maximum depth shows that 'gini' is the better parameter at all tree depths up to 10. The shape of the ROC curve and the corresponding ROC_AUC value of 0.9073 are indicative of a good fit. The extremely high precision (0.85) and recall (0.99) values for 0 as compared to the relatively low recall (0.30) value for 1 are due to the unbalanced data set, where of the 1588 instances, 1262 are 0, while 326 are 1.

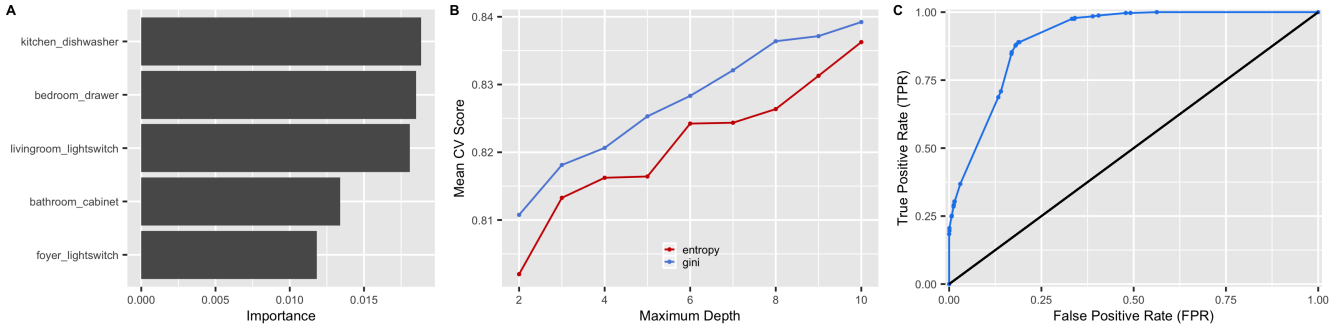


Figure 68: Plot of Mutual Information Feature Importance (A), DT Performance Comparison (B) and ROC Curve of DT (C)

4.1.3.8 Kitchen Refrigerator - Sub-Activity 126

The top five most important features for predicting this sub-activity (as shown in tile 'A' of the plot below) are: kitchen cabinet, kitchen toaster, kitchen drawer, kitchen light switch and kitchen burner. The kitchen cabinet and kitchen toaster are significantly more important than the other three. For the analysis of the kitchen refrigerator feature it was determined that the best parameters were 'gini' with a maximum tree depth of 10. The plot of Mean CV Score versus Maximum depth shows that 'gini' and 'entropy' alternate as the better parameter depending on the tree depth. The shape of the ROC curve and the corresponding ROC_AUC value of 0.9534 are indicative of a good fit. The extremely high precision (0.97) and recall (1.00) values for 0 as compared to the recall (0.51) value for 1 are due to the unbalanced data set, where of the 1588 instances, 1506 are 0, while 82 are 1. The model has successfully categorised 42 of the 82 instances of 1, and the model has performed adequately.

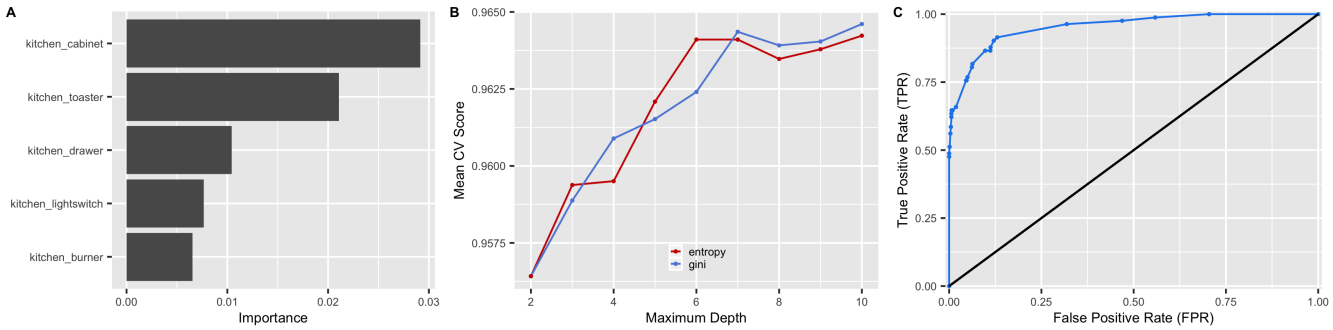


Figure 69: Plot of Mutual Information Feature Importance (A), DT Performance Comparison (B) and ROC Curve of DT (C)

4.1.3.9 Foyer Lightswitch - Sub-Activity 104

The top five most important features for predicting this sub-activity (as shown in tile 'A' of the plot below) are: kitchen burner, foyer light switch, kitchen coffee machine, kitchen dishwasher and bathroom light switch. The kitchen burner is significantly more important than the other four. For the analysis of the foyer light switch feature it was determined that the best parameters were 'gini' with a maximum tree depth of 4. The plot of Mean CV Score versus Maximum depth shows that 'gini' and 'entropy' alternate as the better parameter depending on the tree depth. The shape of the ROC curve and the corresponding ROC_AUC value of 0.9394 are indicative of a good fit. The extremely high precision (0.99) and recall (1.00) values for 0 as compared to the reasonable recall (0.77) value for 1 are despite the unbalanced data set, where of the 1588 instances, 1528 are 0, while 60 are 1. The model has successfully categorised 46 of the 60 instances of 1, and the model has performed excellently.

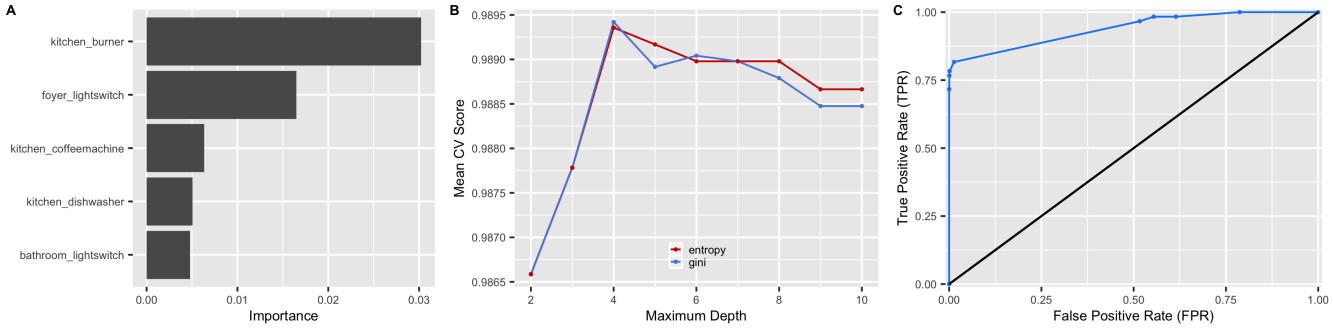


Figure 70: Plot of Mutual Information Feature Importance (A), DT Performance Comparison (B) and ROC Curve of DT (C)

4.1.3.10 Kitchen Burner - Sub-Activity 140

The top five most important features for predicting this sub-activity (as shown in tile 'A' of the plot below) are: kitchen light switch, kitchen door, bathroom sink faucet hot, kitchen drawer and kitchen burner. The kitchen light switch and kitchen door are significantly more important than the other three. For the analysis of the kitchen burner feature it was determined that the best parameters were 'entropy' with a maximum tree depth of 8. The plot of Mean CV Score versus Maximum depth shows that 'gini' and 'entropy' alternate as the better parameter depending on the tree depth. The shape of the ROC curve and the corresponding ROC_AUC value of 0.9433 are indicative of a good fit. The extremely high precision (0.97) and recall (1.00) values for 0 as compared to the relatively low recall (0.34) value for 1 are due to the unbalanced data set, where of the 1588 instances, 1506 are 0, while 82 are 1. The model has successfully categorised only 28 of the 82 instances of 1, and even given the unbalanced nature of the dataset, the model has performed poorly.

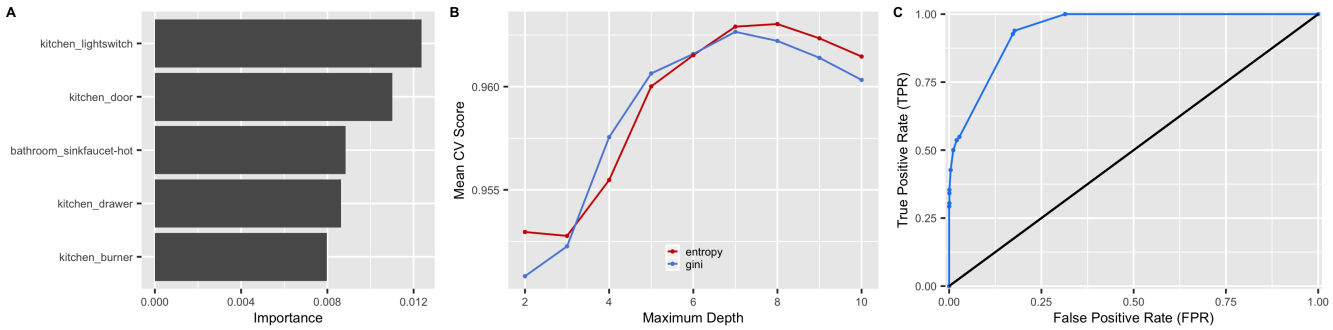


Figure 71: Plot of Mutual Information Feature Importance (A), DT Performance Comparison (B) and ROC Curve of DT (C)

4.1.3.11 Study Lightswitch - Sub-Activity 92

The top five most important features for predicting this sub-activity (as shown in tile 'A' of the plot below) are: bathroom cabinet, livingroom lamp, livingroom light switch, kitchen light switch and bedroom light switch. The bathroom cabinet is significantly more important than the other four. For the analysis of the study light switch feature it was determined that the best parameters were 'entropy' with a maximum tree depth of 8. The plot of Mean CV Score versus Maximum depth shows that 'gini' and 'entropy' alternate as the better parameter depending on the tree depth. The shape of the ROC curve and the corresponding ROC_AUC value of 0.8689 are indicative of a good fit. The high precision (0.89) and recall (1.00) values for 0 as compared to the extremely low recall (0.07) value for 1 are due to the unbalanced data set, where of the 1588 instances, 1407 are 0, while 181 are 1. The model has successfully categorised only 13 of the 181 instances of 1, and even given the unbalanced nature of the dataset, the model has performed extremely poorly.

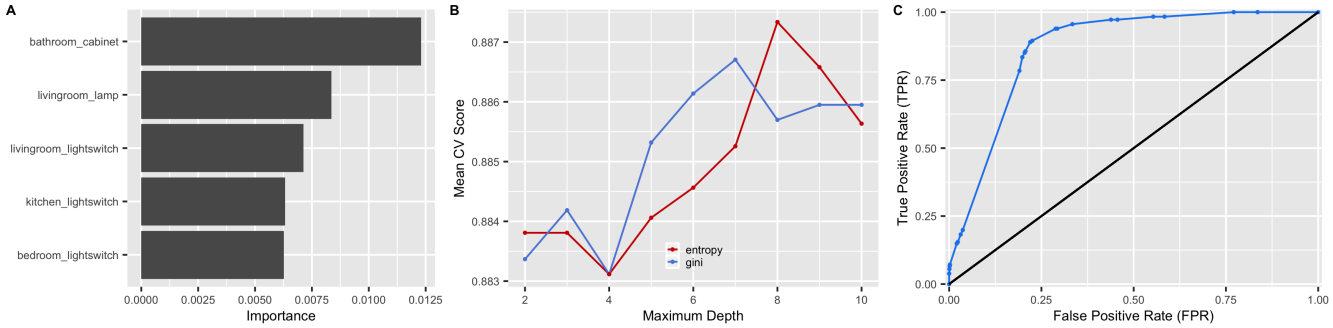


Figure 72: Plot of Mutual Information Feature Importance (A), DT Performance Comparison (B) and ROC Curve of DT (C)

4.1.3.12 Kitchen Washingmachine - Sub-Activity 142

The top five most important features for predicting this sub-activity (as shown in tile 'A' of the plot below) are: bathroom sink faucet cold, kitchen door, kitchen light switch, bathroom exhaust fan and kitchen dishwasher. The bathroom sink faucet cold and kitchen door are significantly more important than the other three. For the analysis of the kitchen washing machine feature it was determined that the best parameters were 'gini' with a maximum tree depth of 3. The plot of Mean CV Score versus Maximum depth shows that 'gini' and 'entropy' alternate as the better parameter depending on the tree depth. The shape of the ROC curve and the corresponding ROC_AUC value of 0.8698 are indicative of a good fit. The extremely high precision (0.99) and recall (1.00) values for 0 as compared to the relatively low recall (0.19) value for 1 are due to the unbalanced data set, where of the 1588 instances, 1562 are 0, while 26 are 1.

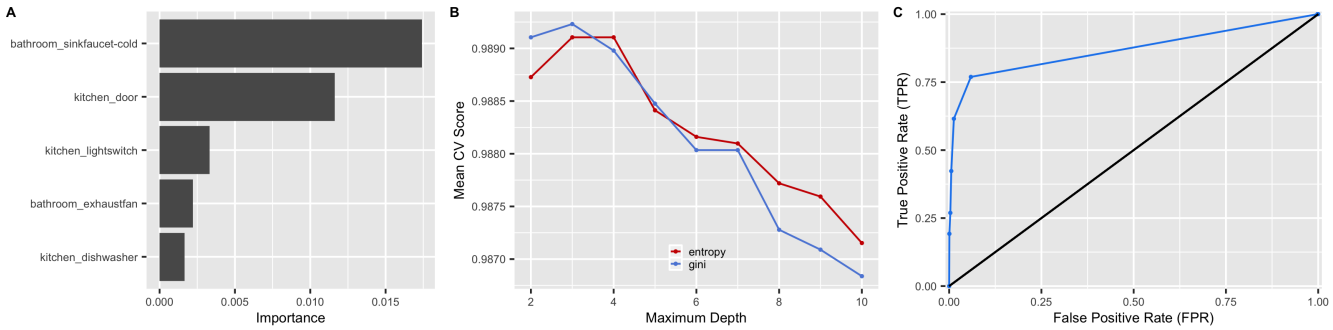


Figure 73: Plot of Mutual Information Feature Importance (A), DT Performance Comparison (B) and ROC Curve of DT (C)

4.1.3.13 Kitchen Lightswitch - Sub-Activity 105

The top five most important features for predicting this sub-activity (as shown in tile 'A' of the plot below) are: foyer light switch, kitchen refrigerator, kitchen drawer, bathroom shower faucet and bathroom cabinet. All five of these features have similar importance. For the analysis of the kitchen light switch feature it was determined that the best parameters were 'gini' with a maximum tree depth of 10. The plot of Mean CV Score versus Maximum depth shows that 'gini' is the better parameter at all tree depths up to 10. The shape of the ROC curve and the corresponding ROC_AUC value of 0.8868 are indicative of a good fit. The extremely high precision (0.88) and recall (0.87) values for 0 as compared to the reasonable recall (0.74) value for 1 are despite the unbalanced data set, where of the 1588 instances, 1100 are 0, while 488 are 1. The model has successfully categorised 361 of the 488 instances of 1, and the model has performed excellently.

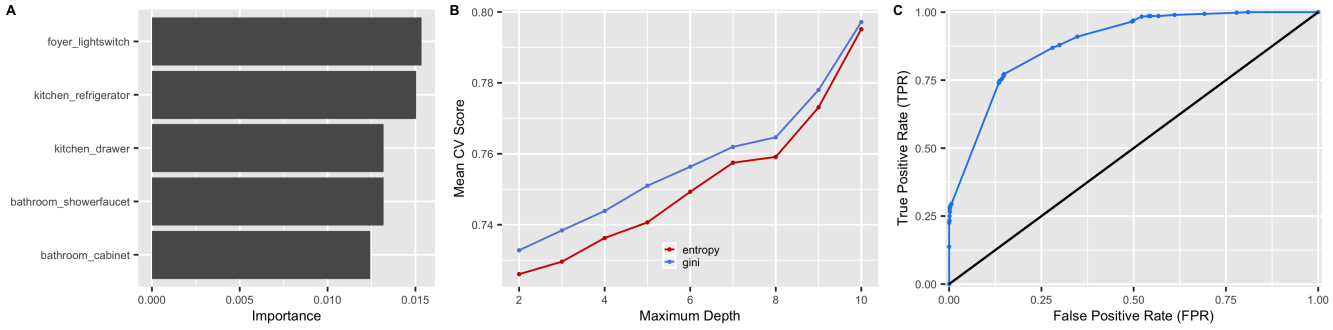


Figure 74: Plot of Mutual Information Feature Importance (A), DT Performance Comparison (B) and ROC Curve of DT (C)

4.1.3.14 Livingroom Lamp - Sub-Activity 76

The top five most important features for predicting this sub-activity (as shown in tile 'A' of the plot below) are: bathroom light switch, bathroom door, kitchen light switch, study drawer and livingroom light switch. The bathroom light switch is significantly more important than the other four. For the analysis of the livingroom lamp feature it was determined that the best parameters were 'gini' with a maximum tree depth of 8. The plot of Mean CV Score versus Maximum depth shows that 'gini' and 'entropy' alternate as the better parameter depending on the tree depth. The shape of the ROC curve and the corresponding ROC_AUC value of 0.8639 are indicative of a good fit. The high precision (0.81) and recall (0.99) values for 0 as compared to the low recall (0.16) value for 1 are due to the unbalanced data set, where of the 1588 instances, 1252 are 0, while 336 are 1. The model has successfully categorised only 54 of the 336 instances of 1, and even given the unbalanced nature of the dataset, the model has performed poorly.

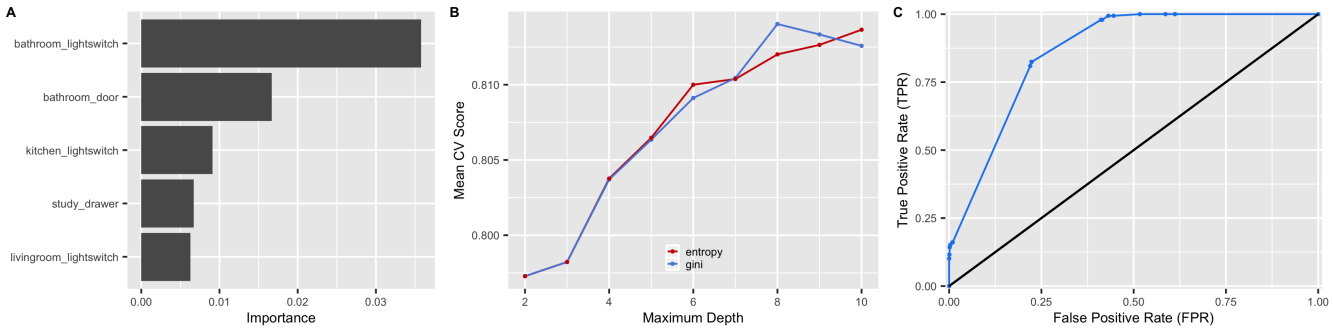


Figure 75: Plot of Mutual Information Feature Importance (A), DT Performance Comparison (B) and ROC Curve of DT (C)

4.1.3.15 Kitchen Microwave - Sub-Activity 143

The top five most important features for predicting this sub-activity (as shown in tile 'A' of the plot below) are: kitchen cabinet, kitchen refrigerator, kitchen door, bedroom light switch and kitchen drawer. All five of these features have similar importance. For the analysis of the kitchen microwave feature it was determined that the best parameters were 'entropy' with a maximum tree depth of 2. The plot of Mean CV Score versus Maximum depth shows that 'entropy' is the better parameter at all tree depths up to 10. The shape of the ROC curve and the corresponding ROC_AUC value of 0.5899 are indicative of a poor fit. The extremely high precision (0.99) and recall (1.00) values for 0 as compared to the recall (0.00) value for 1 are due to the unbalanced data set, where of the 1588 instances, 1575 are 0, while 13 are 1. The model has successfully categorised 0 of the 13 instances of 1. Thus, the model has not successfully fit.

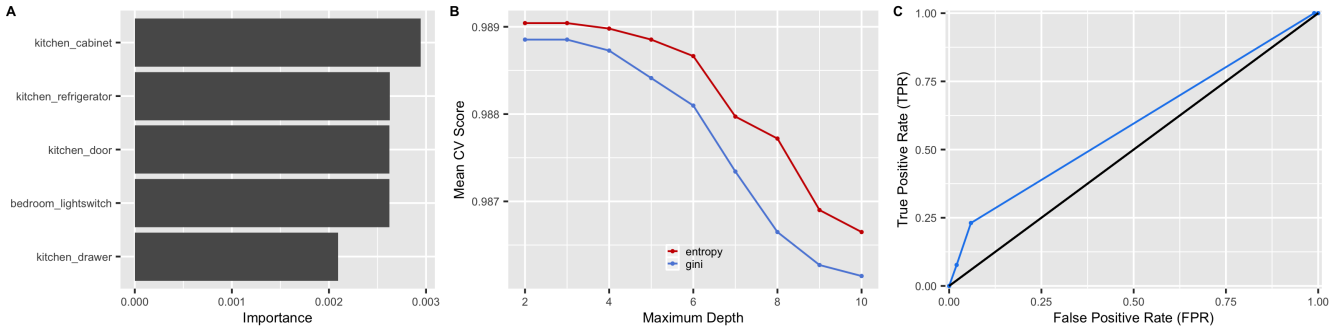


Figure 76: Plot of Mutual Information Feature Importance (A), DT Performance Comparison (B) and ROC Curve of DT (C)

4.1.3.16 Kitchen Garbage Disposal - Sub-Activity 98

The top five most important features for predicting this sub-activity (as shown in tile 'A' of the plot below) are: livingroom light switch, kitchen cabinet, bathroom door, kitchen door, livingroom lamp. The livingroom light switch is significantly more important than the other four. For the analysis of the kitchen garbage disposal feature it was determined that the best parameters were 'gini' with a maximum tree depth of 2. The plot of Mean CV Score versus Maximum depth shows that 'entropy' is equally good at this depth, and that 'gini' and 'entropy' alternate as the better parameter depending on the tree depth. The shape of the ROC curve and the corresponding ROC_AUC value of 0.7035 are indicative of a moderate fit. The extremely high precision (1.00) and recall (1.00) values for 0 as compared to the recall (0.00) value for 1 are due to the unbalanced data set, where of the 1588 instances, 1586 are 0, while 2 are 1. The model has successfully categorised 0 of the 2 instances of 1. Thus, the model has not successfully fit.

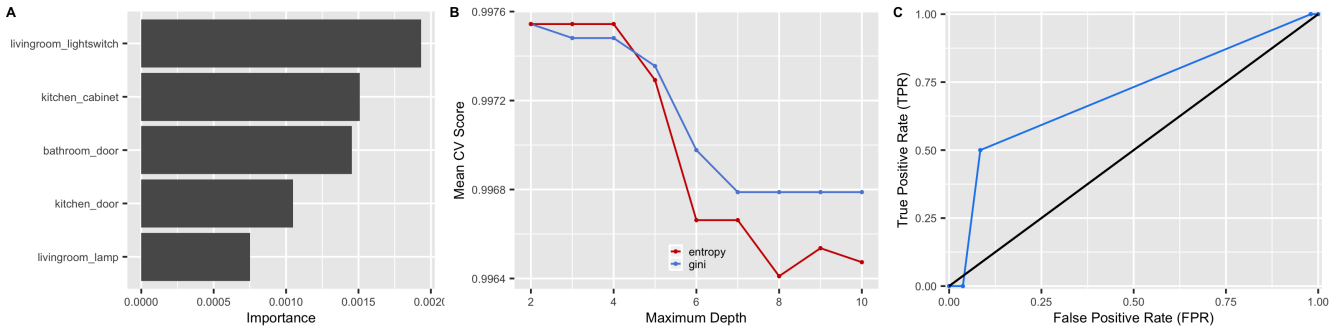


Figure 77: Plot of Mutual Information Feature Importance (A), DT Performance Comparison (B) and ROC Curve of DT (C)

4.1.3.17 Kitchen Coffee Machine - Sub-Activity 119

The top five most important features for predicting this sub-activity (as shown in tile 'A' of the plot below) are: kitchen toaster, foyer closet, bathroom shower faucet, bathroom cabinet and bathroom sink faucet cold. The kitchen toaster is significantly more important than the other four. For the analysis of the kitchen coffee machine feature it was determined that the best parameters were 'gini' with a maximum tree depth of 2. The plot of Mean CV Score versus Maximum depth shows that 'entropy' and 'gini' are equal at all tree depths. The shape of the ROC curve and the corresponding ROC_AUC value of 0.9600 are indicative of a good fit. The extremely high precision (1.00) and recall (1.00) values for 0 as compared to the recall (0.00) value for 1 are due to the unbalanced data set, where of the 1588 instances, 1587 are 0, while 1 is 1. The model has successfully categorised 0 of the 1 instances of 1. Thus, the model has not successfully fit.

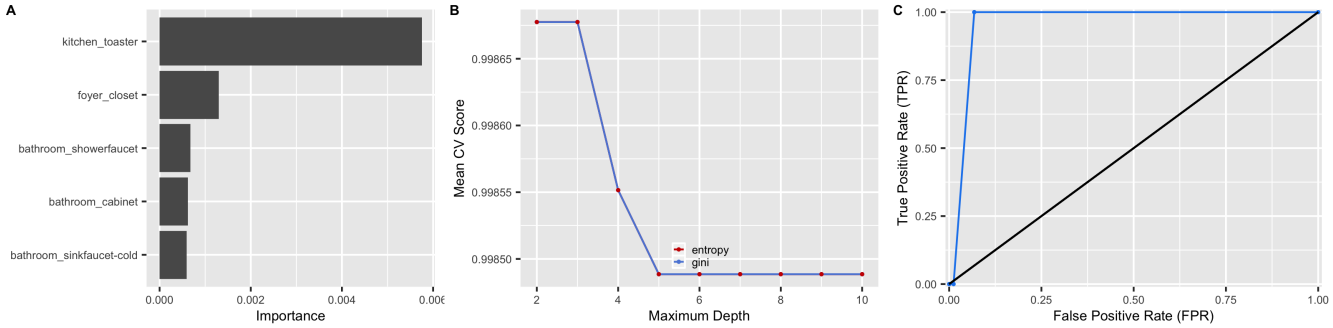


Figure 78: Plot of Mutual Information Feature Importance (A), DT Performance Comparison (B) and ROC Curve of DT (C)

4.1.3.18 Livingroom Lightswitch - Sub-Activity 107

The top five most important features for predicting this sub-activity (as shown in tile 'A' of the plot below) are: foyer light switch, bathroom shower faucet, bedroom drawer, livingroom light switch and foyer door. The foyer light switch is significantly more important than the other four. For the analysis of the livingroom light switch feature it was determined that the best parameters were 'entropy' with a maximum tree depth of 7. The plot of Mean CV Score versus Maximum depth shows that 'gini' and 'entropy' alternate as the better parameter depending on the tree depth. The shape of the ROC curve and the corresponding ROC_AUC value of 0.9178 are indicative of a good fit. The extremely high precision (0.91) and recall (1.00) values for 0 as compared to the relatively low recall (0.28) value for 1 are due to the unbalanced data set, where of the 1588 instances, 1386 are 0, while 202 are 1. The model has successfully categorised only 57 of the 202 instances of 1, and even given the unbalanced nature of the dataset, the model has performed poorly.

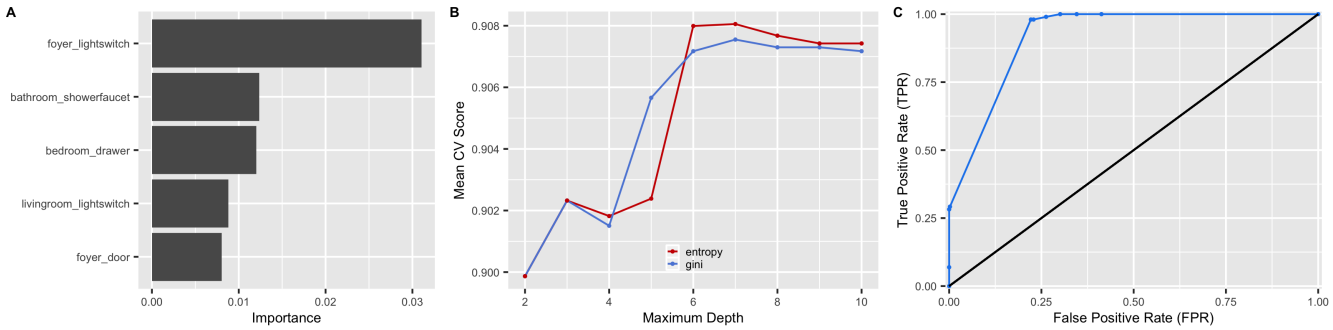


Figure 79: Plot of Mutual Information Feature Importance (A), DT Performance Comparison (B) and ROC Curve of DT (C)

4.1.3.19 Kitchen Oven - Sub-Activity 129

The top five most important features for predicting this sub-activity (as shown in tile 'A' of the plot below) are: foyer door, kitchen drawer, bathroom toilet flush, bathroom shower faucet and bedroom light switch. The foyer door is significantly more important than the other four. For the analysis of the kitchen oven feature it was determined that the best parameters were 'entropy' with a maximum tree depth of 2. The plot of Mean CV Score versus Maximum depth shows that 'gini' and 'entropy' alternate as the better parameter depending on the tree depth. The shape of the ROC curve and the corresponding ROC_AUC value of 0.7051 are indicative of a moderate fit. The extremely high precision (0.99) and recall (1.00) values for 0 as compared to the recall (0.00) value for 1 are due to the unbalanced data set, where of the 1588 instances, 1579 are 0, while 9 are 1. The model has successfully categorised 0 of the 9 instances of 1. Thus, the model has not successfully fit.

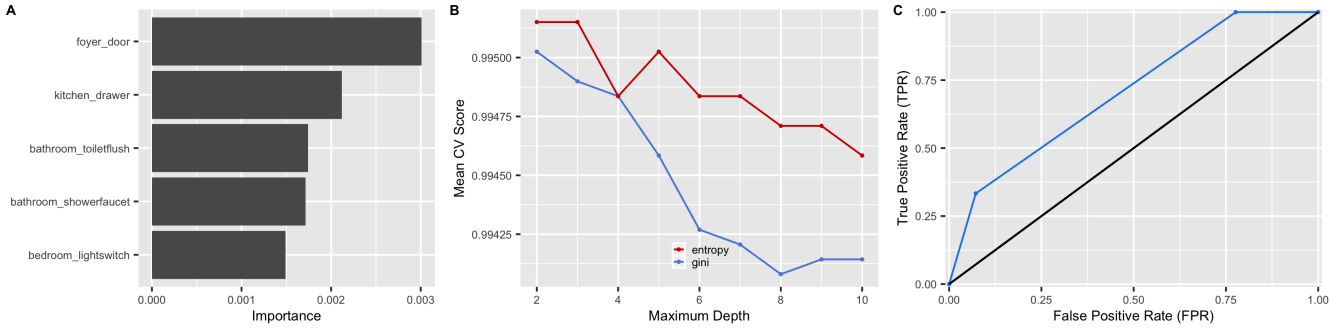


Figure 80: Plot of Mutual Information Feature Importance (A), DT Performance Comparison (B) and ROC Curve of DT (C)

4.1.3.20 Kitchen Dishwasher - Sub-Activity 70

The top five most important features for predicting this sub-activity (as shown in tile 'A' of the plot below) are: kitchen cabinet, kitchen light switch, foyer closet, kitchen burner and livingroom light switch. The kitchen cabinet and kitchen light switch are significantly more important than the other three. For the analysis of the kitchen dishwasher feature it was determined that the best parameters were 'entropy' with a maximum tree depth of 8. The plot of Mean CV Score versus Maximum depth shows that 'entropy' is the better parameter at all tree depths up to 10. The shape of the ROC curve and the corresponding ROC_AUC value of 0.8826 are indicative of a good fit. The extremely high precision (0.96) and recall (0.99) values for 0 as compared to the relatively low recall (0.26) value for 1 are due to the unbalanced data set, where of the 1588 instances, 1496 are 0, while 92 are 1. The model has successfully categorised only 24 of the 92 instances of 1, and even given the unbalanced nature of the dataset, the model has performed poorly.

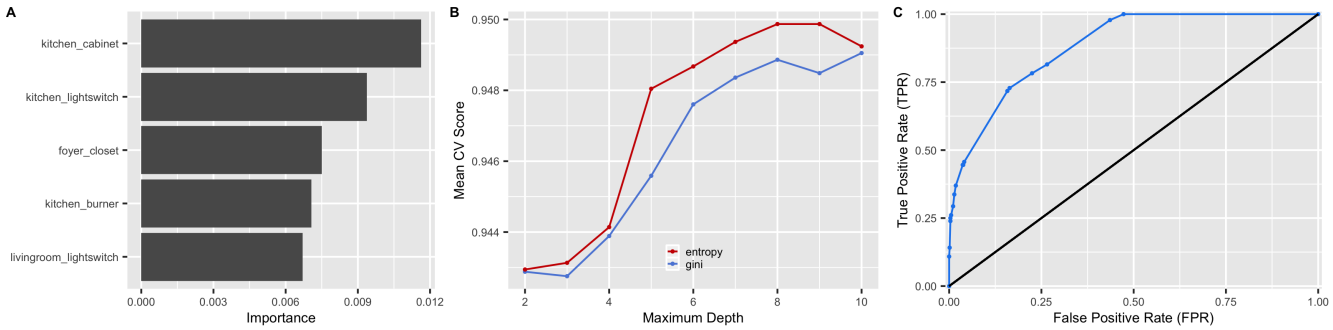


Figure 81: Plot of Mutual Information Feature Importance (A), DT Performance Comparison (B) and ROC Curve of DT (C)

4.1.3.21 Bathroom Sink Faucet (Hot) - Sub-Activity 68

The top five most important features for predicting this sub-activity (as shown in tile 'A' of the plot below) are: study drawer, bathroom toilet flush, bathroom light switch, bathroom medicine cabinet and bathroom door. The study drawer is significantly more important than the other four. For the analysis of the bathroom sink faucet hot feature it was determined that the best parameters were 'entropy' with a maximum tree depth of 6. The plot of Mean CV Score versus Maximum depth shows that 'gini' and 'entropy' alternate as the better parameter depending on the tree depth. The shape of the ROC curve and the corresponding ROC_AUC value of 0.9066 are indicative of a good fit. The extremely high precision (0.97) and recall (1.00) values for 0 as compared to the recall (0.42) value for 1 are due to the unbalanced data set, where of the 1588 instances, 1514 are 0, while 74 are 1. The model has successfully categorised 31 of the 74 instances of 1, and the model has performed adequately.

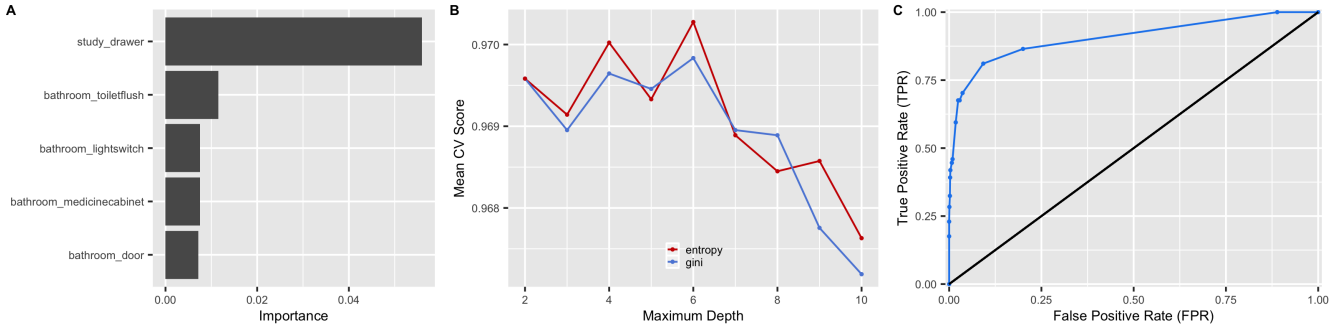


Figure 82: Plot of Mutual Information Feature Importance (A), DT Performance Comparison (B) and ROC Curve of DT (C)

4.1.4 Training using only Energy-Intensive Sub-Activities

The above model was re-trained using as input parameters only those subactivies that were energy-intensive. Figure 83 shows the semi-quantitative results. Overall there is minimal difference with respect to training in the absense of non-energy intensive sub-activities.

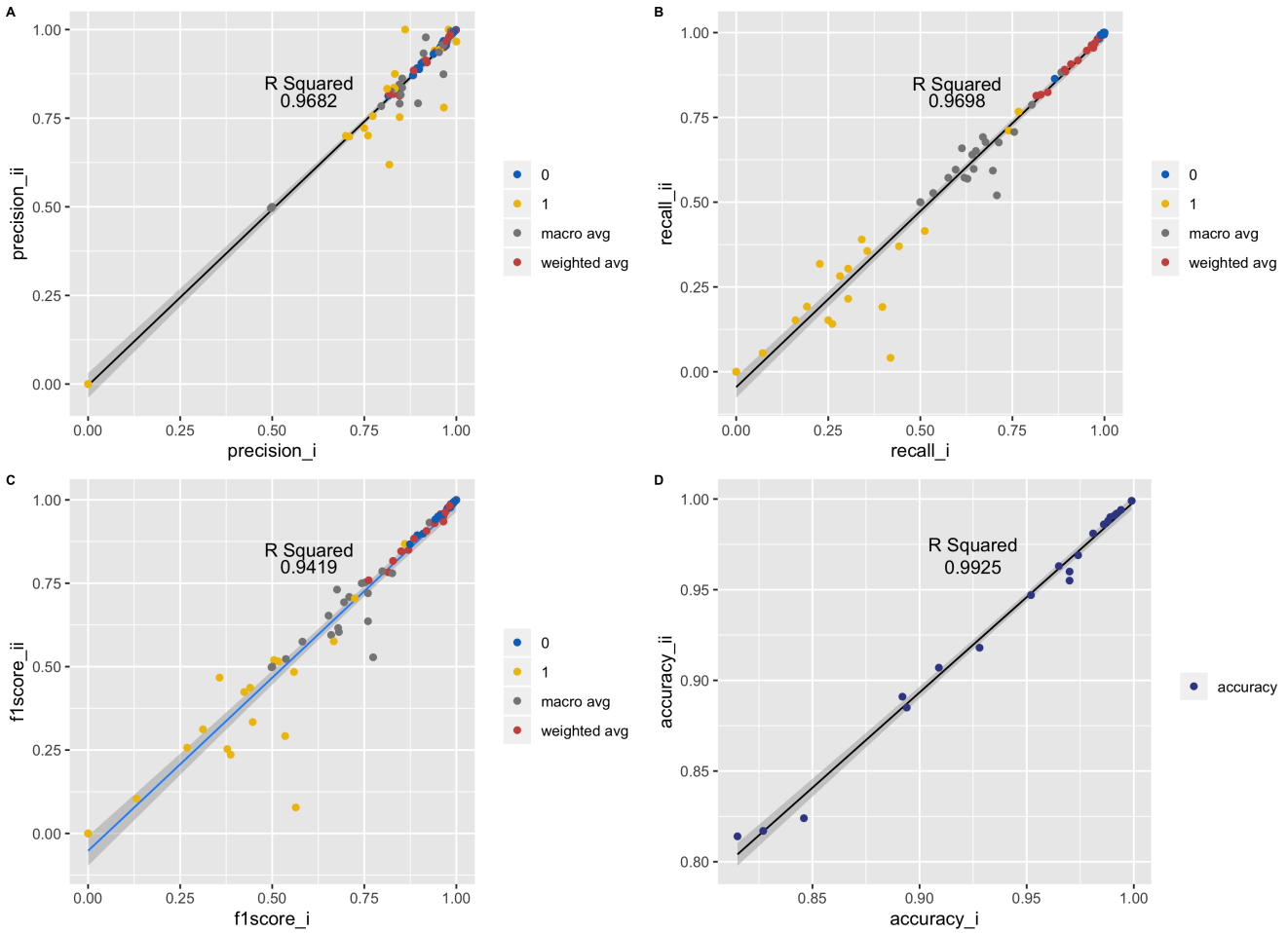


Figure 83: Semi-quantitative plots of machine learning performance metrics when comparing training on all features (i) to training with only energy-intensive features (ii). Tile A corresponds to precision metrics, tile B corresponds to recal metrics, tile C corresponds to F1-score metrics and tile D corresponds to the accuracy metrix

4.2 Antagonistic Machine Learning Model

The following model builds on all the previous work to build a model that acts in an antagonistic manner as a way to reduce overall power consumption. The inputs were as follows; the boolean timeseries array on the minute scale to train the model, the sensor (sub-activity) meta data with an additional column for wattage, data with proposed power costs (**kWh**) and pre-processed event-row data from earlier in our analysis. The iterative `calc_subAct` algorithm has the following stages:

1. Trains a decision tree classifier for the current target feature (as per the previous section)
2. Segments the event-row dataset into 6 sub-sections, weekend and weekday by morning, afternoon and evening
3. Calculates the mean value associated with each segment
4. Using the classifier model, creates a predicited boolean column (`prediction`) of on or off states for the current target feature
5. Sums the duration of each uninterrupted sequence of 1's in the predicted boolean feature
6. Compares the summed duration to the mean from the segmented event-row data
7. If the predicted value (summed duration) is less than the mean, there is no intervention
8. If the predicted value (summed duration) is more than the mean, there is potential intervention (a constant determines the weighting the difference in mean and summed duration is given)

9. These 'interventions' are used to antagonistically reduce the overall duration of the sub-activity in an 'on' state, and this reduce power consumption.

```
ds = pd.read_csv('S1SubActivities_temporalFeaturesPreprocessed.csv', index_col = None)
ds_new = ds.copy()
ds_new['Phase'] = "Afternoon"
ds_new.loc[ds_new['HOUR'] < 12, 'Phase'] = "Morning"
ds_new.loc[ds_new['HOUR'] >= 18, 'Phase'] = "Evening"
benchmark_usage = ds_new.groupby(['subAct','WDWE','Phase'])['durationSec'].mean()


def calc_subAct(dataframe, subAct, wattage, df_costs):

    df = dataframe.copy()

    Data = df.drop(columns = subAct).values
    target = df[subAct]
    D_train, D_test, t_train, t_test = train_test_split(Data, target, test_size = 0.3,
                                                        random_state=999)
    dt_classifier = DecisionTreeClassifier(max_depth=10, criterion='entropy',
                                           random_state = 999)
    dt_classifier.fit(D_train, t_train)
    confidence = dt_classifier.score(D_test, t_test)
    df['prediction'] = dt_classifier.predict(Data)
    df['intervention'] = (df['prediction'].diff() == -1) & (df[subAct] == 1)
    dfIDX = pd.read_csv('S1SubAct_B_m_NoDupes.csv', index_col = None)
    dfIDX.duration = pd.to_datetime(dfIDX.duration, format='%Y-%m-%d %H:%M:%S')
    df['timestamp'] = dfIDX['duration']

    df = add_DAY_WDWE_phaseII(df)
    df['Phase'] = "Afternoon"
    df.loc[df['Hour'] < 12, 'Phase'] = "Morning"
    df.loc[df['Hour'] >= 18, 'Phase'] = "Evening"

    # Calculate approx durations
    duration = 0
    duration_col = []

    for row in df.iterrows():
        if row[1][subAct] == 1:
            duration += 1
        else:
            duration = 0
        duration_col.append(duration)

    df['duration'] = duration_col

    cancelled_interventions = 0
    completed_interventions = 0
    possible_intervention = False
```

```
    intervening = False
    total_minutes_saved = 0
    total_kwh_saved = 0
    total_dollars_saved = 0

    for row in df.iterrows():
        if row[1]['intervention'] and not intervening:
            possible_intervention = True
        if possible_intervention:
            if row[1][subAct] == 0:
                possible_intervention = False
                cancelled_interventions += 1
            else:
                if row[1]['duration'] >
                          benchmark_usage[subAct][row[1]['WDWE']][row[1]['Phase']] / 60:
                    intervening = True
                    completed_interventions += 1
                    possible_intervention = False
        if intervening:
            if row[1][subAct] == 0:
                intervening = False
            else:
                total_minutes_saved += 1
                kwh_saved = wattage / 60 / 1000
                total_kwh_saved += kwh_saved
                hour = row[1]['Hour']
                wdwe = row[1]['WDWE']
                rate = df_costs[(df_costs['Hour'] == hour) &
                  (df_costs['WDWE'] == wdwe)].iloc[0]['cost_per_kwh']
                dollars_saved = rate * kwh_saved
                total_dollars_saved += dollars_saved

for row in df_sensors.iterrows():
    subAct = row[1]['concat']
    wattage = row[1]['wattage']
    calc_subAct(df, subAct, wattage, df_costs)
```

4.2.1 Results

4.2.1.1 subAct: bathroom_lightswitch

- Classifier accuracy metric: 0.847
- Number of completed interventions: 11
- Number of interventions cancelled due to not meeting mean number of minutes usage: 12
- Total minutes saved: 420 min
- Total minutes saved, accounting for accuracy metric: 355.914 min
- Total electricity saved (kwh): 0.168 kWh
- Total electricity saved, accounting for accuracy metric (kwh): 0.142 kWh
- Total money saved: $ 0.039 AUD

- Total money saved accounting for confidence: $ 0.033 AUD

4.2.1.2 SubAct: foyer_lightswitch

- Classifier accuracy metric: 0.992
- Number of completed interventions: 0
- Number of interventions cancelled due to not meeting mean number of minutes usage: 1
- Total minutes saved: 0 min
- Total minutes saved, accounting for accuracy metric: 0.0 min
- Total electricity saved (kwh): 0 kWh
- Total electricity saved, accounting for accuracy metric (kwh): 0.0 kWh
- Total money saved: $ 0 AUD
- Total money saved accounting for confidence: $ 0.0 AUD

4.2.1.3 SubAct: kitchen_lightswitch

- Classifier accuracy metric: 0.805
- Number of completed interventions: 12
- Number of interventions cancelled due to not meeting mean number of minutes usage: 6
- Total minutes saved: 440 min
- Total minutes saved, accounting for accuracy metric: 354.275 min
- Total electricity saved (kwh): 0.352 kWh
- Total electricity saved, accounting for accuracy metric (kwh): 0.283 kWh
- Total money saved: $ 0.086 AUD
- Total money saved accounting for confidence: $ 0.069 AUD

4.2.1.4 SubAct: kitchen_burner

- Classifier accuracy metric: 0.965
- Number of completed interventions: 5
- Number of interventions cancelled due to not meeting mean number of minutes usage: 0
- Total minutes saved: 50 min
- Total minutes saved, accounting for accuracy metric: 48.266 min
- Total electricity saved (kwh): 1.25 kWh
- Total electricity saved, accounting for accuracy metric (kwh): 1.207 kWh
- Total money saved: $ 0.29 AUD
- Total money saved accounting for confidence: $ 0.28 AUD

4.2.1.5 SubAct: livingroom_lightswitch

- Classifier accuracy metric: 0.904
- Number of completed interventions: 3
- Number of interventions cancelled due to not meeting mean number of minutes usage: 0
- Total minutes saved: 21 min
- Total minutes saved, accounting for accuracy metric: 18.987 min
- Total electricity saved (kwh): 0.017 kWh
- Total electricity saved, accounting for accuracy metric (kwh): 0.015 kWh
- Total money saved: $ 0.004 AUD
- Total money saved accounting for confidence: $ 0.003 AUD

4.2.1.6 SubAct: bedroom_lightswitch

- Classifier accuracy metric: 0.979
- Number of completed interventions: 2
- Number of interventions cancelled due to not meeting mean number of minutes usage: 0
- Total minutes saved: 7 min
- Total minutes saved, accounting for accuracy metric: 6.85 min
- Total electricity saved (kwh): 0.004 kWh
- Total electricity saved, accounting for accuracy metric (kwh): 0.004 kWh
- Total money saved: $ 0.001 AUD
- Total money saved accounting for confidence: $ 0.001 AUD

4.2.1.7 SubAct: kitchen_coffeemachine

- Classifier accuracy metric: 0.998
- Number of completed interventions: 0
- Number of interventions cancelled due to not meeting mean number of minutes usage: 0
- Total minutes saved: 0 min
- Total minutes saved, accounting for accuracy metric: 0.0 min
- Total electricity saved (kwh): 0 kWh
- Total electricity saved, accounting for accuracy metric (kwh): 0.0 kWh
- Total money saved: $ 0 AUD
- Total money saved accounting for confidence: $ 0.0 AUD

4.2.1.8 SubAct: kitchen_refrigerator

- Classifier accuracy metric: 0.961
- Number of completed interventions: 8
- Number of interventions cancelled due to not meeting mean number of minutes usage: 0
- Total minutes saved: 51 min
- Total minutes saved, accounting for accuracy metric: 49.006 min
- Total electricity saved (kwh): 0.128 kWh
- Total electricity saved, accounting for accuracy metric (kwh): 0.123 kWh
- Total money saved: $ 0.028 AUD
- Total money saved accounting for confidence: $ 0.027 AUD

4.2.1.9 SubAct: kitchen_oven

- Classifier accuracy metric: 0.994
- Number of completed interventions: 0
- Number of interventions cancelled due to not meeting mean number of minutes usage: 0
- Total minutes saved: 0 min
- Total minutes saved, accounting for accuracy metric: 0.0 min
- Total electricity saved (kwh): 0 kWh
- Total electricity saved, accounting for accuracy metric (kwh): 0.0 kWh
- Total money saved: $ 0 AUD
- Total money saved accounting for confidence: $ 0.0 AUD

4.2.1.10 SubAct: kitchen_toaster

- Classifier accuracy metric: 0.989
- Number of completed interventions: 1
- Number of interventions cancelled due to not meeting mean number of minutes usage: 0
- Total minutes saved: 1 min
- Total minutes saved, accounting for accuracy metric: 0.989 min
- Total electricity saved (kwh): 0.016 kWh
- Total electricity saved, accounting for accuracy metric (kwh): 0.016 kWh
- Total money saved: $ 0.003 AUD
- Total money saved accounting for confidence: $ 0.003 AUD

4.2.1.11 SubAct: kitchen_freezer

- Classifier accuracy metric: 0.924
- Number of completed interventions: 22
- Number of interventions cancelled due to not meeting mean number of minutes usage: 7
- Total minutes saved: 249 min
- Total minutes saved, accounting for accuracy metric: 230.003 min
- Total electricity saved (kwh): 0.622 kWh
- Total electricity saved, accounting for accuracy metric (kwh): 0.575 kWh
- Total money saved: $ 0.145 AUD
- Total money saved accounting for confidence: $ 0.134 AUD

4.2.1.12 SubAct: kitchen_washingmachine

- Classifier accuracy metric: 0.982
- Number of completed interventions: 6
- Number of interventions cancelled due to not meeting mean number of minutes usage: 0
- Total minutes saved: 11 min
- Total minutes saved, accounting for accuracy metric: 10.799 min
- Total electricity saved (kwh): 0.403 kWh
- Total electricity saved, accounting for accuracy metric (kwh): 0.396 kWh
- Total money saved: $ 0.089 AUD
- Total money saved accounting for confidence: $ 0.087 AUD

4.2.1.13 SubAct: kitchen_microwave

- Classifier accuracy metric: 0.987
- Number of completed interventions: 0
- Number of interventions cancelled due to not meeting mean number of minutes usage: 0
- Total minutes saved: 0 min
- Total minutes saved, accounting for accuracy metric: 0.0 min
- Total electricity saved (kwh): 0 kWh
- Total electricity saved, accounting for accuracy metric (kwh): 0.0 kWh
- Total money saved: $ 0 AUD
- Total money saved accounting for confidence: $ 0.0 AUD

4.2.1.14 SubAct: bathroom_sinkfaucet-hot

- Classifier accuracy metric: 0.975
- Number of completed interventions: 14
- Number of interventions cancelled due to not meeting mean number of minutes usage: 0
- Total minutes saved: 17 min
- Total minutes saved, accounting for accuracy metric: 16.582 min
- Total electricity saved (kwh): 5.497 kWh
- Total electricity saved, accounting for accuracy metric (kwh): 5.362 kWh
- Total money saved: $ 1.261 AUD
- Total money saved accounting for confidence: $ 1.23 AUD

4.2.1.15 SubAct: kitchen_dishwasher

- Classifier accuracy metric: 0.955
- Number of completed interventions: 9
- Number of interventions cancelled due to not meeting mean number of minutes usage: 1
- Total minutes saved: 106 min
- Total minutes saved, accounting for accuracy metric: 101.255 min
- Total electricity saved (kwh): 3.887 kWh
- Total electricity saved, accounting for accuracy metric (kwh): 3.713 kWh
- Total money saved: $ 0.855 AUD
- Total money saved accounting for confidence: $ 0.817 AUD

4.2.1.16 SubAct: livingroom_lamp

- Classifier accuracy metric: 0.804
- Number of completed interventions: 2
- Number of interventions cancelled due to not meeting mean number of minutes usage: 1
- Total minutes saved: 570 min
- Total minutes saved, accounting for accuracy metric: 458.228 min
- Total electricity saved (kwh): 0.114 kWh
- Total electricity saved, accounting for accuracy metric (kwh): 0.092 kWh
- Total money saved: $ 0.027 AUD
- Total money saved accounting for confidence: $ 0.021 AUD

4.2.1.17 SubAct: kitchen_laundrydryer

- Classifier accuracy metric: 0.985
- Number of completed interventions: 5
- Number of interventions cancelled due to not meeting mean number of minutes usage: 0
- Total minutes saved: 12 min
- Total minutes saved, accounting for accuracy metric: 11.826 min
- Total electricity saved (kwh): 0.6 kWh
- Total electricity saved, accounting for accuracy metric (kwh): 0.591 kWh
- Total money saved: $ 0.134 AUD
- Total money saved accounting for confidence: $ 0.132 AUD

4.2.1.18 SubAct: study_lightwitch

- Classifier accuracy metric: 0.885
- Number of completed interventions: 4
- Number of interventions cancelled due to not meeting mean number of minutes usage: 3
- Total minutes saved: 39 min
- Total minutes saved, accounting for accuracy metric: 34.525 min
- Total electricity saved (kwh): 0.023 kWh
- Total electricity saved, accounting for accuracy metric (kwh): 0.021 kWh
- Total money saved: $ 0.006 AUD
- Total money saved accounting for confidence: $ 0.005 AUD

4.2.1.19 SubAct: bathroom_showerfaucet

- Classifier accuracy metric: 0.959
- Number of completed interventions: 7
- Number of interventions cancelled due to not meeting mean number of minutes usage: 0
- Total minutes saved: 49 min
- Total minutes saved, accounting for accuracy metric: 46.992 min
- Total electricity saved (kwh): 15.843 kWh
- Total electricity saved, accounting for accuracy metric (kwh): 15.194 kWh
- Total money saved: $ 3.524 AUD
- Total money saved accounting for confidence: $ 3.38 AUD

4.2.1.20 SubAct: bathroom_exhaustfan

- Classifier accuracy metric: 0.875
- Number of completed interventions: 5
- Number of interventions cancelled due to not meeting mean number of minutes usage: 2
- Total minutes saved: 24 min
- Total minutes saved, accounting for accuracy metric: 21.004 min
- Total electricity saved (kwh): 0.024 kWh
- Total electricity saved, accounting for accuracy metric (kwh): 0.021 kWh
- Total money saved: $ 0.005 AUD
- Total money saved accounting for confidence: $ 0.005 AUD

4.2.1.21 SubAct: kitchen_garbagedisposal

- Classifier accuracy metric: 0.997
- Number of completed interventions: 0
- Number of interventions cancelled due to not meeting mean number of minutes usage: 0
- Total minutes saved: 0 min
- Total minutes saved, accounting for accuracy metric: 0.0 min
- Total electricity saved (kwh): 0 kWh
- Total electricity saved, accounting for accuracy metric (kwh): 0.0 kWh
- Total money saved: $ 0 AUD
- Total money saved accounting for confidence: $ 0.0 AUD

5 Discussion

It was our intention to develop a data collection and processing methodology with subsequent machine learning analysis that would allow for the consideration of the interplay between end user convenience, enery saving and cost in an IoT Smart Home. Review of current literature showed that in the space of energy saving, consideration is rarely given to the convenience of end users, and how this will affect overall outcomes in the long term. A large volume of literature proposes that through the provisioning of display terminals in the home, users can monitor their energy usage and intervene accordingly. We proposed that by leveraging the emerging technologies of IoT and cloud computing, the nessescity for an end user to intervene to diminish cost an be reduced, and thus increase convenience.

We initially created a predictive machine learning model using only for a sub-activity on or off states based on historical data. As compared to other work in the IoT Smart Home predictive analytics space, our model used only the on-off states of other sub-activities to train a decision tree classifier. One large challenge in this work was imbalance, whereby the number of 1 values in many of the target features was heavily overwhelmed by the 0 values. One such example of this was the model derived for the kitchen coffee machine. Inspection of the results revealed that in the source dataset out of 1588 instances, 1587 were 0 and only one was 1. In this case, the model was overfit, as any cross validation testing for 0 values will be extremely likely to appear correct.

After the first iteration of our model and subsequent result analysis, another evaluation was conducted whereby the non-energy requiring sub-activities were stripped from the training dataset. It was found through a semi-quanitative comparision methodogy that this has little affect on the overall performance of the model. However, this may also be attributed to the imbalance in the dataset towards values of 0. Some of the results from the analysis were promising, and using the original model an antagonistic model for reducing energy usage was proposed. The logic of this model was sound such that for energy-intensive sub-activities overall useage duration was able to be reduced in some cases. Due to the large imbalance in the dataset, future work is needed to optimize parameters.

The overall proposed hypothetical model would be one whereby an IoT Smart home has one or more occupants who initially train the model with their daily activities over a certain period of time. When they are ready, they can activate the AI to help reduce power, as per the proposed mechanism above. As the model is antagonistic, is always aims to drive energy usage down by performing switching off events at the end or start of a sequence. In the case of the smarthome users, if they themselves intervened to re-activate an activity that has been switched off, this could be used to further train the model. The user would potentially interact with this model through a smart phone application, as shown in the mock below, Figure 84.

Convenience is factored into the overall proposed model in two main ways

1. A predictive model is created to mediate on-off events of smart home appliances reducing the need of an end user to intervene, thus increasing convenience.
2. The end user does not have to expend energy analysing a feeback system, based on their historical behaviour a model can be trained and then the level of convenience, energy saving and dollar saving can be paramatised as shown below.

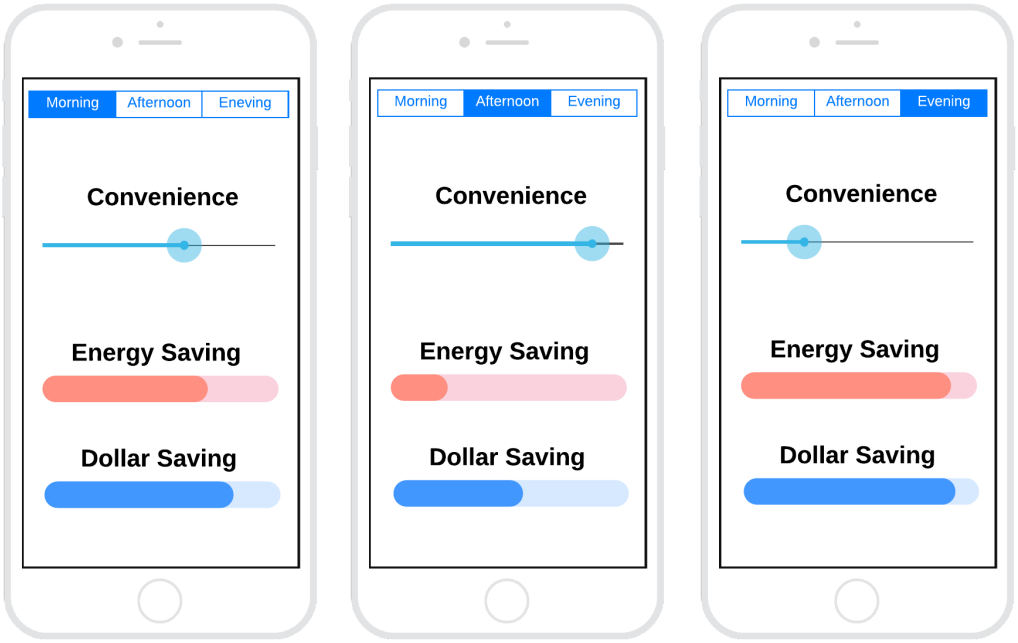


Figure 84: A proposed end user UI for the functioning model

6 Conclusion

Using previously collected data on end user activity, we were able to build a model that can predict the on-off state of activities in the home. Unlike other work in this space, the model uses only the on-off state of other features as predictors. The model was combined with usage statistics, wattage data and electricity pricing data to make an antagonistic mechanism to reduce overall power consumption.

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