



# Detection of life habits evolution of frail people in a smart dwelling

Kevin Fouquet

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# Detection of life habits evolution of frail people in a smart dwelling

*Détection des évolutions d'habitudes de vie de personnes fragiles dans un habitat intelligent*

**Thèse de doctorat de l'Université Paris-Saclay**

École doctorale n° 580, Sciences et Technologies de l'Information et de la Communication - STIC  
Spécialité : Automatique  
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**Thèse présentée et soutenue à Paris-Saclay le 24 novembre 2021 par**

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In order to make my acknowledgments understandable by the concerned people, this page is written in French.

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---

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# Contents

---

<b>Contents</b>	<b>e</b>
<b>List of Figures</b>	<b>i</b>
<b>List of tables</b>	<b>m</b>
<b>Introduction</b>	<b>1</b>
<b>1 Ambient Assisted Living and Health at Home issues and objectives</b>	<b>5</b>
1.1 Motivation . . . . .	6
1.2 Literature review . . . . .	8
1.2.1 Smart Homes . . . . .	8
1.2.2 Ambient Assisted Living and Health at Home . . . . .	12
1.2.3 Activity of Daily Living discovery and recognition . . . . .	14
1.3 Existing public smart home databases for AAL . . . . .	15
1.4 Conclusion . . . . .	16
<b>2 Health at Home needs and work positioning</b>	<b>19</b>
2.1 Behavioral features and related symptoms and diseases . . . . .	20
2.1.1 Activity ordering . . . . .	21
2.1.2 Activity duration . . . . .	23
2.1.3 Activity execution . . . . .	25
2.1.4 Activity time . . . . .	26
2.1.5 Activity number . . . . .	27
2.1.6 Behavior features summary . . . . .	29
2.2 Anomaly and long term deviation . . . . .	30
2.3 Problem statement . . . . .	32
2.3.1 Thesis objective . . . . .	32
2.3.2 Positioning . . . . .	33
2.3.3 Work hypothesis . . . . .	34
2.3.4 Proposed framework . . . . .	35
2.4 Proposed databases . . . . .	36
2.4.1 Selection of databases . . . . .	36
2.4.2 Data pretreatment . . . . .	38
2.5 Conclusion . . . . .	38

<b>3</b>	<b>Smart home inhabitant life habits modeling</b>	<b>41</b>
3.1	Life habits model definition . . . . .	42
3.1.1	Life habits identification framework . . . . .	42
3.1.2	Work assumptions . . . . .	43
3.1.3	Model selection . . . . .	44
3.1.4	Model definition . . . . .	45
3.2	STA generation . . . . .	47
3.2.1	STA structure . . . . .	48
3.2.2	Transitions probability generation . . . . .	51
3.2.3	Probabilistic distribution generation . . . . .	57
3.3	Training phase duration assessment . . . . .	64
3.4	Application to a public database . . . . .	68
3.4.1	DOMUS smart home . . . . .	68
3.4.2	Hh103 CASAS smart home . . . . .	73
3.5	Conclusion . . . . .	78
<b>4</b>	<b>Anomaly detection in human behavior</b>	<b>79</b>
	Introduction . . . . .	80
4.1	Anomaly detection framework . . . . .	80
4.2	Activity ordering anomalies . . . . .	81
4.2.1	Symptoms and diseases which may influence activity ordering . . . . .	81
4.2.2	Distance between observed behavior and life habits . . . . .	82
4.3	Activity duration anomalies . . . . .	86
4.3.1	Symptoms and diseases which may influence activity duration . . . . .	86
4.3.2	Distance between observed duration and expected behavior . . . . .	87
4.4	Application on smart home databases . . . . .	90
4.4.1	Limits of existing databases and artificial data generation . . . . .	90
4.4.2	DOMUS smart home . . . . .	90
4.4.3	Hh103 CASAS smart home . . . . .	94
4.5	Conclusion . . . . .	97
<b>5</b>	<b>Long term deviation detection</b>	<b>99</b>
	Introduction . . . . .	100
5.1	Medical motivation and needs . . . . .	100
5.1.1	Symptoms and health trouble associated to long term behavioral deviation . . . . .	100
5.1.2	Objective and proposed framework . . . . .	101
5.2	Long term deviation detection . . . . .	101
5.2.1	Industrial system predictive maintenance . . . . .	101
5.2.2	Existing data forecasting methods . . . . .	103
5.2.3	Choice of a model . . . . .	109
5.3	Case study . . . . .	115
5.3.1	Artificial data generation . . . . .	115
5.3.2	Results . . . . .	116
5.3.3	Hh103 smart home . . . . .	118
5.4	Conclusion . . . . .	123

<b>Conclusion</b>	<b>125</b>
<b>Bibliography</b>	<b>129</b>
<b>A Ethical Impact Assessment</b>	<b>141</b>
Introduction . . . . .	141
A.1 Framework to assess well-being implications of AI . . . . .	142
A.1.1 Required definitions . . . . .	142
A.1.2 Proposed framework . . . . .	142
A.1.3 IEEE 7010 Well-being Impact Assessment . . . . .	143
A.1.4 Application to our work: Limitations and adjustments . . . . .	147
A.2 Results . . . . .	147
A.3 Discussion and further works . . . . .	155
<b>B Proof</b>	<b>157</b>
B.1 Probability computation with deterministic PFA structure . . . . .	157



# List of Figures

---

1	Contribution of this thesis. . . . .	2
1.1	Percentage of population aged 65 or over in 2020 (a) and projection for 2050 (b) [United Nations and Social Affairs, 2020]. . . . .	6
1.2	Potential support ratio (number of people aged 25-64 over those aged 65+) in 2020 (a) and projection for 2050 (b) [United Nations and Social Affairs, 2020] . . . . .	7
1.3	Example of a smart home equipment. Extracted and adapted from [Asadullah and Ullah, 2017] . . . . .	8
1.4	Smart home energy management system (HEMS) functionalities [Zhou et al., 2016] . . . . .	10
1.5	Examples of wearable sensors and e-textile equipment [Patel et al., 2012].	13
1.6	Examples of medical implants to monitor inhabitant's vital signs [Hodgins et al., 2008] . . . . .	13
1.7	Simulation of a fall in front of a camera to generate data. Adapted from [Bhandari and Babar, 2018] . . . . .	15
1.8	Floor plan of smart homes hh103 (a), hh104 (b) and hh102 (c) from the CASAS database [Cook et al., 2013]. . . . .	17
2.1	List of diseases and health problems of interest with associated symptoms, and behavioral features affected by each symptom. . . . .	21
2.2	Examples of mobility model: weighted directed graph of mobility between four places of interest [Payandeh and Chiu, 2019] (on the left); Room-to-room state transition model for mobility between six different rooms [Eisa and Moreira, 2017] (on the right). . . . .	22
2.3	3D plot of sleeping activity of real data of two individuals (R1 and R2) and synthetic data built (S1 and S2) [Yahaya et al., 2019]. . . . .	24
2.4	Example of task model presented in [Parvin et al., 2018]. . . . .	26
2.5	Sample of a smart home energy consumption between 5am and 12am [Chalmers et al., 2019]. . . . .	27
2.6	Life routine of a smart home inhabitant regarding the start time feature (a) and the normal, alert and critical time ranges (b) [Forkan et al., 2015].	27
2.7	Example of a requirement flower depicting medical recommendations regarding activities "Having breakfast", "Washing dishes", and "Use toilet" [Saives et al., 2015]. . . . .	28
2.8	Relation between the five identified behavioral features and the symptoms they can detect. . . . .	30
2.9	Detected change point in daily evolution of overall activity duration for a resident of a nursing home [Kaddachi et al., 2018]. . . . .	32

## LIST OF FIGURES

---

2.10	Proposed framework for behavioral anomaly and long-term deviation. .	35
2.11	DOMUS smart home plan [Kadouche et al., 2010, Chikhaoui et al., 2010] with sensor and activity databases . . . . .	37
2.12	Hh103 smart home plan from the CASAS project [Cook et al., 2013]. .	38
2.13	Modification applied to activities enter and leave home to be more rep- resentative of the inhabitant behavior. . . . .	39
3.1	Proposed methodology for life habits model generation. . . . .	43
3.2	Example of an STA structure. . . . .	46
3.3	Example of a PFA. . . . .	46
3.4	Example of an STA. . . . .	47
3.5	Example of a PFA. It can be remarked that $A$ is not a deterministic structure. . . . .	53
3.6	Duration of activities dress (a), wash breakfast dishes (b), and other various activities for 60 days from the CASAS hh103 smart home database	59
3.7	Duration of activities eat dinner (a), relax (b), and other various activ- ities for 60 days from the CASAS hh109 smart home database . . . . .	60
3.8	Duration of activities house keeping (a), eating (b), and other various activities for 60 days from the CASAS aruba smart home database . .	61
3.9	Example of overfitting: the linear regression offer a better representation of the data than the Lagrange polynomial even if it fit less properly the training data. . . . .	62
3.10	Evolution of entropy and perplexity for models generated each day for 90 days. . . . .	67
3.11	Evolution of the Wasserstein distance for most activities for 90 days. .	68
3.12	Evolution of entropy and perplexity from day 1 to day 10 for DOMUS smart home, user 1. . . . .	69
3.13	Evolution of the Wasserstein distance for every DOMUS smart home monitored activities carried out by user 1 for 10 days. . . . .	69
3.14	Evolution of entropy and perplexity from day 1 to day 10 for DOMUS smart home, user 2. . . . .	70
3.15	Evolution of the Wasserstein distance for every DOMUS smart home monitored activities carried out by user 2 for 10 days. . . . .	70
3.16	STA models depicting life habits for user 1 (top) and user 2 (bottom) from the DOMUS smart home . . . . .	72
3.17	Evolution of entropy and perplexity from day 1 to day 60. . . . .	73
3.18	Evolution of the Wasserstein distance for every hh103 smart home mon- itored activities for 60 days. . . . .	75
3.19	Trimmed STA representing the life habits of smart home hh103 inhabitant.	76
3.20	Life habits model of smart home hh103 inhabitant . . . . .	77
4.1	Proposed framework for behavioral anomaly detection. . . . .	81
4.2	Examples of life habits model for two inhabitants. Transitions corre- sponding to the sequences with the highest likelihood are highlighted. .	84
4.3	Relation between $\tau_N$ and $\tau_{LogN}$ distances with the observation expecta- tion ranges. . . . .	89

4.4	Normalized likelihood (left) and time distance (right) of each activity for each scenario. . . . .	93
4.5	Normalized likelihood and time distance for scenario 1 of hh103 case study.	95
4.6	Normalized likelihood and time distance for scenario 2 of hh103 case study.	96
5.1	Exponential smoothing applied to body temperature to detect potential trends and fever symptoms after the 40th time period [Forkan et al., 2015].	104
5.2	Example of time series with and without trend and seasons [Hyndman and Athanasopoulos, 2018]. . . . .	105
5.3	Proposed methodology to assess existence of autocorrelation within human behavior. . . . .	109
5.4	Relation between the five identified behavioral features and the symptoms they can detect. . . . .	110
5.5	Autocorrelation score for various activities for aruba smart home: Bed to toilet (a), sleeping (b), wash dishes (c) and work (d) . . . . .	112
5.6	Autocorrelation score for activities cook breakfast (a), eat dinner (b), and other various activities for hh103 smart home. . . . .	113
5.7	Autocorrelation score for activities cook breakfast, sleep, and other various activities for hh109 smart home. . . . .	114
5.8	Methodology for healthy and sick behavior generation. . . . .	115
5.9	Prediction for activities Wake up, Having breakfast and Other activities for original artificial data (a, b, c). First 60 days are training data in red, last 60 days are validation data in green, ARIMA forecasting in black.	117
5.10	Prediction for activities Wake up, Having breakfast and Other activities for artificially trended data (d, e, f). First 60 days are training data in red, last 60 days are validation data in green, ARIMA forecasting in black.	118
5.11	Prediction for activities Sleep, Bed to Toilet transition and Leave home for original data (a, b, c). The first 30 days are training data in red, last 30 days are validation data in green and ARIMA forecasting is in black.	121
5.12	Prediction for activities Sleep, Bed to Toilet transition and Leave home for original data (a, b, c). The first 30 days are training data in red, last 30 days are validation data in green and ARIMA forecasting is in black.	122
A.1	Illustration of proposed framework by IEEE 7010. Extracted from [IEEE, 2020] . . . . .	144
A.2	Well-being indicators dashboard for autonomous vehicles [Schiff et al., 2019] . . . . .	145



# List of Tables

---

3.1	Examples of a STA structure generation from a smart home enabling monitoring of activities Wake up, Use Toilet, Having breakfast and Leave home. . . . .	50
3.2	Example of probability generation in a PFA by a training sample $S$ . . .	56
3.3	Wasserstein distance between activity duration histograms and different probabilistic distributions for various activities for home hh103. . . . .	61
3.4	Wasserstein distance between activity duration histograms and different probabilistic distributions for various activities for home hh109. . . . .	62
3.5	Wasserstein distance between activity duration histograms and different probabilistic distributions for various activities for home aruba. . . . .	62
4.1	Likelihood and normalized likelihood of main life habits of users 1 and 2.	85
4.2	Activity sequence and duration for each simulated scenario. . . . .	91
4.3	List of index and associated activity . . . . .	92
4.4	Activity sequence and duration for each scenario. . . . .	94
4.5	List of index and associated activity for hh103 case study. . . . .	95
A.1	List of well-being domains, subdomains, and description. Adapted from [IEEE, 2020] . . . . .	146
A.2	Well-being impact assessment - User dashboard . . . . .	149
A.3	Well-being impact assessment - Health care provider dashboard . . . . .	150
A.4	Well-being impact assessment - Smart home equipment providers and installers dashboard . . . . .	150
A.5	Well-being impact assessment - User's family members and relative dashboard . . . . .	151
A.6	Well-being impact assessment - Society dashboard . . . . .	152
A.7	Source and description for each indicator associated to well-being domains and subdomain . . . . .	153
A.8	Source and description for each indicator associated to well-being domains and subdomain . . . . .	154



# General introduction

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## Motivation

Continuous improvements in medicine and public health lead to an increase of the life expectancy in most countries in the world. However, as stated by the World Health Organization [Ageing, 2002]: "Population ageing is a triumph of humanity but also a challenge to society".

In Europe, North America and east of Asia, 25 to 40% of the population is expected to be aged 65 or over in 2050 [United Nations and Social Affairs, 2020]. Ageing of the population mechanically leads to an increase of the number of people requiring specific health care. On the other hand, population ageing also leads to a decrease of the active part of the population against the retired population [United Nations and Social Affairs, 2020]. This ratio is also called the potential support ration. This situation leads to a decrease of the public funds allocated to the oldest population.

Existing solution to ensure a satisfying quality of life and health to the elderly, such as nursing homes or residential care, are costly solutions which are not scalable to face the upcoming raise of the oldest population. They are moreover rejected by this population as the elderly prefer to stay autonomous the longest possible in their own home [Roy et al., 2018]. Consequently, innovative solutions have to be explored.

Health at Home (HaH) is a scientific field which aims at ensuring a good health care to people staying in their dwelling. Existing works often focus on vital signs monitoring, which is an efficient solution to help medical staff in the prognosis and diagnosis of numerous diseases. They however fail to detect early enough specific diseases which first affect the behavior of an individual, such as Alzheimer's disease or physical decline. This is particularly worrisome as these diseases typically impair the oldest population. Moreover, early detection allow for better treatment and healing [Mortimer et al., 2005].

Consequently, this thesis work focus on behavior monitoring of a smart home inhabitant in order to detect changes due to diseases. Thanks to recent works about activity recognition, it is possible to work on a higher and more explicit level of semantic has the list of activities performed by the inhabitant become accessible.

The inhabitant is supposed to live alone, due to the association between loneliness and higher risks of physical or cognitive decline. Binary information only is considered in order to not be dependant of any technology as any sensor can be used. This way, privacy savings solution which are more easily accepted by the inhabitant can be employed. Human behavior is extremely rich. To identify which features of human behavior is relevant to monitor, an extensive literature review of the medical and AAL fields is proposed to determine which diseases and symptoms are of interest. Details are

provided in chapter 2, and activity ordering and activity duration are highlighted for their wide coverage and efficient diagnosis. This literature review also highlighted two different ways the behavior of an individual might be impacted: behavioral anomalies, which are changes due to an accident or a sudden diseases, and long-term deviations which are slow trends within behavior due to degenerative diseases. This thesis consider the detection of both of these behavioral deviations.

As each individual possesses personal life habits, and in order to ease communication with medical staff, a model-based approach is proposed. The model depicts the usual personal life habits of the smart home inhabitant and is used for behavioral deviations detection. This model also offer to medical staff an interesting overview of the current health status of an individual. In particular, sleeping or eating patterns may offer insightful information.

Detected behavioral deviations are sent to medical staff which will be able to refine their prognosis, and potentially call for a medical appointment in the case of a concerning situation.

The contributions of this thesis are introduced in chapter 2, 3, 4 and 5.

## Contribution and organisation

The contributions of this thesis are illustrated in figure 1.

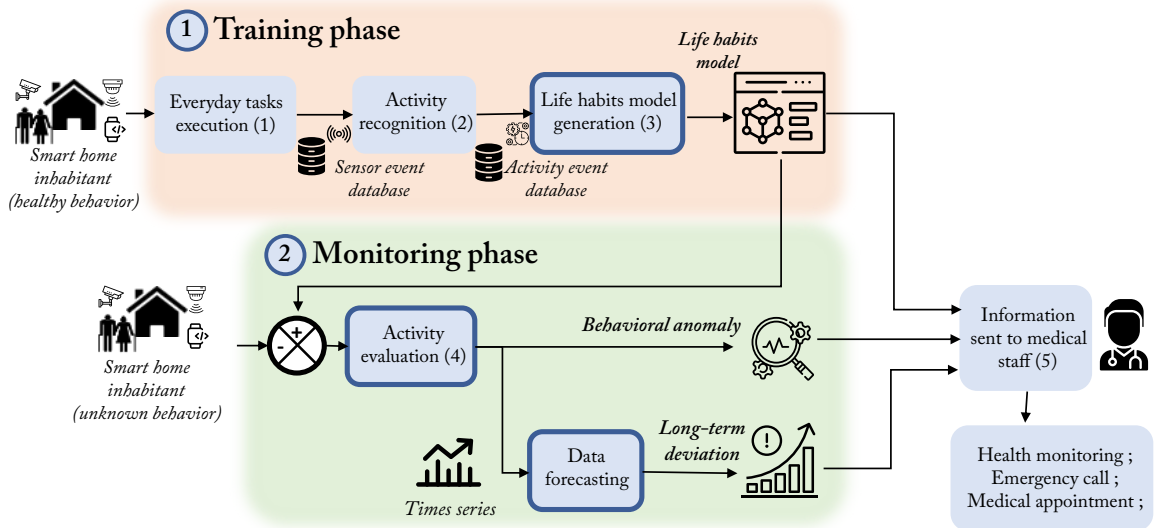


Figure 1: Contribution of this thesis.

The manuscript is organised as follows.

The first chapter proposes a state of the art of Ambient Assisted Living (AAL) and Health at Home (HaH) works. The social context and motivation is explored, and the concept and some applications of smart home are reviewed.

In the second chapter, a review of diseases and associated symptoms the elderly population is likely to suffer is conducted in order to identify the behavior features which are affected and which are consequently relevant to monitor. Concepts of short

and long-term deviation are also introduced. This chapter also proposes the problem statement, including the thesis objective and the work assumptions. Finally, public smart home databases are proposed to test the proposed framework.

Chapter 3 introduces a methodology for modeling of the smart home inhabitant life habits. To this aim, Stochastic Timed Automaton (STA) is defined and its generation procedure introduced. This procedure require a training phase during which the inhabitant behavior is observed, whose length is discussed. A case study is proposed to assess the relevancy of the procedure and the model.

In the fourth chapter, normalized likelihood and distance between an observed duration and a probabilistic distribution are introduced to detect behavioral anomalies. To test these measures, artificially generated or modified database are used as case studies.

Finally, chapter 5 introduces long-term deviation detection. Data forecasting is proposed in order to analyse trends in the inhabitant behavior to detect potential future anomalies before they occur, allowing for preemptive actions and early prognosis for medical team. To conclude the chapter, case studies is proposed on real and artificial data to test various situations.

The last chapter summarize the contribution of this manuscript and review potential future works and outlooks.

As these thesis handles sensible private data, there exist potential ethical negative or invisible impacts. In order to assess these impacts, which is a required step to decrease their effect, a framework is proposed in appendix A. Finally, appendix B proposes a proof of a theorem introduced in chapter 3.



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# CHAPTER 1

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## Ambient Assisted Living and Health at Home issues and objectives

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*"Être vieux, c'est être jeune depuis plus longtemps que les autres. C'est tout."*  
- Philippe Geluck, *Le Chat*, Tome 16 : *Le chat*, acte XVI -

### Abstract

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Due to the population ageing, the number of people requiring specific health care and monitoring is increasing in most countries of the world. Smart home technologies and Health at Home scientific field propose to assess the health status of a smart home inhabitant by monitoring specific vital signs. However, some diseases affect inhabitant's behavior first before being noticeable through vital signs monitoring. Thanks to recent works about activity recognition, the list of activities carried out by the inhabitant is accessible, which enables to assess the health status of an inhabitant by observing his behavior.

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### Contents

---

1.1	Motivation . . . . .	6
1.2	Literature review . . . . .	8
1.2.1	Smart Homes . . . . .	8
1.2.2	Ambient Assisted Living and Health at Home . . . . .	12
1.2.3	Activity of Daily Living discovery and recognition . . . . .	14
1.3	Existing public smart home databases for AAL . . . . .	15
1.4	Conclusion . . . . .	16

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## 1.1 Motivation

Thanks to numerous improvements in public health, medicine, and social development, mortality rate in most societies dropped while life expectancy increased. These improvements, combined with societal factors, also lead in a second step to a fall in birth rates. The temporary difference between mortality and birth rates leads to an important increase of the total population, bringing at the same times opportunities and challenges to our societies. This demographic transition has either already happened or is happening in most countries in the world.

One of the many consequences of this transition is the increase of the number of people aged over 65 years, while the number of people aged 25 or less is stable or decreasing. Figure 1.1 illustrates this phenomenon happening in most countries in America, Europe and east of Asia. However, on the long term, most countries in the world will face this increase.

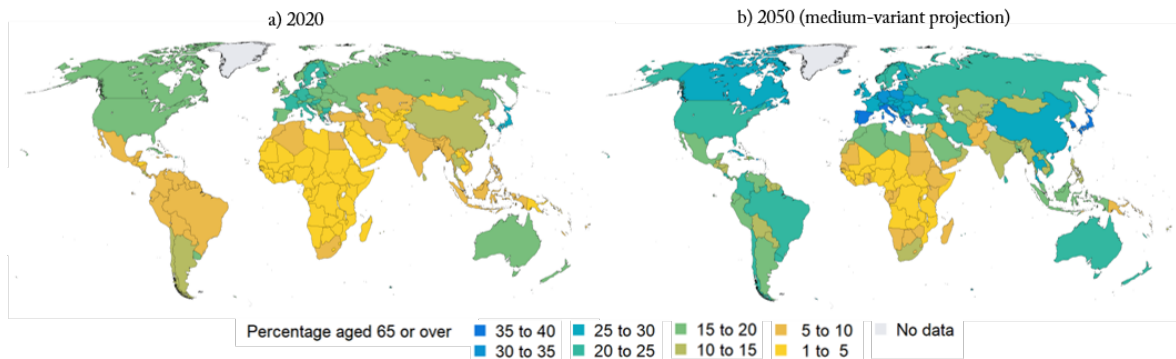


Figure 1.1: Percentage of population aged 65 or over in 2020 (a) and projection for 2050 (b) [United Nations and Social Affairs, 2020].

From this situation, two challenges to our societies emerge.

On the one hand, this part of the population faces more health problems and declines. For instance, in the US, the proportion of older adults reporting one or more chronic diseases was 92.2% in 2008, the proportion reporting impairments was 44.4% and 25.4% declared suffering from activities of daily living disability [Hung et al., 2011]. Consequently, this population requires specific health care, institutional funds and dedicated organization.

On the other hand, population ageing leads to a decrease in the potential support ratio. Potential support ratio is the ratio between the number of people aged between 25 and 65 years old, which typically generates more income than they consume, and people aged 65 or more, which generally consumes more income than they generate. It describes the economic burden placed on the working population to fund needs of retired population. The lower the potential support ratio, the higher this burden. Evolution of the potential support vector is illustrated in figure 1.2. It is expected to decrease in most regions of the world. It implies that financial means allocated to the oldest part of the population are expected to decrease as well.

There already are existing solutions to offer to the elderly satisfying quality of life and health. Dedicated clinics, nursing home, or residential care, such as EHPAD

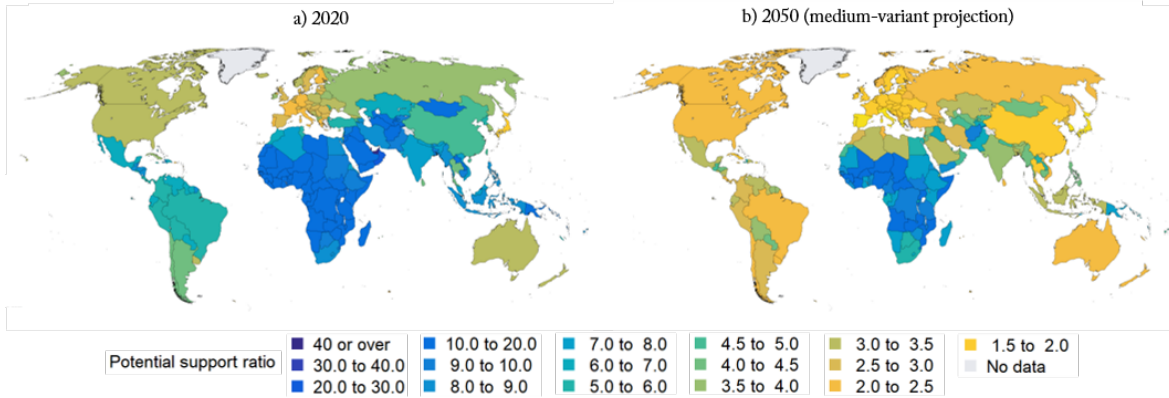


Figure 1.2: Potential support ratio (number of people aged 25-64 over those aged 65+) in 2020 (a) and projection for 2050 (b) [United Nations and Social Affairs, 2020]

(établissement d'hébergement pour personnes âgées dépendantes) in France, are some examples of such solutions.

However, these solutions are not scalable enough to face the upcoming increase of aged people. They are also costly, which is not compatible with the expected reduction of the potential support ratio.

Moreover, most of the elderly prefer staying in their home rather than losing their autonomy for numerous personal, financial, affective, and family reasons [Roy et al., 2018]. Finally, being placed in residential home has been associated with higher risk of solitude and depression, which can heavily impact the health status of an individual [Weyerer et al., 1995].

Consequently, innovative approaches have to be explored to ensure a good quality of life, care, and physical and mental health for the elderly at home, while limiting the economic impact by offering low-priced solutions.

Ambient Assisted Living (AAL) is a field of research which aims at providing adapted solutions to help frail people to live independently in their home.

AAL exploits smart home innovative technologies and equipment to support elderly people in their daily life. It helps population to stay the most autonomous possible by increasing quality of life and safety at home. It is a very large domain as it encompasses multiple applications, such as health, safety, or mobility, through various environment levels: sensors, data capture, data processing, machine learning, etc. [Dohr et al., 2010]

The AAL European program proposes a list of objectives AAL has to fulfill. It includes:

- Improving safety at home, for instant with fall detection systems;
- Maintaining interaction with other people;
- Maintaining physical and mental abilities;
- Assisting carers by offering them information and coordination tools;
- Early detection of risk to reduce the number of accidents.

This chapter proposes a review of existing solutions within AAL scientific field and their limits. First, smart home concepts and technologies are introduced, as well as various domains in which smart home equipment offer interesting opportunities. Then, AAL definitions and some works are explored, before focusing on Health at Home (HaH) issues, existing solutions, and limits.

## 1.2 Literature review

### 1.2.1 Smart Homes

Smart home (SH) definition varies depending on the scientific field considered [Solaimani et al., 2015]. A common, broad definition is offered by [Aldrich, 2003]:

**Definition 1.1 (Smart Home)** *A smart home can be defined as a residence equipped with computing and information technology which responds and anticipates the needs of the occupants, working to promote their comfort, convenience, security and entertainment through the management of technology within the home and connections to the world beyond [Aldrich, 2003].*

Smart home is the adjunction of four main components to a home [Gunge and Yalagi, 2016]. A user interface which can consist in a smartphone, a monitor, or a personal assistant; a mode of transmission which can be classified into two categories: wired connections, typically Ethernet connection, and wireless connections such as infrared or Bluetooth connection ; home electronic devices which can be active appliances such as lamps and heaters, or control devices such as sensors or switches; These devices are connected to a central controller, communicating through the user interface and controlling the domestic services.

An example of these components is proposed in figure 1.3 from [Asadullah and Ullah, 2017]

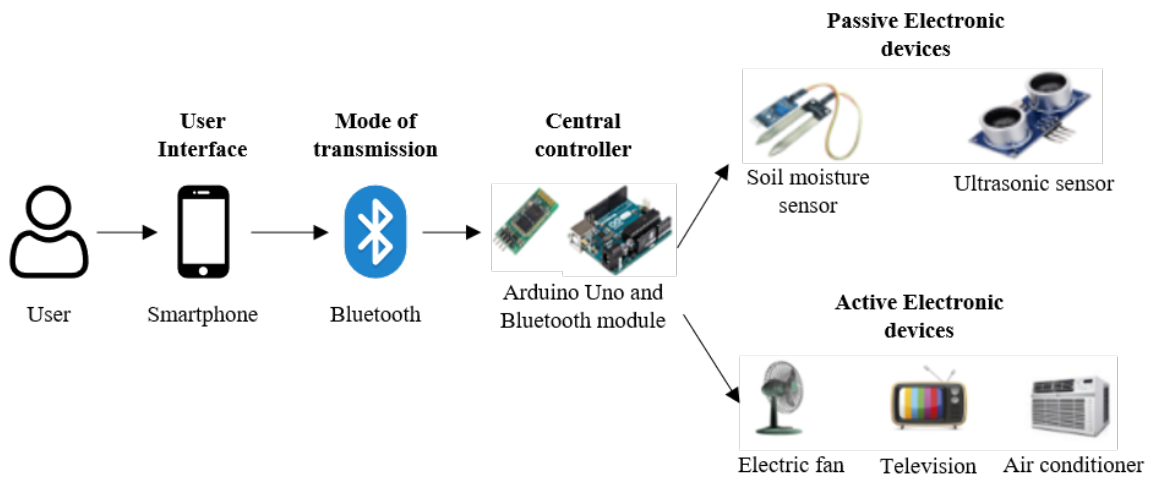


Figure 1.3: Example of a smart home equipment. Extracted and adapted from [Asadullah and Ullah, 2017]

Smart home differs from a simple automated home in the sense that it is able to connect and exchange information with the outside world [Solaimani et al., 2015, Gann et al., 1999]. Home is interactively connected to other homes and various stakeholders depending on the offered services -for instance energy provider or health care institutions- and exchanges information. Smart home is consequently not limited to the residence area, but consists in a whole environment. Consequently, some authors consider that the term "smart home" is limited, preferring the term "Smart living" [Solaimani et al., 2015]. In this thesis, denomination "smart home" is adopted.

The concept of smart home appears in the eighties under various terms: "electronic home", "intelligent home" [Gann et al., 1999] or "domotique" in France. It grows rapidly since the start of the two-thousands with the development of powerful processors, data storage capabilities, and the growth of wireless communication protocols and adapted appliances which reduce the cost of smart home equipment while increasing their ease of use.

Smart homes offer multiple opportunities for various domains. A non-exhaustive list is proposed in the next subsections.

### Home automation

One of the first applications of smart home was to automate tasks in the home to reduce human labor. Applications can be very diverse.

For instance, authors in [Vázquez et al., 2013] propose to control air quality and thermal comfort of a smart home by analyzing the habits of the users in terms of room occupancy, consumption and preferred temperatures, humidity and ventilation. To achieve this task, HVAC (Heating, Ventilation, and Air Conditioning) systems are coupled with agents dedicated to decision-making, conflict resolution, user preferences, global goals, etc. Depending on the preference of the user and its habits learned through observations, decision-making agents controls HVAC systems to optimize comfort and energy saving. Contrary to existing automated applications, this work fully embraces the concept of smart home by considering the individual preferences and communication with external stakeholders to optimize its performances.

[Kim et al., 2013] also considered thermal comfort by analyzing the activity level of the inhabitant and adapting the air conditioner accordingly. Location and speed of the inhabitant is estimated by observing the occurrence of pyroelectric infrared (PIR) sensor events located all over the dwelling. They are then used to estimate the physical activity and metabolic rate of the inhabitant to provide adapted room temperature.

[Asadullah and Ullah, 2017] proposes an implementation of a low-cost and robust home automation system by considering Arduino board and Bluetooth technology, testifying for the ease of installation and the possibility for most traditional homes to be equipped in a near future. Full equipment is depicted in figure 1.3. They considered irrigation automation as a case study, demonstrating that smart home technology is not limited to dwelling but may also be exported to whole buildings, cities or factories.

## Energy management

One of the main objectives of smart home is energy management. New technologies enabled to switch from a centralized energy management system -on the scale of a region or country- to a local management -on the scale of individual dwellings. This transition is motivated by new concerns regarding security, environment, development of intermittent energy, economy and stress over energy grid due to peak of energy consumption at specific hours.

Smart home technology is an adapted solution to monitor and manage energy consumption and storage. These functionalities are illustrated and developed in figure 1.4 from [Zhou et al., 2016].

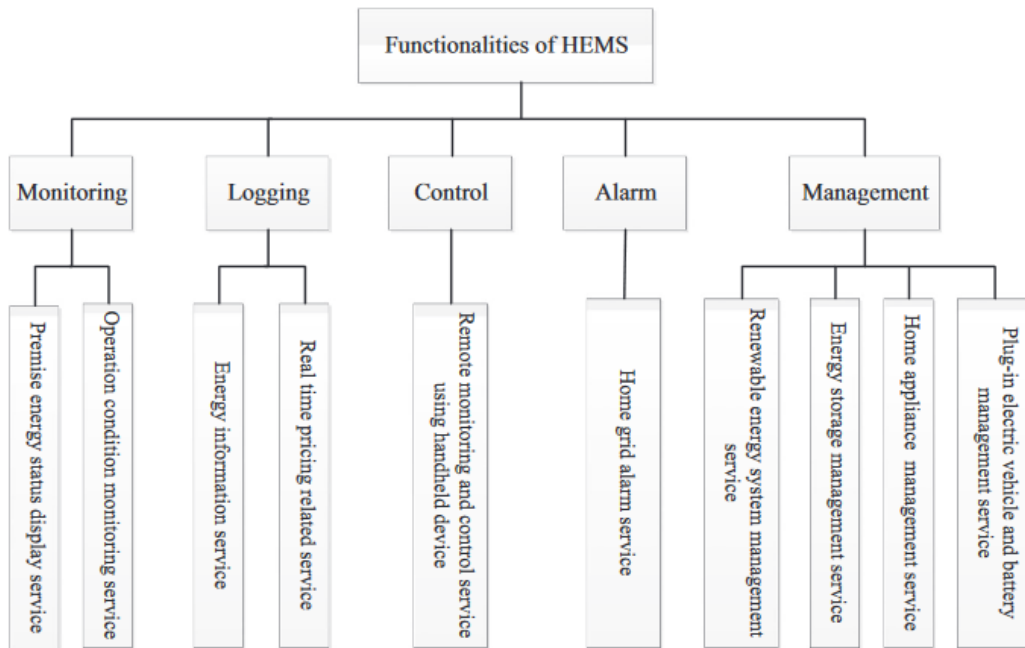


Figure 1.4: Smart home energy management system (HEMS) functionalities [Zhou et al., 2016]

In particular, authors in [Komninou et al., 2014] stated that communication with energy providers and appliances control allows:

- better demand-response programs, reducing user energy bills if his energy consumption complies specific agreements, for instance by avoiding energy peak demands;
- optimization of potential required load shedding, i.e. switching off electrical supply when shortfall;
- limitation of energy wastage, notably by easing communication and feedback from energy providers to users;
- energy exchanges, i.e. allowing scenarios where the user becomes an energy producer, for instance if he possesses renewable energy generators or important storage capabilities due to electric vehicles or others.

Several authors such as [Kuzlu et al., 2012] demonstrated the feasibility of such applications by using a laptop computer with a ZigBee communication module to control a hair dryer, portable AC unit and two heaters simulating heavier loads such as clothes dryer, air conditioner, water heaters and electric vehicles.

### Security

Many research works explore security issues and consider smart home technologies as potential solutions. Threats toward user security can be classified into two categories: inopportune threats to anyone safety, i.e. unintended intrusion and domestic accident such as fire or gas leak, and threats inherent to smart home technologies.

Most existing works focus on intrusion, fire, flood and gas leak detection. Smart home technologies offer new opportunities as the diversity of the sensors which can be used and their intercommunication allows for better context-aware decision. This way, some works such as [Bangali and Shaligram, 2013, Jose and Malekian, 2017] propose decision trees which exploit gas and temperature sensors to detect dangerous situations, with motion and light sensors to adapt their decision-making. Other works exploit the communication protocols of smart home to warn the inhabitant by email or SMS (Short Message Service) and provide him adapted information, such as photo or video, to let him make a decision in case of intrusion [Tanwar et al., 2017]. Feasibility of such approaches was demonstrated by [Ferreira et al., 2018] who proposes a miniature model to test specific scenarios.

Smart home technologies bring many opportunities, but also threats of new nature to our everyday life. These new threats, and potential countermeasures, were explored in [Komninos et al., 2014]. Confidentiality, integrity, service availability or authenticity are some examples among others of the domains which are endangered by new types of security attack. These attacks can be passive, i.e. they do not harm data or systems but allow adversaries to obtain illegally information, or active when data alteration or system damage is the assailant's objective. Traffic analysis is an example of passive attack, while malicious software, denial of service or masquerading, i.e. an intruder pretending to possess the privilege access, are examples of active attacks. Countermeasures of such threats are still an ongoing work. For instance, encryption and anonymization techniques are developed to ensure privacy of user data while ensuring its authenticity.

### Other domains

Many other domains are offering new opportunities thanks to recent smart home technologies. The previous subsection enlists some of the fields that were the most impacted, but many others are or will be influenced by the new offered opportunities: Education by using voice-recognition and cameras to simulate a real classroom and its interactions [Shi et al., 2003], pervasive video games, i.e. game combining virtual elements and the whole surroundings of players [Guo et al., 2012], or even communication and e-commerce [Keegan et al., 2008].

Health is another field which is and will mutate thanks to the smart home technologies. These opportunities are described in more details in the next section.

### 1.2.2 Ambient Assisted Living and Health at Home

#### Ambient Assisted Living

Techniques and applications developed to ease ageing at home are part of Ambient Assisted Living (AAL). AAL aims at providing to anyone, but more specifically frail and old people, tools to prevent, cure, and improve life and health conditions at home [Rashidi and Mihailidis, 2012].

Fall is one of the most common problems faced by the elderly. According to [Ageing and Unit, 2008], 30 to 50% of people living in long-term institutions fall each year, and 40% regularly, while falls accounts for 40% of all injury deaths. Consequently, many AAL works consider fall detection to call for the emergencies when required, reducing the mortality rate. Various technologies are considered. Some authors consider wearable sensors to detect fall and assess of its gravity, for instance with temperature sensors. Smartphones are also considered as they are often carried by individuals, possess many relevant sensors, and ease communication with the inhabitant to confirm if he is injured and require assistance [Ng et al., 2021]. However, the inhabitant might, willingly or not, not wear the sensors at all time. To counter this drawback, some authors exploit vision-based approach thanks to cameras. They offer very satisfying results if the fall detection algorithm is sufficiently trained [De Miguel et al., 2017]. Nonetheless, these solutions raise concerns about life privacy preservation. Solutions based on specific cameras, such as depth cameras [Kong et al., 2018] are proposed as the obtained image does not allow to identify the inhabitant and preserve his privacy, but inhabitant acceptance is still low [Townsend et al., 2011].

AAL encompasses many other various domains. As physical decline is one of the major health problems the elderly will face in their life [Hung et al., 2011], mobility and automation helper solutions are explored. [Dubowsky et al., 2000], among others, proposes a support and mobility system able to communicate with the various sensors within smart home to control inhabitant's speed and know his position to avoid obstacles. Solitude is also subject of interest as social isolation is associated with increased risk of cognitive impairment [Wilson et al., 2007]. Easing communication of elderly people with the outside world, more particularly with relatives from the younger generation, has been explored by some authors [Vetere et al., 2009]. Finally, [Khan et al., 2010] proposes web-based tablet application management tools to help medication of old people as persons suffering from cognitive decline might sometimes be negligent.

#### Health at Home

On the other hand, Health at Home (HaH) aims more specifically at monitoring the health status of a smart home inhabitant to observe the evolution of specific symptoms and even, in some cases, detect new medical symptoms.

Most HaH applications concern continuous vital signs monitoring. To observe relevant vital signs information, many wearable sensors were developed, including e-textile sensors, i.e. sensors embedded in clothes to be more easily accepted by the elderly and to be the most discreet and less invasive possible. Some examples are given in figure 1.5 from [Patel et al., 2012].

With these sensors, vitals signs such as heart rate, blood pressure [Khalil and Sufi,

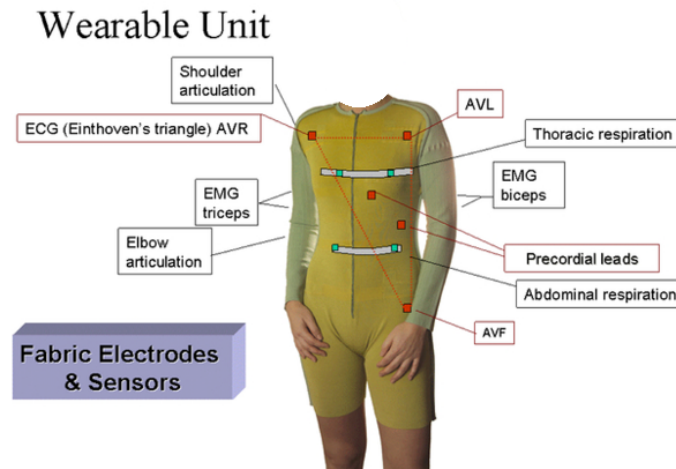


Figure 1.5: Examples of wearable sensors and e-textile equipment [Patel et al., 2012].

2008], or body temperature [Forkan et al., 2015] are monitored to detect anomalies corresponding to specific health problems.

As the inhabitant might forget to wear his sensors, a few authors such as [Hodgins et al., 2008] proposes to use directly medical implants illustrated in figure 1.6, nullifying impact of inhabitant omissions. However, these sensors obviously raise some concerns about ethics and patient acceptability [Reinares-Lara et al., 2018].

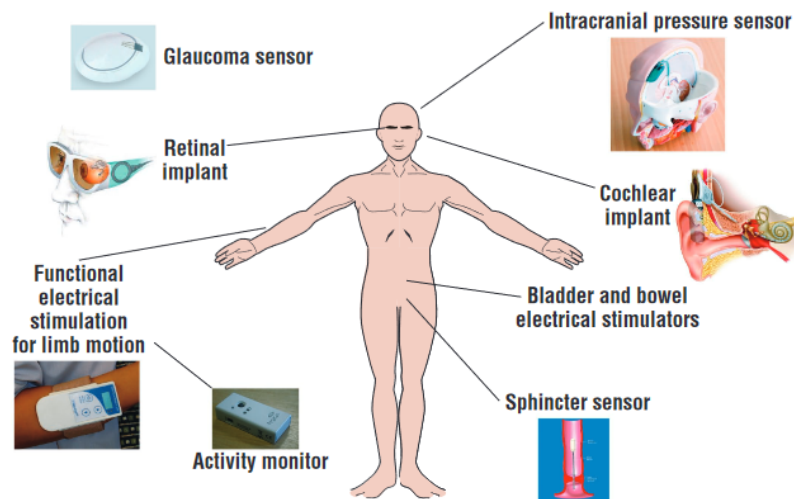


Figure 1.6: Examples of medical implants to monitor inhabitant's vital signs [Hodgins et al., 2008]

Thanks to communication technologies, all these devices are able to contact health care providers, emergencies, or user relatives in case of critical situations. They can also offer a regular check-up to medical staff to ease their medical follow-up. Finally, applications can also warn the inhabitant himself if a vital sign becomes concerning to adapt his behavior.

These works bring interesting results for better health care at home by providing medical staff continuous up-to-date information about precise vital signs. However, these works grow concerns about life privacy invasiveness. Moreover, many diseases do not have direct impact on these vitals signs, but affect behavior first [Chalmers et al., 2019], [Kaddachi et al., 2018]. This is particularly the case for cognitive disease or physical decline. For instance, Alzheimer’s diseases does not directly impact the global health status of an individual, but will disturb his life habits such as his eating or sleeping patterns. These disruptions may in turn disrupt the vital signs of the inhabitant.

This situation raises two concerns:

- As the causal link between the responsible disease and the detected symptoms is indirect, it is very hard for medical staff to diagnose these types of diseases [Blennow et al., 2015];
- Vital signs are affected in a second step. Consequently, detecting health decline means the responsible disease has affected the inhabitant for a long time. This is particularly worrisome as these medical troubles are better healed -or at least better managed in the case of incurable diseases- the earlier they are detected [Mortimer et al., 2005].

As these specific health troubles primarily affect the elderly, innovative solutions in AAL have to be explored to answer this need.

### 1.2.3 Activity of Daily Living discovery and recognition

Obtaining information about the activities carried out by the inhabitant is often required for a better health monitoring. Inhabitant’s behavior refers to the way the inhabitant conducts his activities of everyday life, for instance meal or sleep activities. Several behavioral features can be considered, such as the time or the order in which these activities are performed. These features are discussed in more details in chapter 2. Obviously, possessing more information about the behavior of an individual is also very interesting for other applications, such as energy management or security.

First works proposed to interpret sensor logs in order to know the localization of the inhabitant [Danancher et al., 2013], but more recent works offer to access to a higher level of semantics by detecting and identifying the tasks carried out by the inhabitant during his everyday life. These tasks are denoted as activities of daily living (ADL) which refers to the set of activities an individual performs every day that allows independent living. It includes basic activities such as feeding, dressing or personal hygiene, as well as advanced tasks such as exercising or working [Cook and Krishnan, 2015].

ADL detection is usually performed in two steps: activity discovery, and activity recognition. Activity discovery aims at discovering activities in raw sensors data thanks to unsupervised learning algorithms. In most works, it consists in modeling the usual way for the inhabitant to carry out a given activity. This can be done by pattern mining methods [Agrawal et al., 1994] or manually made by experts [Saives et al., 2015] for instance.

Activity recognition, on the other hand, aims at exploiting the models generated in the activity discovery step to label a sequence of sensor events into activity labels [Cook et al., 2013]. A great variety of methods is used depending on the type of sensors the home or the inhabitant is equipped with. Some of them are intrusive, such as vision-based approaches, which can offer very relevant results when sufficiently trained, but requires to be adapted depending on the home and equipment [Chaaraoui et al., 2012], [Wu and Nevatia, 2005]. Some other works consider accelerometer data obtained by wearable sensors [Ravi et al., 2005] or smartphones [Brezmes et al., 2009]. These solutions are more respectful of privacy, and offer relevant results for physical ADL and actions. However, it is more challenging to obtain satisfying results for specific non-physical activities such as meal preparation or personal hygiene. Moreover, it requires for the inhabitant to always wear the sensors which is an important constraint.

On the other hand, many models consider binary information and sensors as they are considered less intrusive [Townsend et al., 2011] but deliver impactful information when many of them are strategically placed among the smart home. Most of the time, Hidden Markov Model (HMM) or other types of discrete models are used [Van Kasteren et al., 2010]. These methods often require labeled database for training, i.e. set of sensor events where activities carried out are already known. As this assumption is very restrictive, some authors proposed unsupervised approaches instead [Viard et al., 2016].

### 1.3 Existing public smart home databases for AAL

In order to test proposed methodologies and to train the algorithms when required, data is required.

Data can be generated by the authors themselves when the observed feature is easy to reproduce. This is particularly the case for fall detection, where authors can simulate a fall in front of a camera or while wearing a sensor as illustrated in figure 1.7.



Figure 1.7: Simulation of a fall in front of a camera to generate data. Adapted from [Bhandari and Babar, 2018]

However, many works required to obtain thinner information about inhabitant behavior which is personal and cannot be simulated. Consequently, some authors pro-

posed to equip some labs so that participants can carry out a given scenario [Lussier et al., 2019] or act as they would do in their everyday life for a few hours [Kadouche et al., 2010, Chikhaoui et al., 2010]. These approaches offer satisfying data for many applications such as dementia symptoms detection or activity recognition. MIMIC III database furnished by PhysioNet [Johnson et al., 2016], UCI Machine Learning Repository used in [Yahaya et al., 2019], and the Hadaptic platform from Telecom Sud Paris exploited in [Sfar and Bouzeghoub, 2018] are examples of such databases.

Finally, a few works require to know precisely the life habits of the individual to offer relevant results. It means data has to be consequent -a few hours of observation is definitively not enough- and has to be representative of a real behavior. Asking an individual to simulate his everyday life in a lab is consequently not satisfying anymore. In order to access to such data, the personal home of a participant is equipped directly. Such public databases are incredibly scarce, as equipping the dwelling of an individual and making the generated data publicly accessible induces many ethical and administrative constraints.

For instance, [Chalmers et al., 2019] exploits data from the Australian Department of Industry to observe energy consumption of an individual. CASAS databases from the Washington State University offer many different smart home database, including some where the inhabitant behavior is observed for several weeks or even months [Cook, 2010], [Cook et al., 2013]. Floor plans of some of these smart home databases are depicted in figure 1.8.

Instead of smart home databases, some authors provide smartphone data as it offers relevant information about inhabitant daily routine while offering fewer constraints [Berrouguet et al., 2018], [Kyritsis et al., 2018].

When a wide quantity of data is required, another method to obtain them is artificial data augmentation. After observing the inhabitant behavior for a few days, artificial data can be generated if his life habits are identified. It is also possible to voluntarily generate data which does not fit observed behavior in order to test anomaly detection algorithms [Arifoglu and Bouchachia, 2019], [Eisa and Moreira, 2017]. Finally, some recent works explore fully artificial database generation [Renoux and Klugl, 2018], but it is difficult to assess their representativeness.

## 1.4 Conclusion

This chapter highlighted the need for new innovative solutions in order to ensure frail people adapted health care and monitoring at home. Ambient Assisted Living scientific field aims at exploiting smart home technologies to ease ageing at home, for instance by detecting fall to make emergency intervenes the earliest possible. Most existing works focus on vital signs monitoring, which offer relevant information for many medical diseases.

However, some specific alterations affecting particularly the elderly alter their behavior first. This is critical, as it makes diagnosis difficult for medical staff while early detection is crucial for a good healing. Thanks to recent works about activity recognition, new level of semantic is accessible and novel approaches can be explored.





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# CHAPTER 2

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## Health at Home needs and work positioning

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*"Pour résumer le résumé du résumé : les gens sont un vrai soucis."*  
- Douglas Adams, *H2G2 tome 2 : Le dernier restaurant avant la fin du monde* -

### Abstract

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To offer medical staff relevant information, a medical and AAL survey is conducted. It highlights a limited number of diseases and associated symptoms the elderly are likely to suffer. It also underlines the behavioral features which are affected by these symptoms, and which are consequently insightful to monitor. The framework and assumptions of this work are then introduced.

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### Contents

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<b>2.1</b>	<b>Behavioral features and related symptoms and diseases .</b>	<b>20</b>
2.1.1	Activity ordering . . . . .	21
2.1.2	Activity duration . . . . .	23
2.1.3	Activity execution . . . . .	25
2.1.4	Activity time . . . . .	26
2.1.5	Activity number . . . . .	27
2.1.6	Behavior features summary . . . . .	29
<b>2.2</b>	<b>Anomaly and long term deviation . . . . .</b>	<b>30</b>
<b>2.3</b>	<b>Problem statement . . . . .</b>	<b>32</b>
2.3.1	Thesis objective . . . . .	32
2.3.2	Positioning . . . . .	33
2.3.3	Work hypothesis . . . . .	34
2.3.4	Proposed framework . . . . .	35
<b>2.4</b>	<b>Proposed databases . . . . .</b>	<b>36</b>
2.4.1	Selection of databases . . . . .	36
2.4.2	Data pretreatment . . . . .	38
<b>2.5</b>	<b>Conclusion . . . . .</b>	<b>38</b>

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# Introduction

Due to the ageing of the global population, mechanically leading to an increase of the number of people requiring specific health care, applications to ease their life at home have become an important subject of interest. In particular, monitoring the behavior of the inhabitant gives insightful information about his health status to medical staff. Moreover, this information is usually particularly difficult for medical staff to obtain.

Recent works about activity recognition enabled new innovative solutions to observe the behavior of a smart home inhabitant. Instead of just observing the sensors the inhabitant triggers while performing his everyday tasks, it is now possible to know precisely which activity was carried out, making new level of semantics accessible.

A few works offer to monitor inhabitants' behavior by observing the activities carried out. However, these works are scarce and scattered. If most of these works offer to detect anomalies in behavior, no global definition of behavioral anomalies or deviation is proposed. Moreover, human behavior possesses a considerable number of features, for instance the number of activities carried out or the time they were achieved. To the best of our knowledge, no existing work offers a review of these features and which ones are interesting to observe.

Consequently, in this chapter is proposed a short classification of existing works regarding the observed features and how their observation delivers insightful information about the health status of an individual regarding the type of anomaly to observe.

## 2.1 Behavioral features and related symptoms and diseases

In order to propose a relevant approach for medical staff, a state of the art has been conducted to know the diseases and symptoms of interest, and the way they influence the inhabitant's behavior.

The state of the art includes both works from the AAL community and medical community. Identified health problems and associated symptoms are depicted in figure 2.1.

It mainly includes various cognitive impairments such as Alzheimer or Parkinson's diseases [Sharma and Ghose, 2018a], [Elbayoudi et al., 2019], as well as physical decline due to ageing [Tsipouras et al., 2018] and fall which can be critical for the elderly [Planinc and Kampel, 2014]. More common diseases are also considered as they might trigger complications for the elderly.

For each disease or health problem is associated symptoms impacting the behavior of the sufferer. For instance, cognitive impairments might trigger confusion episode in the Activities of Daily Life (ADL) execution [Sharma and Ghose, 2018a], while a fall can be followed by an unusual period of inactivity if the inhabitant is not able to get up again [Planinc and Kampel, 2014].

These symptoms affect the inhabitant's behavior in many ways. These disruptions can be classified into five different categories: activity time, activity duration, activity execution, activity ordering and activity number. These categories are referred as

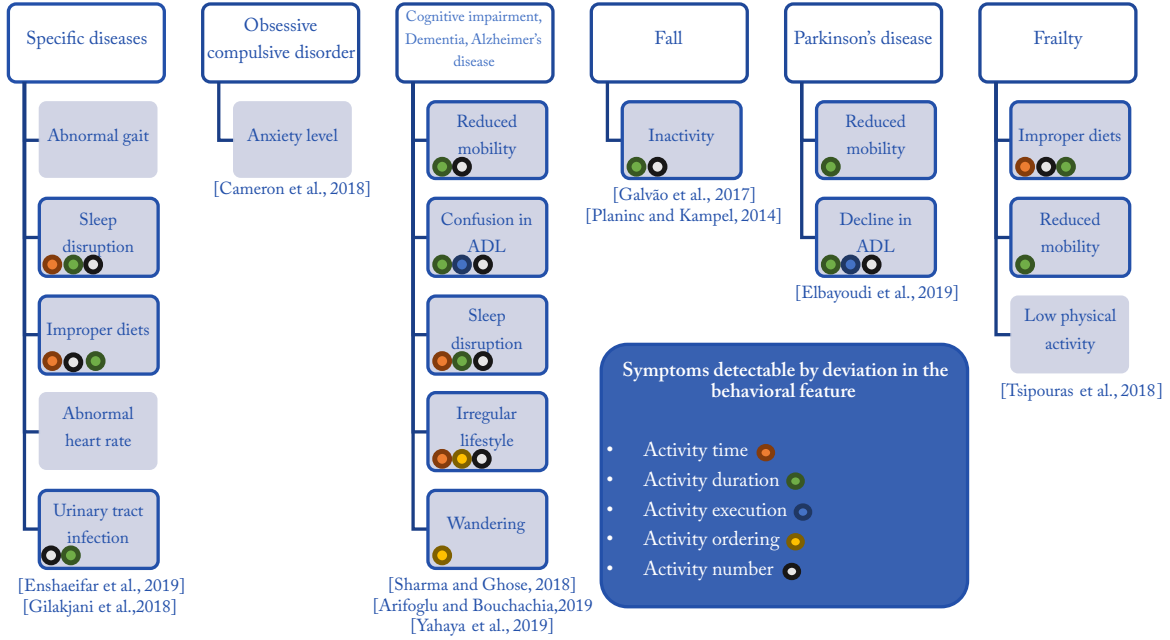


Figure 2.1: List of diseases and health problems of interest with associated symptoms, and behavioral features affected by each symptom.

behavioral features. For instance, frailty might cause a reduction in the mobility of the sufferer [Iaboni et al., 2018]. This symptom translates into a disruption in the activity duration as the inhabitant requires more time to perform his activities, or to move from a room to another [Tsipouras et al., 2018]. Some symptoms might affect several behavioral features. Sleep disruption due to common diseases such as influenza or more severe problems such as dementia may disrupt the time and duration of sleep activities [Yahaya et al., 2019] and causes unexpected naps during the day due to tiredness [Candás et al., 2014]. Finally, some symptoms require specific wearable devices, such as abnormal heart rate or anxiety level which can be detected by specific vision based process [Cameron et al., 2018].

It can be seen that the five identified behavioral features allow a good coverage of the symptoms and health problems the elderly are likely to suffer.

These behavioral features are explored in more details in the following subsections.

### 2.1.1 Activity ordering

Activity ordering, i.e. the order in which everyday tasks are executed, offers interesting information about the health status of an individual.

Before activity recognition was accessible, some authors have already explored this feature by observing inhabitant localization within his home. Cameras or simple binary infrared (IR) movement sensors can easily be used to assess the location of the inhabitant [Danancher et al., 2013]. By observing the evolution of his location during the day, it is possible to assess his movements within his home and to build a model

depicting his usual mobility in terms of room ordering. Some examples of mobility models are given in figure 2.2.

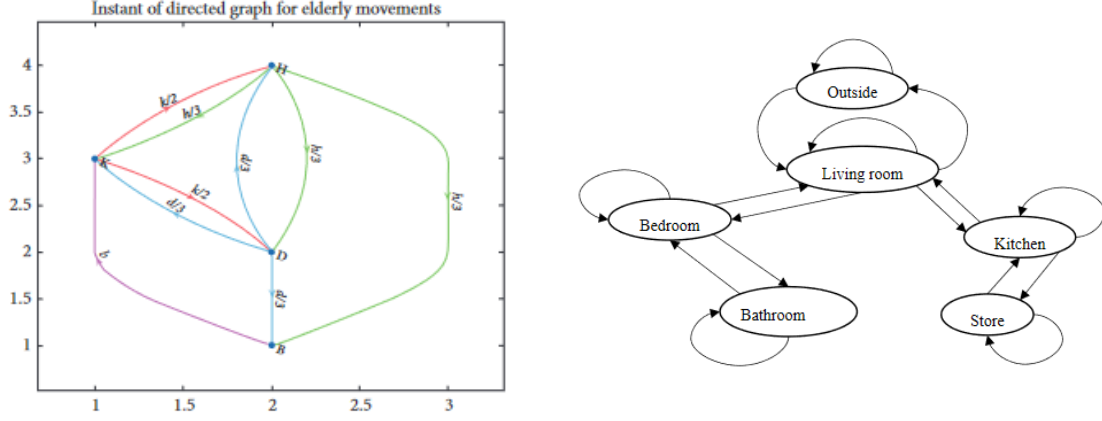


Figure 2.2: Examples of mobility model: weighted directed graph of mobility between four places of interest [Payandeh and Chiu, 2019] (on the left); Room-to-room state transition model for mobility between six different rooms [Eisa and Moreira, 2017] (on the right).

Observing changes in the movement habits of an individual can help diagnose dementia [Payandeh and Chiu, 2019] as unusual mobility can be associated with wandering or episodes of confusion. It also allows to assess the activity level of the inhabitant in order to detect physical decline or inactivity at unexpected moments [Eisa and Moreira, 2017]. Disruption in sleep, which can be detected by observing abnormal mobility at night and inactivity during the day, is another typical symptom which can be detected through this feature.

As a new level of semantics is now accessible thanks to activity recognition algorithms, recent works consider activity sequence to obtain more refined information about inhabitant behavior. Most of these works considered Hidden Markov Model (HMM) as it is a powerful tool to learn usual activity sequence performed by the inhabitant from training data [Forkan et al., 2015], [Sharma and Ghose, 2018b]. Some authors also use probabilistic models such as Bayesian models [Xu and Damen, 2018] which offer comparable results. In each of these works, the usual routine of the inhabitant is modeled from a training phase, i.e. a few days long period where the behavior of the inhabitant is observed. Once the model is built, newly observed behavior are compared to it to assess a change in the behavior. If a new behavior does not fit the model, i.e. possess for instance a low likelihood or log-likelihood score [Forkan et al., 2015], [Xu and Damen, 2018], an anomaly is detected. The model can also be used to predict what is the next expected activity and, if the model is sufficiently trained, an error can be imputed to the inhabitant [Sharma and Ghose, 2018b]. A few other approaches exploit Convolutional Neural Networks (CNN) or other types of Neural Network [Arifoglu and Bouchachia, 2019] to automatically raise anomalies within activity sequences. These approaches offer interesting results. However, they also grow concerns as they are black box approaches, which means it is not possible to precisely know for which reasons a behavior has been classified as anomalous. As the objectives

of our works is to offer information to medical staff to help their prognosis, these types of approaches are not well-suited.

Anomaly in human behavior regarding the activity ordering feature can be associated to many health troubles depending on the faulty activity sequence. For instance, forgetting to take his medicine, skipping a meal or having unexpected rest activities are anomalies which can be detected by focusing on this feature.

Nevertheless, activity ordering is particularly efficient to detect dementia and other cognitive impairment related symptoms. [Cankurtaran, 2014] proposes a list of symptoms for dementia, including wandering and sundowning syndrome. Wandering describes short episodes where the inhabitant is lost in his own home and do not know what to do, while sundowning syndrome designates confusion in behavior which typically happens in the end of the day. These symptoms are very difficult to assess for medical staff. However, they heavily affect the activity ordering feature of human behavior. When the inhabitant faces an episode of confusion, he is likely to perform activities in an unusual and irrational way. This feature is consequently well adapted to detect such symptoms.

### 2.1.2 Activity duration

Observing the time required to carry out specific activities is a very important feature of human behavior. It is useful for many diseases detection as numerous symptoms affect the time the inhabitant dedicates to specific activities.

Before activity recognition gained interest, a few works observed duration of room occupancy and transition between rooms to assess the physical status of the inhabitant. [Tsipouras et al., 2018] observe several features including the average time the inhabitant takes to move from a room to another in order to assess his frailty. This observation is performed thanks to Bluetooth beacons placed in each room. If room transition duration is significantly long, it might attest for the development of frailty and loss of mobility in general. Reduction of mobility is a concerning problem for the elderly as it is often associated with high risks of falls [Iaboni et al., 2018]. [Zamanifar and Nazemi, 2019] proposed a similar work by dividing the dwelling into cells instead of rooms to detect abnormally long stay duration in a cell. They combine the information with heart-rate from ECG sensors to offer relevant context-aware information to medical staff.

Thanks to activity recognition techniques, a few authors focus on the duration of specific activities to offer more diverse and refined information about the inhabitant's health status. Sleep activity has been the center of interest as sleep impairment is a common symptom to many diseases and negatively affect the inhabitant's ability to carry out normally physical activities [Chalmers et al., 2019]. Thus, [Yahaya et al., 2019] uses One-Class Support Vector Machine (SVM) to detect anomalies in sleeping patterns by considering sleep duration and time features. Figure 2.3 illustrates data used for SVM training. New data which is not part of the aggregate is considered as outliers and consequently considered as anomalous. In a similar way, [Kyritsis et al., 2018] detect anomalies within resting times of the elderly thanks to dedicated smartphone applications. An outlier is detected if the resting time is longer than a

specified threshold depending on the observed habits of the user, or does not fit a bi-variate normal distribution where variables are resting time and number of steps walked during the day or the application usage duration. However, these results are informative only if the user actually wears his smartphone during most of his day activities, which might not always be the case.

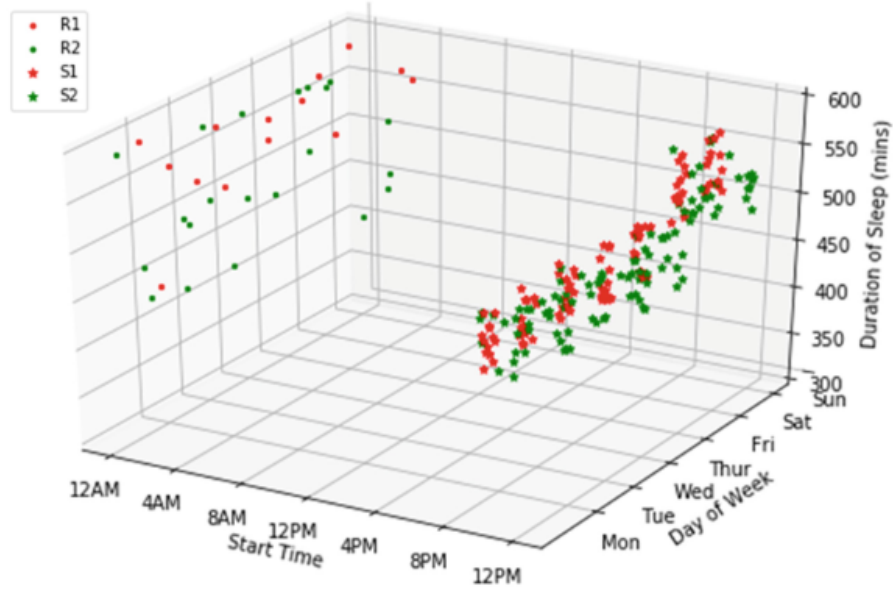


Figure 2.3: 3D plot of sleeping activity of real data of two individuals (R1 and R2) and synthetic data built (S1 and S2) [Yahaya et al., 2019].

Finally, authors in [Forkan et al., 2015] propose minimum and maximum duration for various activities, such as sleep, breakfast, or exercise activity, to detect abnormal behavior. For instance, abnormal breakfast duration might attest unbalanced diet which can trigger other consequences. These observations also allow for context-aware decision. As an example, if activity exercise is longer than usual, an increase in some vital signs, such as body temperature and heart rate can be considered as normal. This way, number of false alerts is greatly reduced.

In a slightly different way, observing activity duration is also a very efficient feature to assess physical state of a patient by making him run a dedicated scenario. [Lussier et al., 2019] proposed a list of 5 successive tasks, where the patient is asked to enter an equipped dwelling, cook and store groceries in the kitchen, use his bathroom and complete cognitive tasks. Within all these activities, time required to perform cooking activity was demonstrated as an efficient indicator to assess mild cognitive impairment. However, as some cognitive diseases' symptoms are episodic, continuous monitoring of inhabitant's behavior offers more information than scenario-based approaches which allow behavior observation only during a specific period of time.

### 2.1.3 Activity execution

Cognitive impairments, such as Alzheimer or Parkinson's diseases, mainly impair the old population. These diseases cause difficulties in execution of everyday activities as they reduce the physical and psychological capability of the sufferers and may cause episodes of confusion where the patient's behavior becomes chaotic and unusual. These symptoms can be detected by observing the way the inhabitant orders his everyday tasks, as stated in previous subsections. But some authors proposed instead to detect such symptoms by observing the way the inhabitant perform a given activity.

First works consider vision-based approach to detect abnormal gait or typical movements of anxious and stressed people. In particular, [Cameron et al., 2018] uses temporal motion heat map and classification models to detect checking behavior, i.e. actions which are irrationally repeated. These compulsions are typical of behavioral anxiety which can be caused by obsessive compulsive disorders or other cognitive impairments.

However, these types of approach are very challenging as it is difficult to interpret exactly the actions performed by an individual without adapted training data. Moreover, cameras and other vision-based sensors are often less accepted by the inhabitants as they are considered as intrusive [Townsend et al., 2011].

Instead, binary sensors offer a very interesting alternative. They are more easily accepted by the inhabitant and give very clear and precise information about his actions as there can only be one way to trigger these sensors. In particular, the order in which the inhabitant triggers the home sensors while performing a given task give insightful information about the way he is carrying this task.

If the sensor events sequence does not correspond to a model depicting the usual or normal way to perform the activity, an anomaly is detected. In [Parvin et al., 2018] is introduced a task model various temporal operations to model the activity in a hierarchical way. If the inhabitant actions do not fit this model, an anomaly is detected. The list of these operations and a task model example is illustrated in figure 2.4. This model offers very precise information about the inhabitant behavior. It however requires an expert to manually build an adapted task model depending on the activity of interest, which can be time consuming and not scalable to the massive number of dwellings to be equipped in the near future. Moreover, to avoid false alerts, the experts must consider various situations and ensure that the model is consistent with all of them, which can be challenging.

To counter these drawbacks, inhabitant behavior can rather be compared to the usual way the inhabitant performs a given activity. Authors in [Park et al., 2010] propose similarity functions to compare newly observed sequence of events with sequence of events performed during a training phase. Similarity function consider the number of common events between two sequences, but also consider their ordering and the time elapsed between sensor events firing.

Black box approaches can also offer relevant information, such as in [Arifoglu and Bouchachia, 2019], with the drawbacks which have already been introduced in previous subsection.

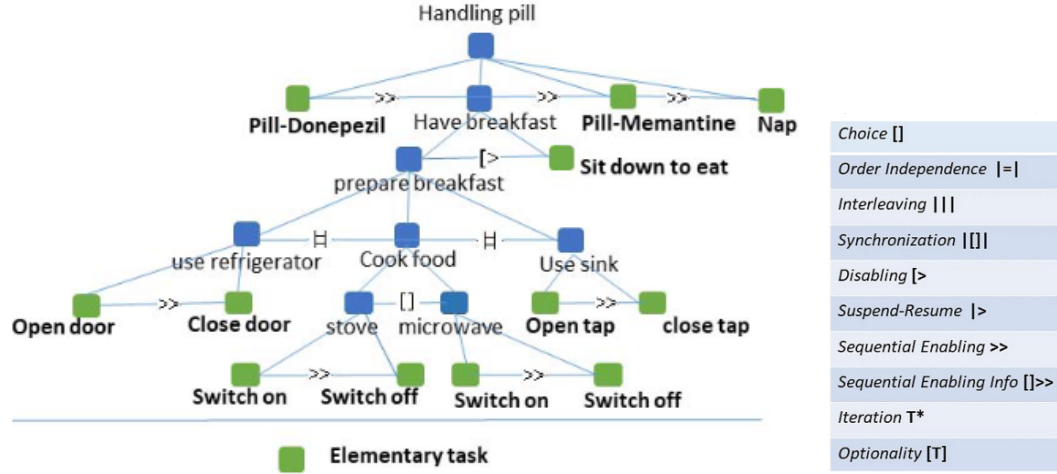


Figure 2.4: Example of task model presented in [Parvin et al., 2018].

### 2.1.4 Activity time

Many activities of every-day life are performed at specific hours, due to our routine or imperative biological needs. For instance, most people take their breakfast at a specific hour every day, and go to sleep between 9pm and midnight. Consequently, a change in these habits often conveys critical information about the health status of an individual. For instance, changes in sleep or meal time can attest for the existence of mental health problems, or may trigger other physical problems due to fatigue [Chalmers et al., 2019].

[Yahaya et al., 2019] cited earlier in subsection 2.1.2 use SVM classifiers to analyze the sleep pattern of an individual and detect potential sleep disruption. As illustrated in figure 2.3, sleep start time is an important feature to efficiently classify observed behavior. An early sleep time might testify of a fatigue symptom which can be due to physical decline or various common diseases, such as a cold, while late sleep time might attest for sleep disruption due to mental health problems which can in turn badly impact the overall health status of the inhabitant.

Sleep patterns can also be assessed in a less invasive way by observing the energy consumption peaks of a smart home. Energy consumption is associated with devices turned on, which attest that the inhabitant is active. Consequently, energy consumption the morning is particularly interesting to observe as it evidences that the inhabitant woke up. Authors in [Chalmers et al., 2019] propose a case study where energy consumption of a smart home between 5am and 12am is observed. A sample of this data is illustrated in figure 2.5. It consists in the energy consumption for the same dwelling for three different mornings. It can be seen that the first two mornings propose very similar schemes. The inhabitant wakes up and starts his daily activities between 5am and 6am. The third morning shows a clear change in this pattern. It might testify that he was not in his home this morning, that he oversleeps, or even worse scenarios.

Finally, [Forkan et al., 2015] observes a more important number of activities, such as meal activities, exercising, etc. The usual life routine of the inhabitant regarding activity time is represented through normal distribution. Parameters of such normal distribution can be determined after a training phase. It can also be manually deter-

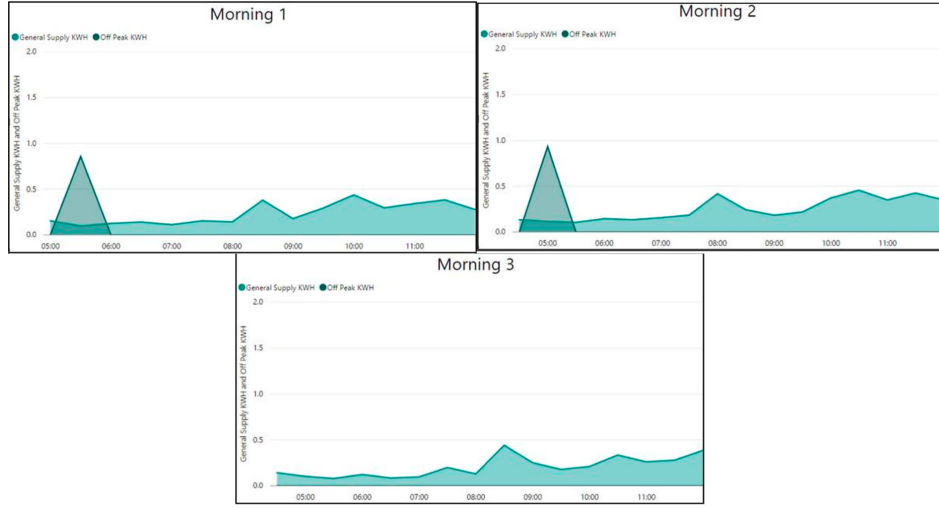
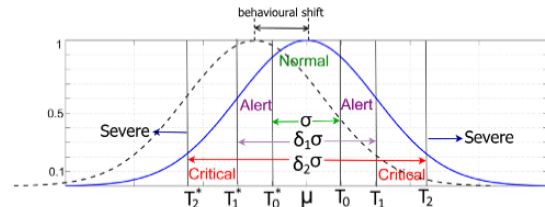


Figure 2.5: Sample of a smart home energy consumption between 5am and 12am [Chalmers et al., 2019].

mined by an expert stating which behavior is considered healthy. These parameters can evolve over time as long as no anomaly is detected to take into consideration potential behavior changes due to seasons. Examples of normal routine behavior regarding start time for various activities are illustrated in figure 2.6 a) (standard deviation, minimum and maximum duration are in minutes). From these parameters are built normal, alert and critical time ranges, displayed in figure 2.6 b). Depending on how much a newly observed activity time differs from the computed mean, new observed activity is labeled normal, concerning or anomalous.

Activity	Mean	SD	Min	Max
Sleep	22:30	30	400	500
Wake up	06:00	15	-	-
Breakfast	08:00	20	20	30
Exercise	10:00	20	15	30
Lunch	13:15	40	25	40
Dinner	19:30	30	30	40

(a)



(b)

Figure 2.6: Life routine of a smart home inhabitant regarding the start time feature (a) and the normal, alert and critical time ranges (b) [Forkan et al., 2015].

### 2.1.5 Activity number

The last human behavior feature observed in the literature is the number of activities the inhabitant carries out during a given period. This feature can be exploited in two different manners.

On the one hand, observing the total number of activities the inhabitant has performed for a day or a week is a reliable indicator of his overall physical status. The more the inhabitant is active within his home, the more he is likely to possess healthy habits.

This was explored by [Tsipouras et al., 2018] who uses various Bluetooth beacons to assess the mobility of the inhabitant. The number of times the inhabitant moves from a room to another is a relevant feature to assess his frailty level. In a similar way, [Planinc and Kampel, 2014] offer to detect abnormal behaviors by comparing the activity level of an inhabitant represented in a histogram with his routine. Moreover, inactivity is also explored as it might attest for serious health problems such as falls or fainting. If the inhabitant is inactive for too long and at an unusual moment in the day, an alarm is triggered.

On the other hand, it is possible to count the number of times a specific activity has been carried out to obtain more refined information about inhabitant's status. For instance, the number of meals an individual takes every day is a relevant indicator of his overall health. A decrease in the number of meals can be caused by various health problems, and may in turn decrease the overall physical status of the inhabitant, while an increase of meal frequency is associated with higher risk of obesity in adults [Tumin and Anderson, 2017]. The number of activities performed at night and the number of naps during the day is also a precious information to assess sleep impairments for medical staff [Candás et al., 2014]. On a different note, number of bathroom activities can also be used as a feature to detect Urinary Tract Infection (UTI) [Enshaeifar et al., 2019] which is a common disease in the elderly which can lead to serious medical complications. To assess if the observed number of activities is abnormal, comparison to the usual life habits of the inhabitant is often proposed [Enshaeifar et al., 2019], [Candás et al., 2014]. Usual life habits are extracted after observation of the daily life of the inhabitant for a few days. Other authors propose instead a model depicting the recommended practices from a medical team. [Saives et al., 2015] introduces the requirement flower which models the desired and undesired behaviors according to the recommendations of medical staff through an extended finite automaton. An example of requirement flower is given in figure 2.7.

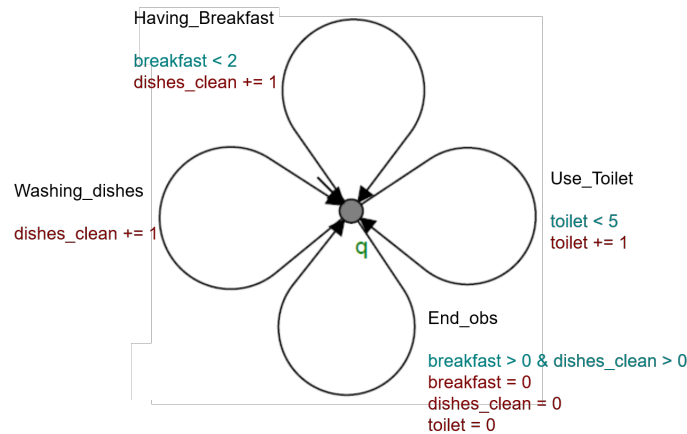


Figure 2.7: Example of a requirement flower depicting medical recommendations regarding activities "Having breakfast", "Washing dishes", and "Use toilet" [Saives et al., 2015].

### 2.1.6 Behavior features summary

The elderly population can be subject to many different diseases. These diseases can cause physical decline such as mobility problems, weakness, and other disturbances in specific activities, while cognitive decline can cause disruption in the usual routine of the inhabitant, and specific symptoms such as wandering or confusion episodes. To detect these health problems, five behavioral features were identified as relevant: activity duration, execution, ordering, time, and number.

Activity ordering is a very efficient feature to consider in order to detect changes in the routine of a smart home inhabitant, which are most of the time due to cognitive impairments.

Activity execution, i.e. the way the inhabitant carries out an activity, is also heavily impacted by these cognitive diseases, while allowing physical decline problem detection as some specific actions cannot be achieved anymore if the inhabitant become too frail.

Frailty is detected as well by activity duration as the inhabitant requires more time to perform specific actions. This feature is also impacted by a large number of health troubles such as mobility problems or health problems affecting specific activities such as sleep or eating patterns.

When the symptoms become severe, the inhabitant is likely not to execute some activities at all. Consequently, most of these symptoms can also be observed by focusing on the number of activities carried out by the inhabitant. Moreover, this feature may be efficient to detect very specific diseases such as urinary tract infection (UTI).

Finally, activity time is an interesting feature to detect disturbances affecting activities which occur at a specific time. Sleep or morning activities are some typical examples.

The coverage of each feature in regards to the symptoms they might detect is illustrated in figure 2.8. From this graph, two conclusions can be drawn:

- On the one hand, the activity duration and the activity ordering features cover the whole symptoms of interest for the elderly. Consequently, considering these two features alone is enough to detect most diseases they might suffer.
- On the other hand, the activity duration feature, besides covering many symptoms, is selective enough to identify a limited number of responsible symptoms when an anomaly is detected. Depending on the responsible disease, the set of affected activities and the way they are impacted differ. For instance, improper diet symptom will impact meal related activities and let the other unaffected, while sleep disturbances will affect only sleep-related activities. Activity ordering feature is mainly affected by wandering, sundowning, and irregular lifestyle symptoms. Identifying the specific symptom triggering an anomaly regarding this feature is trickier. However, these symptoms are all related to cognitive impairment diseases. Consequently, not being able to discriminate them is actually not a problem for prognosis.

Consequently, this work will focus on the activity duration and activity ordering features.

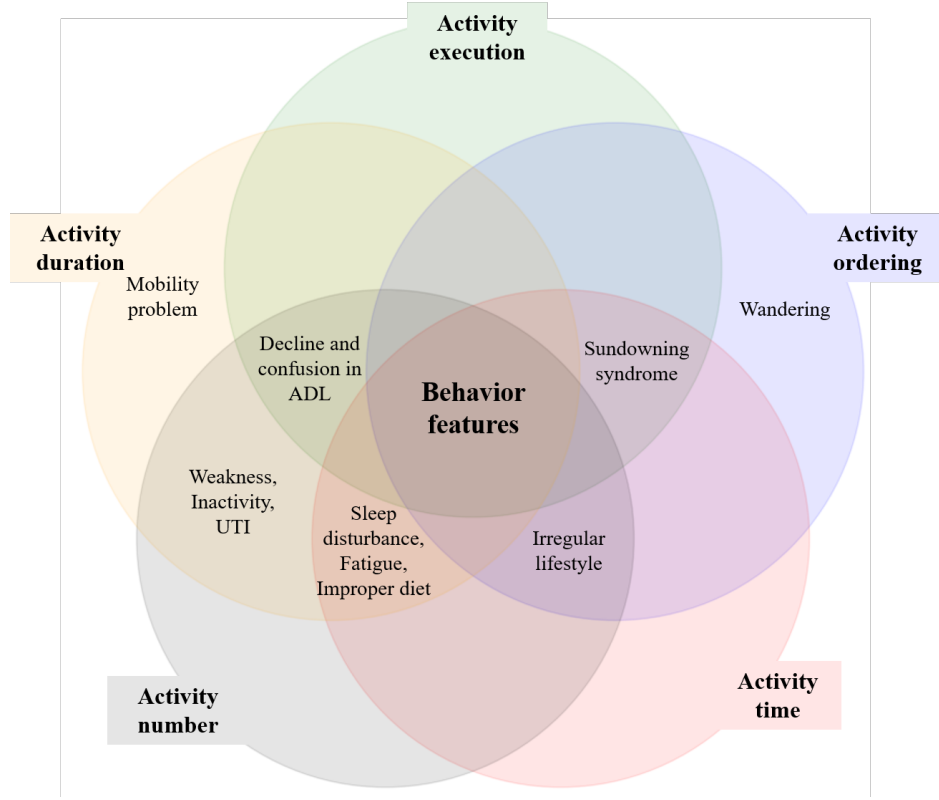


Figure 2.8: Relation between the five identified behavioral features and the symptoms they can detect.

## 2.2 Anomaly and long term deviation

When an individual is sick, his behavior is modified. As seen in the previous section, depending on the responsible disease, several behavior features might be affected. However, the way these features are impacted also varies from a disease to another. These impacts can be divided into two categories: behavioral anomalies and long term deviations.

**Definition 2.1 (Behavioral anomaly)** *A behavioral anomaly is a short-term behavior change which affect people's behavior at specific moments for a short time [Kaddachi et al., 2018]. They typically correspond to a fall, a wound, or to diseases appearing abruptly such as a cold or an infection.*

Most existing works considering behavior change detection focus on behavioral anomaly. These sudden changes can be detected by comparing the observed behavior to the usual routine of the inhabitant [Yahaya et al., 2019], [Eisa and Moreira, 2017] or to a model depicting healthy habits a healthy individual is expected to follow [Saives et al., 2015], [Parvin et al., 2018]. If the observed behavior fit the model, it is labeled as healthy: the inhabitant is carrying his everyday life as expected. Otherwise, the behavior is labeled as abnormal and might be affected by a health problem.

Some authors propose automatic diagnosis through decision trees [Eisa and Moreira, 2017] or rule-based methods [Forkan et al., 2015]. The disease the inhabitant is suffering

is automatically diagnosed by observing the way his behavior is affected. However, these approaches offer moderate results as medical diagnosis require specific expertise which is challenging to automatize. Consequently, most of existing works propose instead to provide information to medical staff to help them make a diagnosis rather than replacing them.

As it offers many advantages when applied to medical field, data forecasting has already been explored by some works for vital signs monitoring. For instance, [Khalil and Sufi, 2008] explored exponential smoothing forecasting method to monitor heart rate and blood pressure in order to detect early signs of tachycardia and fibrillation. [Forkan et al., 2015] also uses exponential smoothing to monitor numerous vital signs and detect problematic situations before they become critical. Figure 5.1 illustrates an example of body temperature monitoring and forecasting.

Some other diseases affect the inhabitant behavior in another manner. Degenerative diseases provoke slow declines in the physical and mental health status of the sufferer. Detection of such degeneration within the vital signs of a patient has already been explored, for instance for heart rate and blood pressure monitoring [Khalil and Sufi, 2008] to detect early signs of tachycardia and fibrillation.

Some of them, such as Frailty, Alzheimer or Parkinson’s diseases, are typical degenerative diseases which affect the elderly by triggering slow evolution of their behavior. In this thesis, these behavioral changes are denoted as long-term behavioral deviations.

**Definition 2.2 (Long-term deviation)** *A long-term deviation designates a change in behavior which continuously increases in amplitude over time for a few weeks, months, and some cases even year-long period. They are most of the time due to degenerative diseases which slowly degrade the health of the patient.*

Anomaly detection is not well-suited to detect these types of diseases for various reasons:

- As they gradually impact the behavior and the health status of the sufferer, they generate detectable behavioral alterations only after several weeks or months of affliction. Consequently, if an abnormal behavior due to such disease is detected, it means the responsible health problem has already affected the inhabitant for a long time. This is particularly critical as the earlier these diseases are detected, the better their negative effects can be countered or, at least, their evolution can be slowed down [Blennow et al., 2015].
- Their prognosis is difficult for medical staff as it is not possible to distinguish behavioral anomalies due to sudden diseases to anomalies which result to a long-term degeneration without any adapted tool. As these kinds of diseases, and mainly cognitive diseases, are already difficult to diagnose [Blennow et al., 2015], these approaches have limited interest for medical staff.

A very few works have proposed to detect these long-term deviations by considering Change Point Detection (CPD). It consists in identifying the moment when the behavior of the inhabitant changes from a routine to another. Times series depicting the

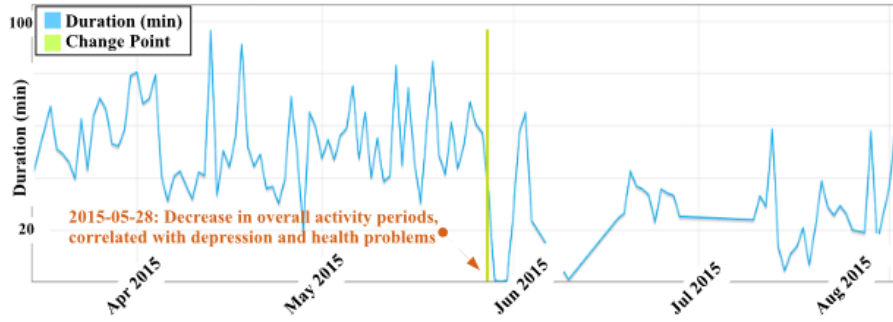


Figure 2.9: Detected change point in daily evolution of overall activity duration for a resident of a nursing home [Kaddachi et al., 2018].

activity level, sleep or other activities duration are often considered [Kaddachi et al., 2018], [Aminikhanghahi et al., 2018], such as illustrated in figure 2.9.

CPD is an adapted tool to detect precisely when an inhabitant became sick as it provokes an abrupt change in his behavior which lasts in time. However, it offers a moderate contribution for long-term deviations due to slow health decline diseases as it possesses the same limitations as anomaly detection: detecting an abrupt change in the inhabitant's behavior means he was sick for an already long time, and diagnosis is still difficult.

As it offers many advantages when applied to medical field, data forecasting has already been explored by some works for vital signs monitoring. For instance, [Khalil and Sufi, 2008] explored exponential smoothing forecasting method to monitor heart rate and blood pressure in order to detect early signs of tachycardia and fibrillation. [Forkan et al., 2015] also uses exponential smoothing to monitor numerous vital signs and detect problematic situations before they become critical. Figure 5.1 illustrates an example of body temperature monitoring and forecasting.

## 2.3 Problem statement

Previous sections offer an overview of the existing works and challenges behavior monitoring has to face to assess the health status of a smart home inhabitant and to offer medical staff the most relevant information. In this section is developed the objectives of our work, the associated assumptions and required definitions.

### 2.3.1 Thesis objective

Due to the world population ageing, the number of people requiring specific health care is increasing, while the financial means of public institutions is expected to decrease. Additionally, most of the elderly prefer to stay in their homes for public, financial, family and personal reasons.

From this situation emerges a new issue: how to help this population staying at home to have access to a quality of health and life comparable to the people moving to dedicated institutions?

To face this situation, new innovative solutions have to be explored. Smart home technologies offer new opportunities to ease life at home. Smart home concept and technologies were explored in chapter 1. In particular, Health at Home (HaH) scientific fields offer promising solutions by offering medical monitoring and care to people staying in their home thanks to dedicated wearable sensors. However, most of the existing works focus on vital signs monitoring, while many diseases affecting the elderly influence their behavior first. Consequently, prognosis of such diseases is particularly challenging.

Therefore, the objective of this thesis is to develop a framework to detect changes in the life routine of a smart home inhabitant in order to help medical diagnosis and prognosis. Three types of information have been identified as relevant for medical staff, and are the objectives of this thesis:

- **The life habits of the inhabitant**

Information about the routine of an individual often offers a clear overview about his health status, for instance if his behavior does not comply with some recommended practices. Sleeping or eating patterns are particularly insightful to observe.

- **Behavioral anomalies**

When an inhabitant is sick, his behavior is affected in different manners. Most diseases will make the inhabitant brutally change his life habits. Detecting such sudden changes help medical staff to intervene rapidly and eases diagnosis.

- **Long term deviation**

Some other diseases are degenerative, meaning they provoke a slow decline in the physical or cognitive capabilities of an individual. These diseases are particularly difficult to diagnose for medical staff for reasons raised in section 2.2. Detecting slow changes in the behavior of an individual can offer relevant information for medical staff to ease their prognosis of such critical diseases.

### 2.3.2 Positioning

In order to observe the inhabitant behavior, his dwelling must be equipped with sensors, enabling smart home applications. Thanks to existing activity recognition works, the list of activities carried out by the inhabitant is supposed to be known and feed an activity database. The list of activities to monitor, and consequently the way the smart home is equipped, depends on the medical staff who enlists the activities of interest they want to monitor.

The works proposed in this thesis allow to identify the life habits of a smart home inhabitant and to detect behavioral deviations in order to send them to medical staff. Contrary to some other existing works such as [Eisa and Moreira, 2017], the objective is not to replace medical staff by providing automatic diagnostics, but rather offering them information they do not usually have access which is efficient to assess the health status of an individual and diagnose the disease he is suffering if it is the case.

### 2.3.3 Work hypothesis

In order to achieve the considered objectives, several assumptions have to be assumed.

**Assumption 1 (Binary information)** *In this work, only binary information is considered.*

This assumption induces several advantages:

- Any technology can be used -and not only binary sensors- as any sensor can generate binary information by thresholding an analog or digital signal. For instance, vision-based sensors such as cameras can simply generate an event if a movement is detected. This way, the proposed approach can be applied to any smart home already equipped, and is not technology-dependent. Moreover, numerous smart home technologies are adapted to binary approaches, such as IR movement detectors, switch contacts, etc.
- These sensors enable life privacy saving solutions and are more easily accepted by the inhabitants [Townsend et al., 2011].

However, binary information is the poorest semantic information accessible, and consequently the most challenging to deal with.

**Assumption 2 (Activity recognition)** *The medical staff determines a list of activities to monitor depending on their expertise and the medical history of the inhabitant. Thanks to existing activity recognition algorithms, the activities carried out by the inhabitant is recognized and feed an activity database enlisting all carried out activities with their start and stop time. It is assumed that the activities are correctly recognized and labeled.*

**Assumption 3 (Single inhabitant)** *It is assumed the inhabitant lives alone in his home.*

This assumption is motivated by the association between loneliness and risk of physical and cognitive decline, especially Alzheimer’s disease [Wilson et al., 2007]. Moreover, when several individuals live under the same roof, it eases emergency call if one of the inhabitant suffer from a fall or a critical accident. They can also monitor each other, limiting risks to skip a meal or forget to take his medicine. This limitation can yet be relieved by using wearable sensors to be able to distinguish the inhabitants.

**Assumption 4 (Human behavioral features)** *In order to deliver to medical staff insightful information, proposed methodology focus on the activity ordering and activity duration features.*

To the health status of an individual by observing his behavior, five behavioral features were identified as relevant: activity duration, time, number, ordering, and execution.

However, as stated in subsection 2.1.6, activity duration and activity ordering alone ensure a full coverage of identified symptoms while being selective enough to determine which symptom is affecting the inhabitant’s behavior. Consequently, this work focus on these two features.

### 2.3.4 Proposed framework

Before introducing the global methodology we propose, a few definitions are required.

**Definition 2.3 (Sensor event)** *A sensor event  $e$  is an event generated when a smart home sensor is triggered by the inhabitant. It can be represented as a 3-tuple  $e = \langle s, t, v \rangle$  where  $s$  is the sensor name with potentially its type or location,  $t$  the event occurrence time and  $v$  its value.*

*The possible values a sensor event may take depends on the type of the sensor. For example, a binary sensor can only take ON or OFF values while temperature sensor can take any  $\mathbb{R}^+$  value.*

$e = \langle \text{IR01}, 2021-7-1 \ 8:10:22, \text{ON} \rangle$  is an instance of an event sensor. It designates an event generated by an infra-red sensor labeled IR01 with a ON value the July 1 2021 at 8:10:22.

**Definition 2.4 (Activity event)** *An activity event  $a$  is an event which can be represented as a 3-tuple  $a = \langle \text{activity}, \text{start}, \text{stop} \rangle$  where activity is the activity name, start and stop are respectively the start and stop times of the activity.*

$a = \langle \text{Eat Breakfast}, 2021-7-1 \ 8:10:22, 2021-7-1 \ 8:21:02 \rangle$  is an example of activity event. It designates an activity "Eat Breakfast" starting July 1 2021 at 8:10:22 and ending the same day at 8:21:02.

Proposed methodology is illustrated in figure 2.10. It consists in two main steps.

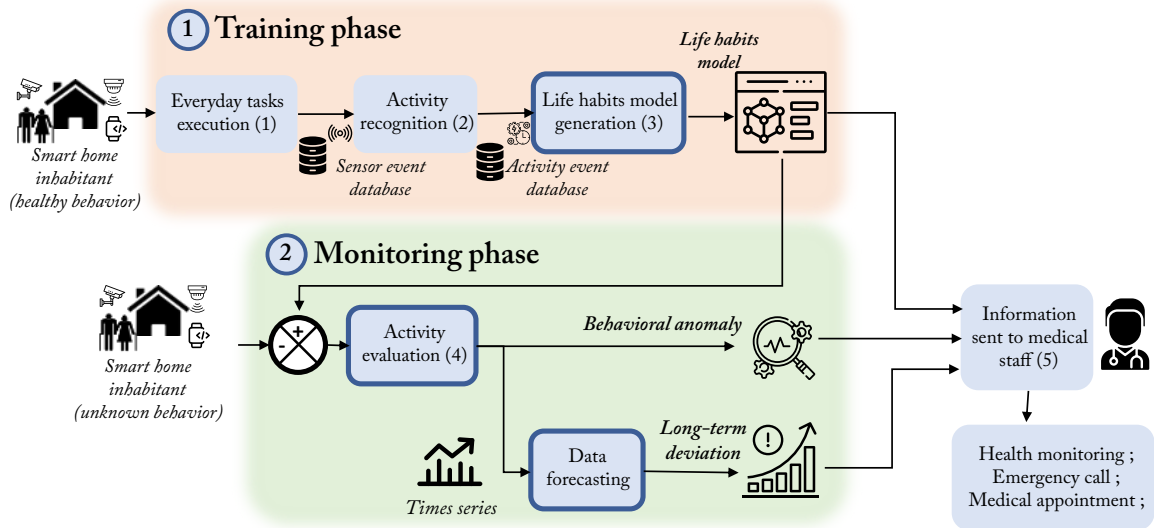


Figure 2.10: Proposed framework for behavioral anomaly and long-term deviation.

First, in order to detect behavioral deviations, a model depicting the usual life routine of the inhabitant must be built. This is done in the **training phase**. For a few days long, the inhabitant carries out his everyday life as usual (1). His behavior is supposed to be mainly healthy, for instance thanks to a visit to the doctor just before the training phase.

By carrying his everyday life, the inhabitant triggers the sensors surrounding him and generates sensor events which are stored in a sensor event database. Thanks to existing activity recognition algorithms (2) such as [Viard et al., 2016], carried out activities are identified from the log of sensors and stored in an activity event database.

Once the activity sequence database is generated, the usual routines of the inhabitant are depicted in a life habits model (3). This model will be used as the reference model for behavioral deviation detection. The generation of such a model is the first contribution of this thesis and is introduced in chapter 3. This model focus on activity ordering and duration as these features were identified as the most relevant for health monitoring and symptoms identification. This model offers medical staff relevant information about some patterns of the inhabitant, such as his sleeping or eating patterns, which can help to assess his health status.

On a second step, generated model is exploited to detect behavioral deviations which are due to medical diseases. This second phase is the **monitoring phase**. The inhabitant continues to carry out his everyday life, but his health status is uncertain. He might be healthy or suffering from various diseases and health declines.

To assess his health status, his behavior is compared to his usual life habits previously modeled (4) to detect two types of deviations: behavioral anomalies and long-term deviation. Anomaly detection is explored in chapter 4, and long-term deviation is introduced in chapter 5.

Potentially detected deviations are sent to medical staff who will be able to act accordingly (5). Medical staff can either record the anomaly to refine the next periodic medical check-up, call for an appointment, or contact emergencies in critical scenarios.

In order to test the proposed methodology, several public databases of smart home inhabitant have been chosen. They are described in next section.

## 2.4 Proposed databases

### 2.4.1 Selection of databases

To validate the approach, a case study is presented throughout this thesis. In order to be the most representative of real-life situations, it is proposed to use public database of real inhabitants. Several of them were presented in chapter 1. However, all of them are not adapted to the objective and the assumptions which just have been introduced as the database must consider binary information, inform about the activities carried out by the inhabitant, and focus on a single inhabitant.

Two of them were identified as relevant, and are presented below.

#### DOMUS database

The DOMUS database [Kadouche et al., 2010, Chikhaoui et al., 2010] proposes to observe the daily routines of 6 participants. Each experimenter is asked to carry his morning routine every day for 10 days in an equipped smart home. They are free to execute their tasks as they desire. DOMUS smart home is equipped with infrared movement detectors, pressure detectors, lamp light switches, door and switch contacts

and flow meters. By triggering these sensors, the inhabitant generates sensor events labeled with the name of the sensor, the occurrence time, and a value depending on the sensor's type. These events are then used by activity recognition algorithm to generate the activity database. Smart home plan, sensors location and examples of sensor events and activity log are depicted in figure 2.11.

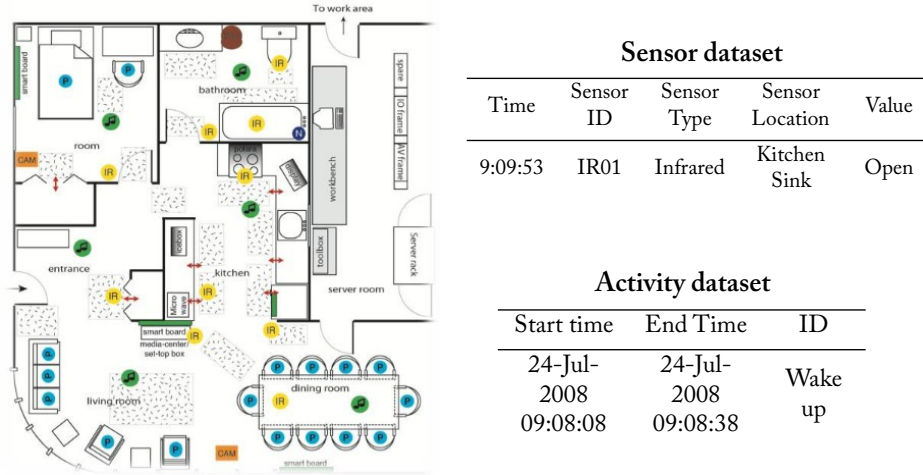


Figure 2.11: DOMUS smart home plan [Kadouche et al., 2010, Chikhaoui et al., 2010] with sensor and activity databases

Observed activities are Waking up, Bathing, Preparing breakfast, Having breakfast, Washing dishes, and Other activities. Two series were carried out. In the first series, participants have to perform these 6 activities in whatever order they desire. In the second one, an additional activity (preparing tea) was imposed.

Only the first series is considered as it proposes the most authentic behavior since no activity was imposed. This database is particularly interesting as it proposes to observe the behavior of several individuals in the same home. This way, it can be assessed if presented methodology is able to extract individual life patterns.

### Hh103 home from CASAS databases

CASAS (Center for Advanced Studies in Adaptive Systems) from the Washington State University aims at developing original AAL solutions to improve the comfort and the safety of smart home residents. In order to test new equipment and methodologies, they equipped numerous smart home and made the obtained databases publicly available to ease collaboration.

From these homes, smart home hh103 was identified as particularly interesting to consider [Cook et al., 2013]. In this database, a single volunteer adult carried out his everyday life for 60 days. Hh103 is one of the only database which observe the behavior of a single inhabitant for such a long period of time. The smart home is equipped with door sensors, light switches, light sensors, infrared and wide-area infrared motion sensors, and temperature sensors.

The smart home plan, sensors location, and list of observed activities are illustrated in figure 2.12.

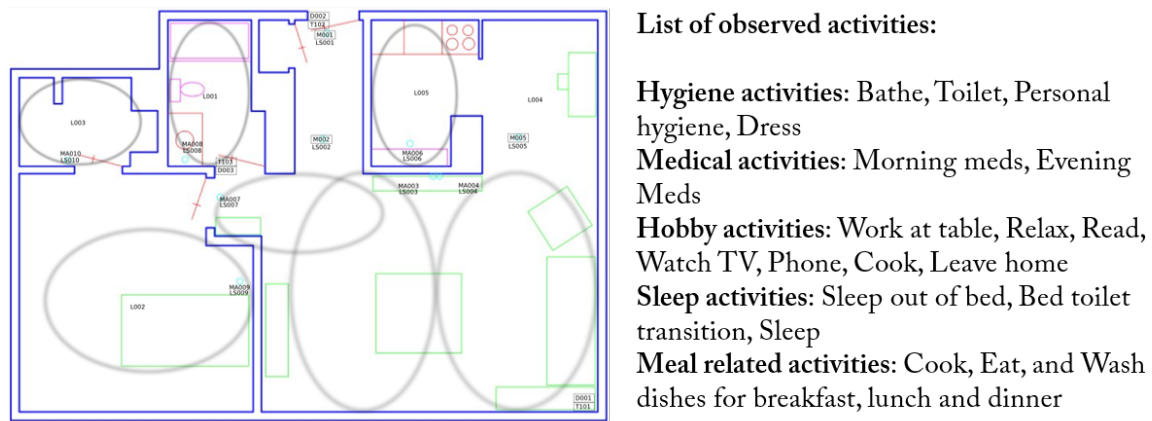


Figure 2.12: Hh103 smart home plan from the CASAS project [Cook et al., 2013].

### 2.4.2 Data pretreatment

In order to exploit these databases, a few modifications are required.

Concerning DOMUS database, only the first series of data is considered as already stated. No other modifications or selection is required.

Regarding the hh103 database, some specific activities are carried out less than once per week, and are consequently not interesting to observe when focusing on the life habits of the inhabitant. Moreover, these activities offer limited insight about the health status of the inhabitant. These activities are consequently removed of the database. Concerned activities are Work at table, morning and evening meds, bathe, relax, sleep out of bed, read, phone and cook -other than cook breakfast, lunch and dinner-. It should be noticed that, in a real case scenario, it is the medical staff who decides which activities should be monitored depending on the medical record of the inhabitant and their expertise.

Moreover, some other activities offer a low interest as they are carried out at anytime during the day and are consequently also eluded. These activities are toilet, Watch TV, and Dress.

Finally, the original database considers leave home and enter home as two distinct activities. Instead, to be more representative of the actual behavior of the inhabitant, these two activities are considered altogether under the name leave home. This activity start when original activity leave home start, and ends when activity enter home ends. Figure 2.13 illustrates the applied modification.

In the end, the considered activities are sleep, bed to toilet transition, cook, eat and wash dishes for breakfast, lunch and dinner, modified leave home and personal hygiene. No other modification is applied to the database.

## 2.5 Conclusion

World population is ageing. Consequently, the number of people requiring adapted health care is increasing. To answer this need, numerous works were developed to moni-

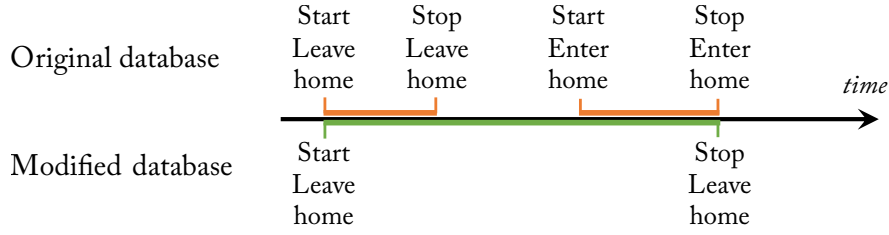


Figure 2.13: Modification applied to activities enter and leave home to be more representative of the inhabitant behavior.

tor the vital signs of smart home inhabitant. However, these works fail to detect specific cognitive or physical decline which affect this population. Innovative approaches have to be explored to detect such health problem by monitoring the inhabitant's behavior in term of Activity of Daily Living (ADL) execution.

The behavior of an individual is extremely complex and full of different features. It is necessary to identify and focus on those of interest for the medical team. To the best of our knowledge, there is no survey enlisting these features. Consequently, a review existing medical and AAL works to determine them is proposed.

This review resulted in the identification of five relevant behavioral features: activity ordering, time, number, duration and execution. However, two features alone offer a satisfying coverage: activity duration and ordering. Activity duration covers most symptoms while being selective enough to propose a limited list of potential responsible disease. Activity ordering, on the other hand, is efficient to detect disturbance in the planning of one's daily life, which is often associated to cognitive impairments.

Additionally, the impacts a disease may have on these features were classified into two categories: short-term behavior change, denoted behavioral anomaly in this work, and long-term deviation. Some existing works consider anomaly detection to assess the health status of an individual, but they fail to detect early enough health declines which are critical for the elderly people. The scarce works considering long-term deviation often consider Change Point Detection (CPD) which face the same drawbacks.

Therefore, this work proposes both anomaly and long-term deviation regarding the activity ordering and activity duration features to assess the health status of the smart home inhabitant. Proposed approach is model-based, meaning the behavior of the inhabitant is compared to a model describing his usual habits to detect changes dues to health problems.

The generation of such a model is described in the next chapter. Anomaly and long-term change detection is presented in chapter 4 and 5 respectively.



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# CHAPTER 3

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## Smart home inhabitant life habits modeling

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*"Sème un acte, tu récolteras une habitude ; sème une habitude, tu récolteras un caractère ; sème un caractère, tu récolteras une destinée."*  
- Dalaï Lama -

### Abstract

---

In order to assess the health status of an individual, information about his daily routine is necessary. A Stochastic Timed Automaton (STA) model depicting the habits of a smart home inhabitant regarding the activity ordering and duration features is introduced, as well as its automatic generation procedure. The approach is then applied to real case study to attest of its efficiency.

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### Contents

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<b>3.1</b>	<b>Life habits model definition . . . . .</b>	<b>42</b>
3.1.1	Life habits identification framework . . . . .	42
3.1.2	Work assumptions . . . . .	43
3.1.3	Model selection . . . . .	44
3.1.4	Model definition . . . . .	45
<b>3.2</b>	<b>STA generation . . . . .</b>	<b>47</b>
3.2.1	STA structure . . . . .	48
3.2.2	Transitions probability generation . . . . .	51
3.2.3	Probabilistic distribution generation . . . . .	57
<b>3.3</b>	<b>Training phase duration assessment . . . . .</b>	<b>64</b>
<b>3.4</b>	<b>Application to a public database . . . . .</b>	<b>68</b>
3.4.1	DOMUS smart home . . . . .	68
3.4.2	Hh103 CASAS smart home . . . . .	73
<b>3.5</b>	<b>Conclusion . . . . .</b>	<b>78</b>

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## 3.1 Life habits model definition

In previous chapter, it has been stated that knowing the life habits of an individual is required to know if his behavior is affected. These life habits are also of interest for medical staff as they offer relevant information about the inhabitant health status. For instance, sleep or eating pattern analysis allows early detection of physical and cognitive declines [Eldib et al., 2015].

Moreover, activity ordering and activity duration have been identified as the most relevant features of human behavior to observe in order to assess the health status of an individual. They are influenced by most diseases a single frail inhabitant may suffer and still allow an efficient identification of the potential diseases responsible of the observed deviation.

In this chapter is introduced a model and a generation procedure to represent the life habits of a smart home inhabitant after a few days long training phase. First, the framework is presented and the work assumptions are reviewed in order to propose an adapted model. Model definition, notation and generation are then introduced. Afterwards, the accuracy of the model is discussed. Finally, a case study is proposed to illustrate the efficiency of the chosen model by applying methodology to public smart homes databases presented in section 2.4.

### 3.1.1 Life habits identification framework

Figure 3.1 depicts the scope of this chapter and the positioning of the life habits model generation within the whole framework of our approach.

The smart home inhabitant carries out his everyday life as usual (1) during a training phase. The training phase is a few days long period in which the inhabitant behavior is supposed to be mainly healthy and representative of his usual behavior. The required duration of this training phase is explored in more details in subsection 3.3.

His home is equipped with different types of sensors, such as binary motion sensors, or more invasive technologies such as wearable sensors or cameras. Any sensor technology can be used, but this thesis only consider binary information (assumption 1). By doing his everyday tasks, the inhabitant triggers some of these sensors and generates sensor events. These events are recorded in a sensor database (2) enlisting every sensor events with the sensor name, its value and the occurrence time.

Thanks to existing activity recognition algorithms, such as [Viard et al., 2016], it is possible to recognize which activity is carried out according to the sensors triggered. Thus, an activity database is generated enlisting every executed activity event (3) composed of the activity name, its start time and stop time.

Life habits model representing the personal life routine of the inhabitant is generated from this database. This model focus on activity ordering and duration as these behavioral features are key information to estimate the health status of an individual. This model is used by medical staff as it offers a clear overview of the routine of the inhabitant, allowing early detection of some specific symptoms. The produced model is also exploited in chapter 4 and 5 to detect behavioral deviations, i.e. behavior that does not correspond to the usual life habits because of health problems.

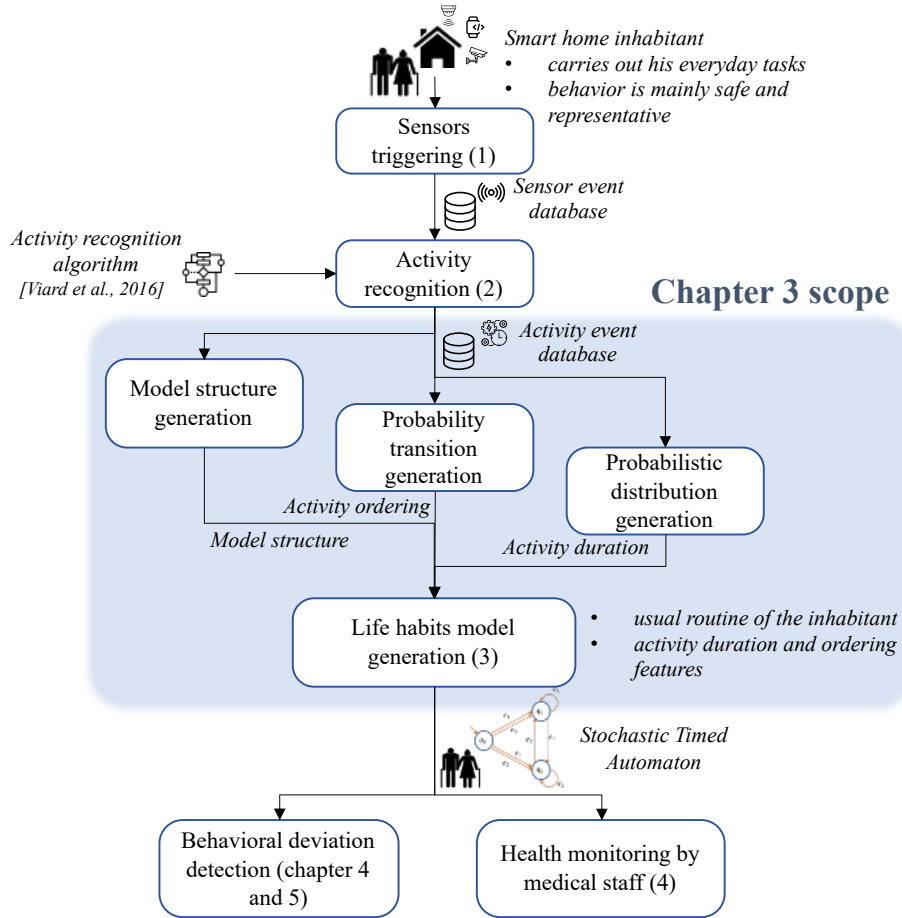


Figure 3.1: Proposed methodology for life habits model generation.

### 3.1.2 Work assumptions

Additional constraints have to be considered to select an appropriate model type.

Human behavior can sometimes be non-deterministic or even random. Although most of people possess habits they tend to follow, external disturbances may occasionally deviate the inhabitant behavior from its standard, consciously or not. Additionally, inhabitant behavior is considered mainly healthy during the training phase. This can be certified by regular medical check-ups throughout the training period. However, punctual behavioral changes may happen even if their number is supposed to be low. Consequently, the behavior during this phase is unsupervised in the sense of [Chandola et al., 2009]:

**Assumption 5 (Unsupervised training data)** *Training data possesses both normal and abnormal data, i.e. activities conforming to the life habits of the inhabitant and activities not belonging to them. Data is unlabeled, meaning it is impossible to know in advance if a specific activity is carried out as usual or not. However, assumption is made that most of the observed behavior is consistent with inhabitant life routine.*

Some individuals might possess several life habits. For instance, the behavior of the inhabitant might be different depending on if he is observed during the week or

the weekend, or depending on the season. The model must be able to represent all of them. This situation leads to the next assumption:

**Assumption 6 (Multi-class)** *Smart home inhabitant's life habits might be multi-class, meaning some inhabitants may possess several life habits. All of them have to be represented by the model.*

Finally, the produced model will be used for deviation detection and has to be chosen adequately to fulfill this task. However, the model alone can give insightful information to medical staff about health status of the inhabitant. Sleep and meal activities are examples of activities which can give relevant information to medical staff [Eldib et al., 2015]. The model must be suited for such communication and analysis.

**Assumption 7 (Medical staff communication)** *To ease communication with medical staff, black box approaches such as Artificial Neural Network or hidden models have to be avoided.*

This assumption is particularly critical as the medical team is the decision maker. They decide which inhabitant and activities should be monitored, and consequently should have a clear overview of the obtained results.

#### 3.1.3 Model selection

In [Chandola et al., 2009] is proposed a classification of existing methods and models used for anomaly detection.

- Classification based methods, such as neural networks, Support Vector Machine or Rule based method offer satisfying results when working with accurate data label. The better the data are labeled, the more efficient these methods are. In particular, a single anomaly may highly disrupt the quality of the model and lead to ruinous results. In our case, training data are unlabeled and are likely to possess a few anomalies which cannot be previously detected (assumption 5). Consequently, these methods are not well-suited regarding this assumption.
- Nearest neighbors based methods rely on distance between data or their density to detect outliers. These methods can cope with unsupervised data if the number of anomalies is low. However, they require to define a distance between activities and human behavior which is not straight forward as we manipulate multi-dimensional data.
- Regression models consist in fitting a mathematical model to training data. A residual between model and test data can be computed to detect anomalies. These methods moderately handle anomalies within training data and may give relevant results only if regression assumption holds true, which is challenging for human behavior.

- Probabilistic automata efficiently handle unsupervised data if outliers within training data are scarce as they will not highly disrupt probability computation. Moreover, these automata can efficiently model multi-class behaviors (assumption 6) and are well suited to deal with events.
- Similarly, parametric techniques efficiently deal with unsupervised data if their numbers is limited. These methods can be especially efficient if the parametric assumption holds true. Several works already investigated this assumption with probabilistic distributions and offer interesting results [Forkan et al., 2015], [Aze-fack et al., 2019]. Section 3.2.3 explores further public databases to validate these assumptions, assessing for relevancy of this technique.

In conclusion, probabilistic automata are well-suited to model smart home inhabitant life habits regarding the activity ordering behavior feature. On the other hand, use of probabilistic distributions is well-adapted for activity duration modeling. Existing works already explored duration modeling, but they often only focus on normal distribution. In section 3.2.3, public databases are explored to assess the validity of this assumption and propose adapted distributions.

A model combining these representations have already been explored in [Bertrand et al., 2014]. Stochastic Timed Automaton (STA) has initially been introduced for model-checking. Next section presents a slightly modified definition of a STA to answer our needs.

### 3.1.4 Model definition

To introduce the definition and notations of STA, several definitions concerning STA structure and Probabilistic Finite Automaton (PFA) are required.

**Definition 3.1** *A STA structure  $A$  is a 4-tuple  $A = \langle Q_A, q_0, \Sigma_A, \delta_A \rangle$  where:*

- $Q_A$  is a non-empty finite set of states;
- $q_0 \in Q_A$  is the initial state;
- $\Sigma_A$  is the alphabet of events;
- $\delta_A = Q_A \times \Sigma_A \times Q_A$  is a set of transitions composed of a departure state, an event conditioning the firing of the transition and an arrival state.

In the following, the subscript  $_A$  designates an element belonging to the STA structure  $A$ . For instance,  $Q_A$  is the set of states of  $A$ . When the context is obvious, the subscript might be eluded.

A STA structure can be graphically represented as a labeled oriented graph. Each state is labeled with its name, each transition with the event conditioning its firing and the initial state is depicted with an in-going edge. Figure 3.2 offers an example of STA structure composed of 3 states, 8 transitions and an alphabet of 3 events.

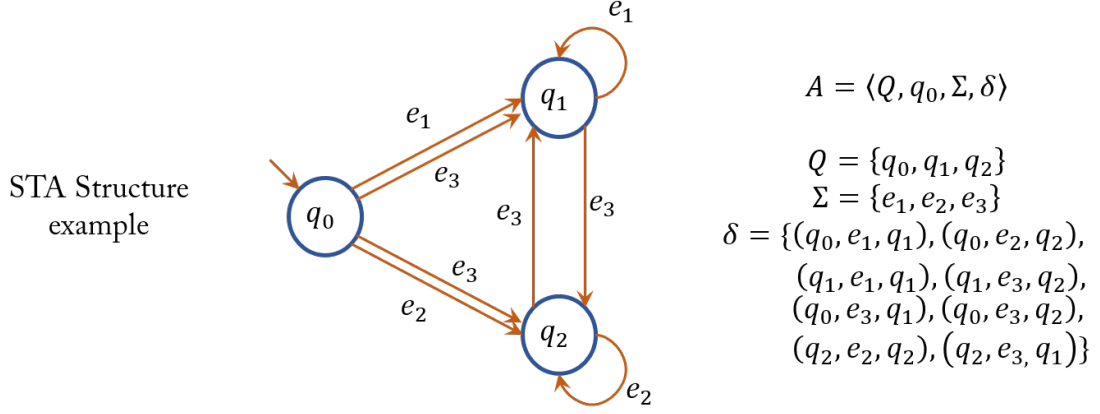


Figure 3.2: Example of an STA structure.

**Definition 3.2** A Probabilistic Finite Automaton (PFA) is a tuple

$$PFA = \langle A, P \rangle$$

where  $A$  is an STA structure introduced in definition 3.1 and  $P : \delta_A \rightarrow [0, 1]$  is the transition probability.

Probability associated to a specific transition  $(q, \sigma, q') \in \delta_A$  is noted  $P(q, \sigma, q')$ .

For the sake of simplicity,  $P(q, \sigma, q')$  is considered null for transitions  $(q, \sigma, q') \notin \delta_A$ . It should be noted that the sum of probability of outgoing transitions for each state must be equal to 1.

$$\forall q \in Q_A, \sum_{q' \in Q_A, \sigma \in \Sigma_A} P(q, \sigma, q') = 1$$

Thanks to these probabilities, a PFA is able to model or generate a probabilistic distribution over set of events. This distribution is written  $D_{PFA}$ .

These probabilities are graphically depicted as an additional label on the associated transition. An example of PFA is proposed in figure 3.3.

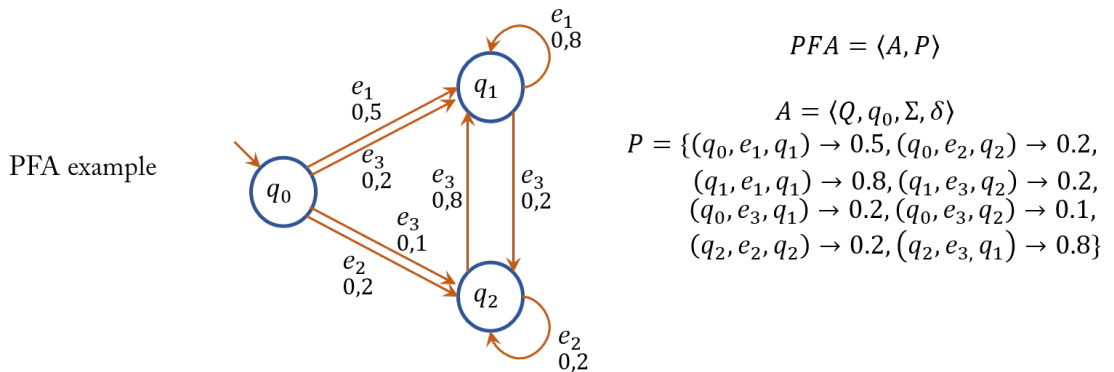


Figure 3.3: Example of a PFA.

Now that STA structure and PFA are defined, STA is introduced below.

**Definition 3.3** A Stochastic Timed Automaton is defined by  $STA = \langle A, P, \mu \rangle$  with:

- $A$  the STA structure (definition 3.1);
- $P$  the transition probabilities (definition 3.2);
- $\mu$  the probability measure over state delay  $\mu : Q_A \rightarrow f$  with  $f : \mathbb{R}^+ \rightarrow [0, 1]$ .

Probability measure over a specific state  $q$  is written  $\mu_q$ . It defines the expected state delay, i.e. the expected time elapsed between the firing of an in-going transition and the firing of an out-going transition of  $q$ .

If the state  $q$  delay is expected to follow a specific probabilistic distribution, for instance a normal or an exponential distribution,  $\mu_q$  can be seen as the probability density function of this distribution.

It should also be noted that  $\forall q \in Q_A, \int_{t \in \mathbb{R}^+} \mu_q(t) dt = 1$

An example of STA is illustrated in figure 3.4. All probability measures over state delay corresponds to probability density function, respectively uniform, normal and log-normal distribution for states  $q_0$ ,  $q_1$  and  $q_2$ .

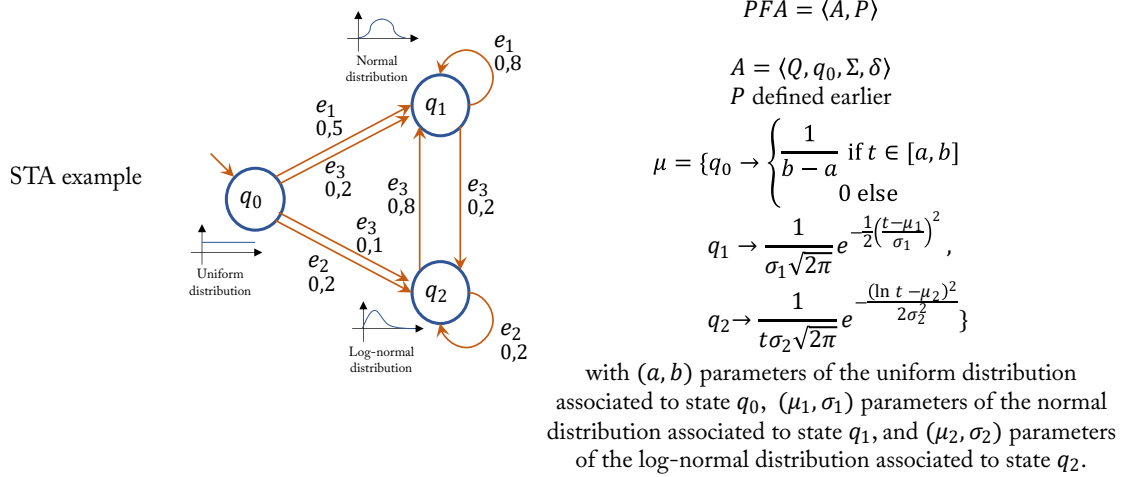


Figure 3.4: Example of an STA.

## 3.2 STA generation

In this section is introduced a methodology to build an STA representing the life habits of a smart home inhabitant. By carrying his everyday life, the inhabitant triggers sensors which allow to identify which activity he is currently executing and feed an activity database.

After a training phase of a few days, this activity database is used to generate first the structure of the STA then the probabilities associated with transitions and the state delays.

### 3.2.1 STA structure

#### Existing paradigms

The first step of STA generation is the creation of its structure. Generating STA structure can be seen as a similar problem of PFA structure generation which has already been explored in [Vidal et al., 2005b].

Several learning paradigms exist:

- A first possibility consists in generating the structure thanks to a priori knowledge in the application domain, or constraints due to the type of model employed and its future uses [Viard et al., 2020]. This procedure can be automatic or may require expert involvement. Applicability of this method widely rely on the application field and the type of model used.
- Second solution relies on learning approaches. State-merging strategies is an example of learning method adapted to automata [Klein et al., 2005]. These solutions may offer satisfying results if the training data is consequent enough.
- Finally, frameworks used for hidden model generation can also be exploited. Structure and probabilities are computed altogether so that distribution expressed by the model fit the training data. Hidden Markov Model is an example of such model.

In hidden model, the states are generated for the sole sake of probability generations. This is not consistent with STA as states needs to be associated to specific activities to possess a relevant probability measure associated to their delay. Moreover, as the model has to be read by medical staff (assumption 7), hidden models don't offer the best results.

To produce relevant results, learning based approaches require large amount of data. This is difficult to achieve in the case of life habits modeling as only one activity sequence is produced per training day. Several months of observation would be necessary to have confidence in the obtained model. Moreover, specific constraints due to the type of model used, more specifically the fact that we define probability measure over state delay, are difficult to involve in the generation process.

On the other hand, as the list of observed activities is already known, structure generation through prior knowledge offer an adequate solution. Moreover, as probabilistic distribution depicting activity duration are associated to state, manually creating one state per activity is the most natural way to process. Methodology for structure generation within this paradigm is proposed in next subsection.

#### Proposed Methodology

Methodology is introduced below and is illustrated by a pseudo-code in algorithm 1. For each observed activity  $act$ , a state  $q_{act}$  plus a unique initial state  $q_0$  is created. An individual may possess various life habits, and the model must be able to represent all of them (assumption 6). Consequently, STA structure must be an envelope model, i.e. a model where any sequence of events can be fired. Transitions from any state to every

other states are created, including self-loops, with an associated event corresponding to the arrival state. Only transitions toward the initial state are not created. Generation process complexity is polynomial in regard to the number of observed activities. This is usually not a problem as the number of activities to observe is low. Generally, public databases do not offer more than ten activities to observe.

This process ensures to obtain a deterministic STA structure as defined in definition 3.4.

**Definition 3.4** *A STA structure  $A$  is said to be deterministic if for any state  $q \in Q_A$ , at most one outgoing transition can be fired for each event  $e \in \Sigma_A$ :*

$$\forall q \in Q_A, \forall \sigma \in \Sigma_A, |\{q' : (q, \sigma, q') \in \delta_A\}| \leq 1$$

*In practice, having a deterministic STA structure means that at most one sequence of transitions can be fired within the STA for a given event sequence.*

A deterministic structure brings multiple advantages:

- As only one path at most can be fired from an event sequence, parsing is easier;
- Computational complexity is greatly reduced for many problems, including computing the most probable path within the PFA. This point is explored in more details in chapter 4;
- Probability learning is easier and offers more efficient results for PFA with deterministic structure. This advantage in particular is explored in section 3.2.2.

Moreover, as the structure generation process is automatic and does not require expert involvement, proposed solution is scalable. This is a major benefit as numerous homes are expected to be equipped for health monitoring in the near future.

Table 3.1 illustrates the process on a simple example where 4 activities are monitored: Wake up, Use Toilet, Having breakfast and Leave home.

In the initialization step, the initial state  $q_0$  is created (figure 3.1 step 1) while the alphabet and the set of transitions of the automaton are initialized:  $A = \langle Q_A = \{q_0\}, q_0, \Sigma_A = \emptyset, \delta_A = \emptyset \rangle$ .

In a second step, for each activity monitored, a unique corresponding state is generated (figure 3.1 step 2). Therefore, the STA structure  $A$  possess a set of five states  $Q_A = \{q_0, q_{Wakeup}, q_{Breakfast}, q_{Toilet}, q_{Leave}\}$ .

For each activity monitored, the associated event is added to the STA structure alphabet. Then, transitions are created. For instance, for activity Wake up, event  $e_{Wakeup}$  is created and added to the alphabet  $\Sigma_A$  (figure 3.1 step 3.1.1)). Then, every transition from state  $q \in Q_A$  to state  $q_{Wakeup}$  is created including the self-loop, labeled with event  $e_{Wakeup}$  (figure 3.1 step 3.1.2)). At this step, we consequently have  $\delta_A = \{(q_0, e_{Wakeup}, q_{Wakeup}), \dots, (q_{Leave}, e_{Wakeup}, q_{Wakeup})\}$ . These last two steps are repeated for each monitored activity and are not depicted in the table.

Obtained STA structure is displayed in table 3.1 step 3.n.2.

Final model is  $A = \langle Q_A, q_0, \Sigma_A, \delta_A \rangle$  with  $Q_A, \Sigma_A, \delta_A$  defined in the figure final step.

### 3.2. STA generation


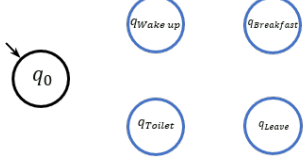
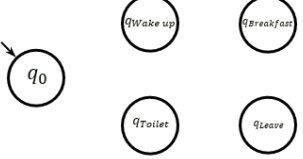
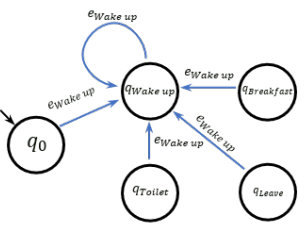
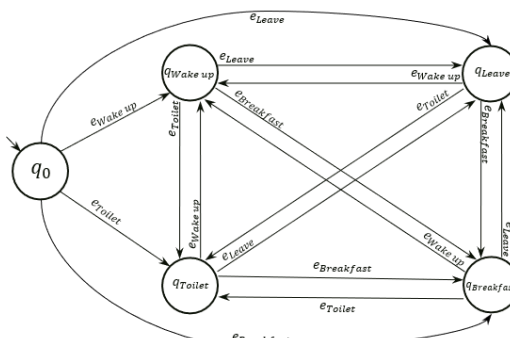
<p>1) Initialization</p>  $Q_A = \{q_0\}$ $\Sigma_A = \emptyset$ $\delta_A = \emptyset$	<p>2) States generation</p>  <p>Set of observed activities:</p> <ul style="list-style-type: none"> <li>Wake up</li> <li>Use toilet</li> <li>Having Breakfast</li> <li>Leave Home</li> </ul> $Q_A = \{q_0, q_{Wake\ Up}, q_{Breakfast}, q_{Toilet}, q_{Leave}\}$ $\Sigma_A = \emptyset$ $\delta_A = \emptyset$
<p>3) Transitions generation</p> <p>3.1) Activity Wake up</p> <p>3.1.1) Wake up event</p>  <p>Set of observed activities:</p> <ul style="list-style-type: none"> <li>Wake up</li> <li>Use toilet</li> <li>Having Breakfast</li> <li>Leave Home</li> </ul> $Q_A = \{q_0, q_{Wake\ Up}, q_{Breakfast}, q_{Toilet}, q_{Leave}\}$ $\Sigma_A = \{e_{WakeUp}\}$ $\delta_A = \emptyset$	<p>3) Transitions generation</p> <p>3.1) Activity Wake up</p> <p>3.1.2) Wake up transitions</p>  <p>Set of observed activities:</p> <ul style="list-style-type: none"> <li>Wake up</li> <li>Use toilet</li> <li>Having Breakfast</li> <li>Leave Home</li> </ul> $Q_A = \{q_0, q_{Wake\ Up}, q_{Breakfast}, q_{Use\ Toilet}, q_{Leave\ Home}\}$ $\Sigma_A = \{e_{Wake\ up}\}$ $\delta_A = \left\{ (q_0, e_{Wake\ up}, q_{Wake\ up}), (q_{Wake\ up}, e_{Wake\ up}, q_{Wake\ up}), (q_{Toilet}, e_{Wake\ up}, q_{Wake\ up}), (q_{Leave}, e_{Wake\ up}, q_{Wake\ up}), (q_{Breakfast}, e_{Wake\ up}, q_{Wake\ up}) \right\}$
<p>3) Transitions generation</p> <p>3.n) Last activity</p> <p>3.n.2) Leave Home transition</p> 	$Q_A = \{q_0, q_{Wake\ Up}, q_{Breakfast}, q_{Use\ Toilet}, q_{Leave\ Home}\}$ $\Sigma_A = \{e_{Wake\ up}, e_{Use\ Toilet}, e_{Breakfast}, e_{Leave\ Home}\}$ $\delta_A = \{(q, \sigma, q') \mid \forall q \in Q_A, \forall q' \in Q_A - \{q_0\}, \forall \sigma \in \Sigma_A \mid \text{label}(\sigma) = \text{label}(q')\}$

Table 3.1: Examples of a STA structure generation from a smart home enabling monitoring of activities Wake up, Use Toilet, Having breakfast and Leave home.

---

**Algorithm 1** STA Structure generation

---

**Require:** Set of observed activities  $s_{Activities}$

**Ensure:** STA Structure  $A$

*Global initialization*

1:  $Q = \{q_0\}, \Sigma = \emptyset, \delta = \emptyset$

*States creation*

2: **for**  $activity \in s_{Activities}$  **do**

3:   append  $q_{activity}$  to  $Q$

4: **end for**

*Transitions creation*

5: **for**  $activity \in s_{Activities}$  **do**

6:   append  $e_{activity}$  to  $\Sigma$

7:    $e = e_{activity}, q' = q_{activity}$

8:   **for**  $q \in Q$  **do**

9:      $tr = (q, e, q')$

10:    append  $tr$  to  $\delta$

11:   **end for**

12: **end for**

13:  $A = \langle Q, q_0, \Sigma, \delta \rangle$

---

From now, as each activity and event will be associated to a specific activity except for the initial state, state and event label is defined to ease their identification. These labels will allow to compare events and states to know if they refer to the same activity

**Definition 3.5** *The label of the state designates the activity it is associated.*

$$label(q) = \begin{cases} act & \text{if activity } act \text{ is associated to state } q; \\ 'initial' & \text{if state } q \text{ is the initial state} \end{cases}$$

*The same operator is defined for events of the alphabet:*

$$label(\sigma) = act \text{ if activity } act \text{ is associated to event } \sigma$$

### 3.2.2 Transitions probability generation

Once the STA structure is constructed, probabilities have to be computed to represent the observed behavior of the smart home inhabitant. In this subsection is presented the method for transition probability generation. These probabilities describe the usual life habits of the experimenter regarding the activity ordering feature. The objective is to compute these probabilities in order that the distribution  $D_{PFA}$  expressed by the model fit the best the distribution  $D_{training}$  in the training data.

As the probability distributions associated with state delays  $\mu$  are not yet computed, this subsection will only consider PFA object for the sake of readability. Methods and results presented in this subsection can be extended without modification to STA model.

Several methods are available to estimate these probabilities. However, before presenting them, several definitions are required. They are introduced below.

### Prerequisite definitions

**Definition 3.6** A sequence  $w = e_1, e_2, \dots, e_n$  is an ordered list of events. In our case, it corresponds to a sequence of activities carried out in the smart home. Its length, denoted  $|w| = n$  is the number of events composing the sequence.

**Definition 3.7** A path  $\theta$  in a PFA  $\langle A, P \rangle$  is a sequence of transition

$$\theta = ((q_a, \sigma_l, q_b), (q_b, \sigma_m, q_c), \dots, (q_d, \sigma_o, q_e))$$

where  $(q_i, \sigma_k, q_j)_{(i,j) \in [(a,b), (b,c), \dots, (d,e)], k \in [l, \dots, o]} \in \delta_A$

Its length denoted  $|\theta|$  is the number of transitions composing the path.

The probability to fire such a path  $\theta$  in a PFA  $\langle A, P \rangle$ , written  $P(\theta|\langle A, P \rangle)$ , is the product of the probability of each transition composing the path:

$$P(\theta|\langle A, P \rangle) = \prod_{\delta_k \in \theta} P(\delta_k)$$

If the sequence of event  $w$  is generated by firing  $\theta$  in PFA  $\langle A, P \rangle$ ,  $\theta$  is said fireable in  $\langle A, P \rangle$  by  $w$ . If  $P(\theta|\langle A, P \rangle) > 0$ ,  $\theta$  is valid in  $\langle A, P \rangle$ .

$\Theta_{\langle A, P \rangle}(w)$  is the set of all valid paths in  $\langle A, P \rangle$  which are fireable by  $w$ . Note that if the STA structure  $A$  is deterministic as defined in definition 3.4,  $\forall w \in \Sigma_A^*$ ,  $|\Theta_{\langle A, P \rangle}(w)| \leq 1$  holds by definition. When the context is unambiguous,  $\Theta_{\langle A, P \rangle}(w)$  can be extended to denote the set of sub-paths rather than full paths, i.e. set of ordered list of states reached by the path.

Finally is defined the likelihood of an event sequence  $w$  within PFA  $\langle A, P \rangle$ .

**Definition 3.8** Likelihood of a sequence  $w$  represents the probability that the PFA generates it, and is the sum of the probability of each path fireable by  $w$ :

$$P(w|\langle A, P \rangle) = \sum_{\theta \in \Theta_{\langle A, P \rangle}(w)} (P(\theta|\langle A, P \rangle))$$

In a model with a deterministic structure, it results:

$$P(w|\langle A, P \rangle) = \begin{cases} P(\theta|\langle A, P \rangle) & \text{with } \theta \in \Theta_{\langle A, P \rangle}(w) \text{ if } |\Theta_{\langle A, P \rangle}(w)| = 1; \\ 0 & \text{else;} \end{cases}$$

In figure 3.5 is given an example of a PFA. With  $w = [e_1, e_1, e_3]$ ,  $\theta = ((q_0, e_1, q_1), (q_1, e_1, q_1), (q_1, e_3, q_2))$  is the only valid path in  $\langle A, P \rangle$  fireable by  $w$ :

$$\Theta_{\langle A, P \rangle}(w) = \langle ((q_0, e_1, q_1), (q_1, e_1, q_1), (q_1, e_3, q_2)) \rangle$$

and

$$\begin{aligned} P(w|\langle A, P \rangle) &= P(\theta|\langle A, P \rangle) \\ &= P(q_0, e_1, q_1) \times P(q_1, e_1, q_1) \times P(q_1, e_3, q_2) \\ &= 0.5 \times 0.8 \times 0.2 \\ &= 0.08 \end{aligned}$$

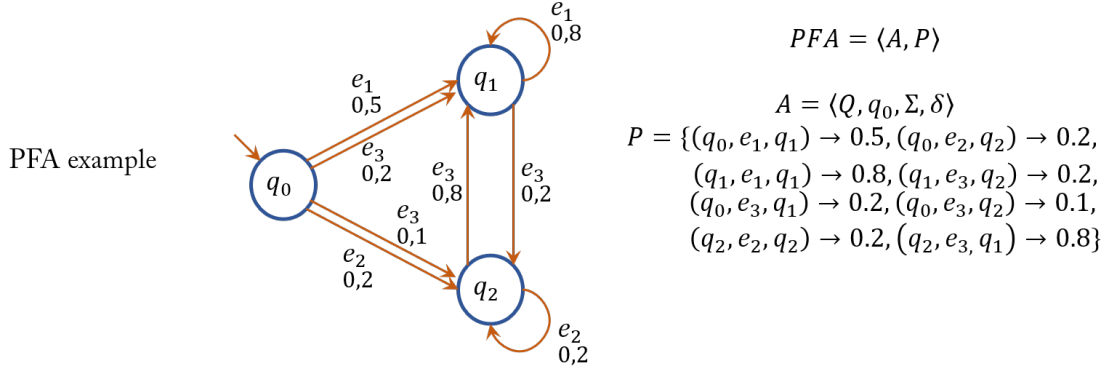


Figure 3.5: Example of a PFA. It can be remarked that  $A$  is not a deterministic structure.

### Probability learning

As stated earlier, the objective is to model the usual activity ordering of the smart home inhabitant through probabilities associated to transitions. In order to achieve this task, an activity database enlisting activities carried out by the inhabitant during a training phase is used. The objective is that the distribution generated by the model  $D_{PFA}$  fit the best way the distribution of the training phase  $D_{training}$  under the assumption that the training database is mostly representative of the usual routine of the inhabitant.

This problem has already been met in numerous domains, and Maximum Likelihood (ML) is a widely used criteria for this estimation. In the present case, it consists in finding the probabilities  $\hat{P}_A$  maximizing the likelihood of the training database.

$$\hat{P}_A = \arg \max_{P_A} \prod_{w \in S} P(w | \langle A, P \rangle)$$

with  $S$  the training database.

In most cases, finding such probabilities is a NP-hard problem as several paths can be fired within a PFA for a given sequence [Vidal et al., 2005b]. Existing solutions propose to find a locally optimal solution to the optimization process such as the Expectation-Maximization (EM) algorithms [Baum, 1972]. It iteratively updates the probabilities  $P$  in a way which guarantees to increase the likelihood at each iteration. Moreover, some existing tools allow to reduce the complexity of the likelihood computation, such as the Viterbi re-estimation algorithm discussed in [Casacuberta, 1996] which uses optimal path approximation rather than the true likelihood, but they do not ensure to avoid local maximum.

However, the situation is widely different for PFA with deterministic structure. As at most one path can be fired for a given event sequence, probability estimation is widely reduced thanks to the following theorem:

**Theorem 1** *Baum-Welch EM algorithm and Viterbi re-estimation algorithm produce the same, unique solution after only one iteration when the structure of the PFA is deterministic (definition 3.4). This solution corresponds to a global maximum and thus is the most satisfying solution.*

This solution can be obtained by using counters and is described below. Proof of the theorem is furnished in Appendix B.

Let  $A = \langle Q_A, q_0, \delta_A, \Sigma_A \rangle$  where  $\delta_A = (q, \sigma, q')$  with  $q \in Q_A$ ,  $q' \in Q_A \setminus \{q_0\}$ ,  $\sigma \in \Sigma_A$  such as  $label(\sigma) = label(q')$  be the STA structure,  $\langle A, P \rangle$  the PFA and  $S$  the training sequence.

A ML estimation of the probability of each transition  $P(q, \sigma, q')$  can be computed by counting the number of times this transition is fired in all fireable paths of the sequence  $S$  and by normalizing this count by the frequency of use of state  $q$ , i.e. the number of times the activity associated to state  $q$  appears in the sequence.

Let name  $N_{a_i \rightarrow a_j}$  number of occurrences of sequence  $[a_i, a_j]$  in sequence  $S$ . It represents the number of time activity  $a_i$  was followed by activity  $a_j$  during the training phase.

In that case, the probability  $P$  defined on each transition  $(q, \sigma, q') \in \delta_A$  is:

$$P(q, \sigma, q') = \begin{cases} \frac{N_{a_i \rightarrow a_j}}{\sum_{a_k \in L_{Act}} N_{a_i \rightarrow a_k}} & \text{if } \sum_{a_k \in L_{Act}} N_{a_i \rightarrow a_k} \neq 0 \\ 0 & \text{else} \end{cases}$$

where  $label(q) = a_i, label(q') = a_j$  and  $L_{act}$  is the list of observed activities.

It obviously respects the transition probability conditions:

$$\forall q \in Q, \sum_{q' \in Q, \sigma \in \Sigma} P(q, \sigma, q') = 1 \text{ and } P(q, \sigma, q') \in [0, 1]$$

Initial state is a specific case as it does not correspond to any activity in particular. This state is created to ensure obtaining a deterministic STA structure and to not assume an activity as systematically the initial one.

As we possess no a priori knowledge about which activity is carried out first and wish to test any sequence of activity in the model including sequences starting in the middle of the day, every event should possess the same probability occurrence from the initial state.

This means we have  $\forall q \in Q_A \setminus \{q_0\}$  and  $\forall \sigma \in \Sigma_A$  such as  $label(\sigma) = label(q)$ ,

$$P(q_0, \sigma, q) = \frac{1}{card(Q_A) - 1}$$

with  $card(Q_A)$  number of states in the STA structure  $A$

Transition probability conditions are also obviously respected.

Algorithm 2 offers a pseudo-code for counters and probability transition generations, while table 3.2 illustrates step by step probabilities computation from a training database. Probability transition generation process complexity is linear in regard to the number of activity events.

---

**Algorithm 2** PFA probability transition generation

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**Require:** STA structure  $A = \langle Q_A, q_0, \Sigma_A, \delta_A \rangle$

**Require:** Training sample  $w = [e_1, e_2, \dots, e_N]$

**Ensure:** PFA  $\langle A, P \rangle$

*Initialization*

1:  $dict\_counters = \{\}$

*Counters computation*

2: **for**  $index$  in  $range(0, |w| - 1)$  **do**

3:    $act_i = label(w[index])$

4:    $act_j = label(w[index + 1])$

5:   **if** key  $act_i$  in  $dict\_counters$  **then**

6:     **if** key  $act_j$  in  $dict\_counters[act_i]$  **then**

7:        $dict\_counters[act_i][act_j] + = 1$

8:     **else**

9:        $dict\_counters[act_i][act_j] = 1$

10:    **end if**

11:   **else**

12:      $dict\_counters[act_i] = \{act_j : 1\}$

13:   **end if**

14: **end for**

*Probability Computation*

15: **for**  $(q, \sigma, q') \in \delta_A$  **do**

16:   **if**  $q == q_0$  **then**

17:      $P(q, \sigma, q') = \frac{1}{|Q_A| - 1}$

18:   **else if** key  $label(q)$  in  $dict\_counters$  **then**

19:     **if** key  $label(q')$  in  $dict\_counters[label(q)]$  **then**

20:        $p = \frac{dict\_counters[label(q)][label(q')]}{\sum_{e \in keys(dict\_counters[label(q)])} dict\_counters[label(q)][e]}$

21:        $P(q, \sigma, q') = p$

22:     **else**

23:        $P(q, \sigma, q') = 0$

24:     **end if**

25:   **else**

26:      $P(q, \sigma, q') = 0$

27:   **end if**

28: **end for**

29:  $PFA = \langle A, P \rangle$

---

### 3.2. STA generation

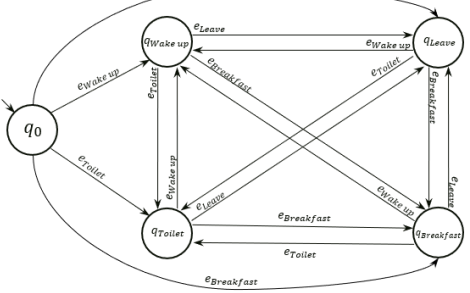
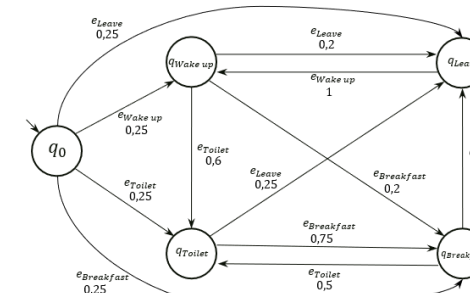
<b>STA Structure A</b>  <div style="display: flex; justify-content: space-between; align-items: flex-start;"> <div> <p><b>Set of observed activities:</b></p> <ul style="list-style-type: none"> <li>Wake up</li> <li>Use toilet</li> <li>Having Breakfast</li> <li>Leave Home</li> </ul> </div> <div> <math display="block">Q = \{q_0, q_{Wake\ up}, q_{Breakfast}, q_{Use\ Toilet}, q_{Leave\ Home}\}</math> <math display="block">\Sigma = \{e_{Wake\ up}, e_{Use\ Toilet}, e_{Breakfast}, e_{Leave\ Home}\}</math> <math display="block">\delta = \{(q, \sigma, q') \mid \forall q \in Q, \forall q' \in Q - \{q_0\}, \forall \sigma \in \Sigma \mid \text{label}(\sigma) == \text{label}(q')\}</math> </div> </div>									
<b>Training sample S</b> <p><math>S = [\text{Wake up, Toilet, Breakfast, Leave, Wake up, Toilet, Breakfast, Leave, Wake up, Breakfast, Toilet, Leave, Wake up, Toilet, Breakfast, Toilet, Leave, Wake up, Leave}]</math></p>	<b>Counters N</b> <table style="width: 100%; border-collapse: collapse;"> <tr> <td style="text-align: right;"><math>N_{Wake\ up \rightarrow Toilet} = 3</math></td> <td style="text-align: right;"><math>N_{Wake\ up \rightarrow Breakfast} = 1</math></td> </tr> <tr> <td style="text-align: right;"><math>N_{Toilet \rightarrow Breakfast} = 3</math></td> <td style="text-align: right;"><math>N_{Breakfast \rightarrow Toilet} = 2</math></td> </tr> <tr> <td style="text-align: right;"><math>N_{Breakfast \rightarrow Leave} = 2</math></td> <td style="text-align: right;"><math>N_{Toilet \rightarrow Leave} = 1</math></td> </tr> <tr> <td style="text-align: right;"><math>N_{Leave \rightarrow Wake\ up} = 4</math></td> <td style="text-align: right;"><math>N_{Wake\ up \rightarrow Leave} = 1</math></td> </tr> </table> <p style="text-align: center;">All other counters are null</p>	$N_{Wake\ up \rightarrow Toilet} = 3$	$N_{Wake\ up \rightarrow Breakfast} = 1$	$N_{Toilet \rightarrow Breakfast} = 3$	$N_{Breakfast \rightarrow Toilet} = 2$	$N_{Breakfast \rightarrow Leave} = 2$	$N_{Toilet \rightarrow Leave} = 1$	$N_{Leave \rightarrow Wake\ up} = 4$	$N_{Wake\ up \rightarrow Leave} = 1$
$N_{Wake\ up \rightarrow Toilet} = 3$	$N_{Wake\ up \rightarrow Breakfast} = 1$								
$N_{Toilet \rightarrow Breakfast} = 3$	$N_{Breakfast \rightarrow Toilet} = 2$								
$N_{Breakfast \rightarrow Leave} = 2$	$N_{Toilet \rightarrow Leave} = 1$								
$N_{Leave \rightarrow Wake\ up} = 4$	$N_{Wake\ up \rightarrow Leave} = 1$								
<b>Probabilities computation P</b>									
<p>From state <math>q_{Wake\ up}</math>:</p> $P(q_{Wake\ up}, e_{Wake\ up}, q_{Wake\ up}) = 0$ $P(q_{Wake\ up}, e_{Toilet}, q_{Toilet}) = \frac{N_{Wake\ up \rightarrow Toilet}}{\sum_{act \in L_{act}} N_{Wake\ up \rightarrow act}} = \frac{3}{3 + 1 + 1} = \frac{3}{5}$ $P(q_{Wake\ up}, e_{Breakfast}, q_{Breakfast}) = \frac{N_{Wake\ up \rightarrow Breakfast}}{\sum_{act \in L_{act}} N_{Wake\ up \rightarrow act}} = \frac{1}{3 + 1 + 1} = \frac{1}{5}$ $P(q_{Wake\ up}, e_{Leave}, q_{Leave}) = \frac{N_{Wake\ up \rightarrow Leave}}{\sum_{act \in L_{act}} N_{Wake\ up \rightarrow act}} = \frac{1}{3 + 1 + 1} = \frac{1}{5}$	<p>From state <math>q_0</math>:</p> $P(q_0, e_{Wake\ up}, q_{Wake\ up}) = \frac{1}{4}$ $P(q_0, e_{Toilet}, q_{Toilet}) = \frac{1}{4}$ $P(q_0, e_{Breakfast}, q_{Breakfast}) = \frac{1}{4}$ $P(q_0, e_{Leave}, q_{Leave}) = \frac{1}{4}$								
<p>The same way:</p>									
$P(q_{Toilet}, e_{Wake\ up}, q_{Wake\ up}) = 0$ $P(q_{Toilet}, e_{Toilet}, q_{Toilet}) = 0$ $P(q_{Toilet}, e_{Breakfast}, q_{Breakfast}) = \frac{3}{4}$ $P(q_{Toilet}, e_{Leave}, q_{Leave}) = \frac{1}{4}$	$P(q_{Breakfast}, e_{Wake\ up}, q_{Wake\ up}) = 0$ $P(q_{Breakfast}, e_{Toilet}, q_{Toilet}) = \frac{1}{2}$ $P(q_{Breakfast}, e_{Breakfast}, q_{Breakfast}) = 0$ $P(q_{Breakfast}, e_{Leave}, q_{Leave}) = \frac{1}{2}$								
<b>PFA <math>\langle A, P \rangle</math></b>  <div style="display: flex; justify-content: space-between; align-items: flex-start;"> <div> <math display="block">Q = \{q_0, q_{Wake\ Up}, q_{Breakfast}, q_{Use\ Toilet}, q_{Leave\ Home}\}</math> <math display="block">\Sigma = \{e_{Wake\ up}, e_{Use\ Toilet}, e_{Breakfast}, e_{Leave\ Home}\}</math> <math display="block">\delta = \{(q, \sigma, q') \mid \forall q \in Q, \forall q' \in Q - \{q_0\}, \forall \sigma \in \Sigma \mid \text{label}(\sigma) == \text{label}(q')\}</math> <p style="text-align: center;"><math>P</math> defined above</p> </div> </div>									

Table 3.2: Example of probability generation in a PFA by a training sample  $S$

### 3.2.3 Probabilistic distribution generation

Once the PFA has been determined, probability distributions associated to state delays  $\mu$ , introduced in definition 3.3, have to be computed. These distributions express how much time is expected for the inhabitant to carry out each specific activity. In the same way that transition probabilities, the model must fit the best way the distributions in the training data.

In this subsection, the relevancy of this approach is discussed by exploring existing AAL works and public smart home database. In particular, several probabilistic distributions are explored, and their efficiency studied to find a distribution which can be suitable in most cases.

#### Literature review

Modeling activity duration or time by probabilistic distribution have already been explored in a few works.

For instance, [Forkan et al., 2015] proposes to model activity time and duration by normal distribution in order to detect anomalies. [Azefack et al., 2019] also proposes to simulate a smart home inhabitant behavior by using normal distribution for activity time and duration to create artificial databases.

The prevalence of normal distribution for activity duration modeling can be explained by several points: Central limit theorem states that the sum of independent or weakly dependent random variables tends to follow a normal distribution, no matter the distribution followed by each variable [Kosobutskyy, 2018]. In the meanwhile, authors in [Viard et al., 2016], [Chaaraoui et al., 2012] or [Cook and Krishnan, 2015] proposes a hierarchical decomposition of activities. An activity can be seen as a sum of actions, and an action as a sum of elementary moves. Consequently, if each carried out actions are independent or weakly dependent, the central limit theorem assumptions hold and activity duration is very likely to follow a normal distribution.

#### Normal distribution limits

However, some problems can be faced when using normal distribution. First, the definition domain is not consistent as an activity duration is positive by definition while the distribution is defined on  $\mathbb{R}$ . This is usually not a problem if the proportion of the distribution in  $\mathbb{R}^-$  is not significant. With  $\mu$  and  $\sigma$  respectively the mean and standard deviation of a normal distribution,  $\mu - 3\sigma > 0$  is a commonly used criterion to validate the normal distribution.

Moreover, previously stated central limit theorem holds only if actions' durations are independent. This hypothesis is likely not to be respected. Several factors may influence the duration required to carry out an action, and these factors might affect each of these actions. Consequently, if an action has taken more or less time than usual to be carried out, other actions might be impacted the same way, contradicting the independence assumption. Such factors might be the level of tiredness of the inhabitant, his health status, his level of concentration, if the inhabitant is in a hurry or have time, etc.

For instance, if an inhabitant is sick and tired, the action "Taking a cup" from activity "Make tea" will probably be longer than usual. However, the other actions composing the same activity, such as "Close cupboard", "Heat water" or "Take tea" are very likely be longer as well. With such observations, the central limit theorem does not hold anymore, and activity "Make tea" duration is not likely to follow a normal distribution.

To assess these flows, and to find a more suitable activity duration distribution, some of the public databases introduced in 1.3 have been explored.

#### Public smart home database exploration

Histograms depicting duration of various activities in several smart homes databases are depicted in figure 3.6, 3.7, 3.8. Smart home databases hh103 and hh109 are both 60-day long, while the aruba database is 90 day long. Activity duration from the DOMUS smart home is not depicted as they only offer a 10-day long database, which is not enough to conclude about the type of distribution to use.

These figures also depict some fitted distributions: normal distribution which is often used, exponential distribution expressed in Markov model, and log-normal distribution. The Wasserstein distance for each distribution is computed and listed in tables 3.3, 3.4, and 3.5. Wasserstein distance  $W_1$  is a commonly used metrics to compare probability distributions [Rüschendorf, 1985].

$$W_1(u, v) = \inf_{\pi \in \Gamma(u, v)} \int_{\mathbb{R} \times \mathbb{R}} |x - y| d\pi(x, y)$$

with  $u, v$  distributions to compare,  $\Gamma(x, y)$  set of distribution on  $\mathbb{R} \times \mathbb{R}$ . The lower the Wasserstein distance, the best the distributions fit the data. If  $U$  and  $V$  are the respective cumulative distribution functions of  $u$  and  $v$ , this distance is equal to:

$$W_1(u, v) = \int_{-\infty}^{+\infty} |U - V|$$

Numerous different activities are displayed to test the wide-coverage of various distributions.

Several information can be drawn from these observations.

First, the number of observations is limited as some activities are carried out once per day or less while monitoring lasts at most 60 days for some databases. Consequently, the amount of data available to model life habits is extremely limited in regard to the complexity of human behavior. This situation may typically lead to overfitting.

Overfitting consists in the use of approaches that are more complex than necessary or that have been over-trained, which leads to a model fitting efficiently training data but poorly general data. For instance, a polynomial function of degree  $n - 1$  offers a perfect fit to data of length  $n$ . However it extrapolates improperly further data. An example of this situation is depicted in figure 3.9. A way to avoid overfitting is to ensure the model used makes sense regarding the data manipulated.

Secondly, normal distribution seems to often failed at describing the data distribution. In particular:

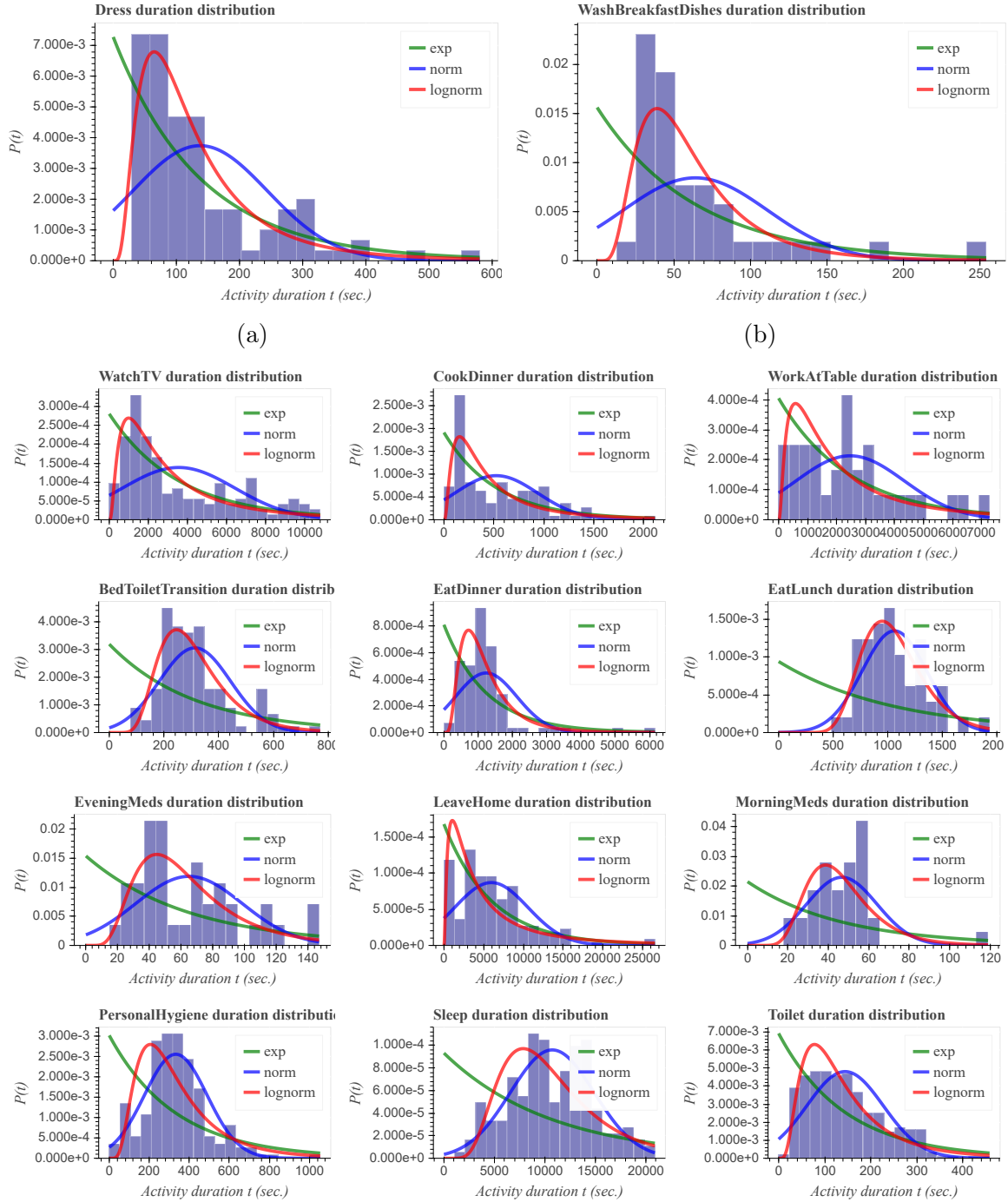


Figure 3.6: Duration of activities dress (a), wash breakfast dishes (b), and other various activities for 60 days from the CASAS hh103 smart home database

### 3.2. STA generation

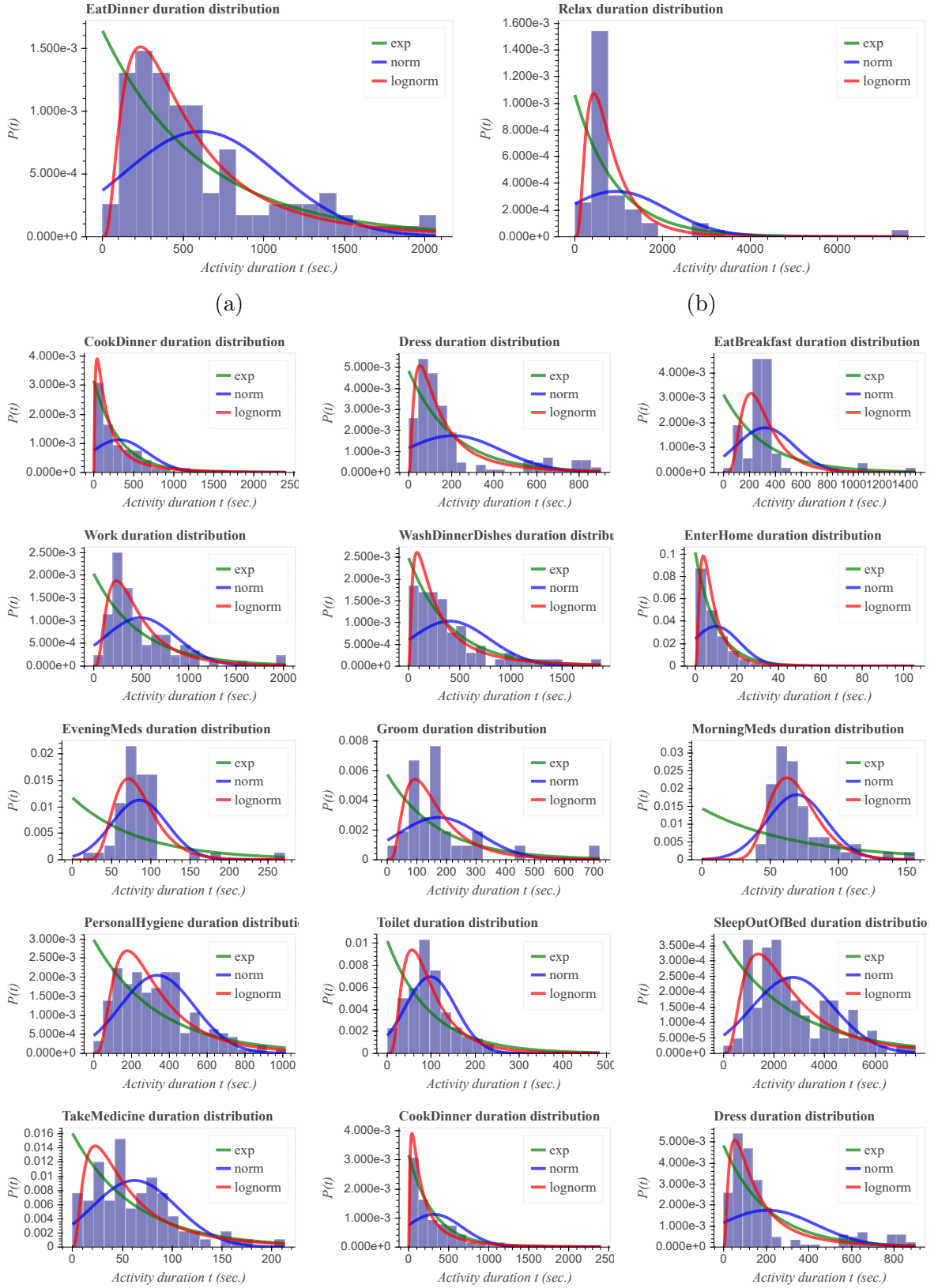


Figure 3.7: Duration of activities eat dinner (a), relax (b), and other various activities for 60 days from the CASAS hh109 smart home database

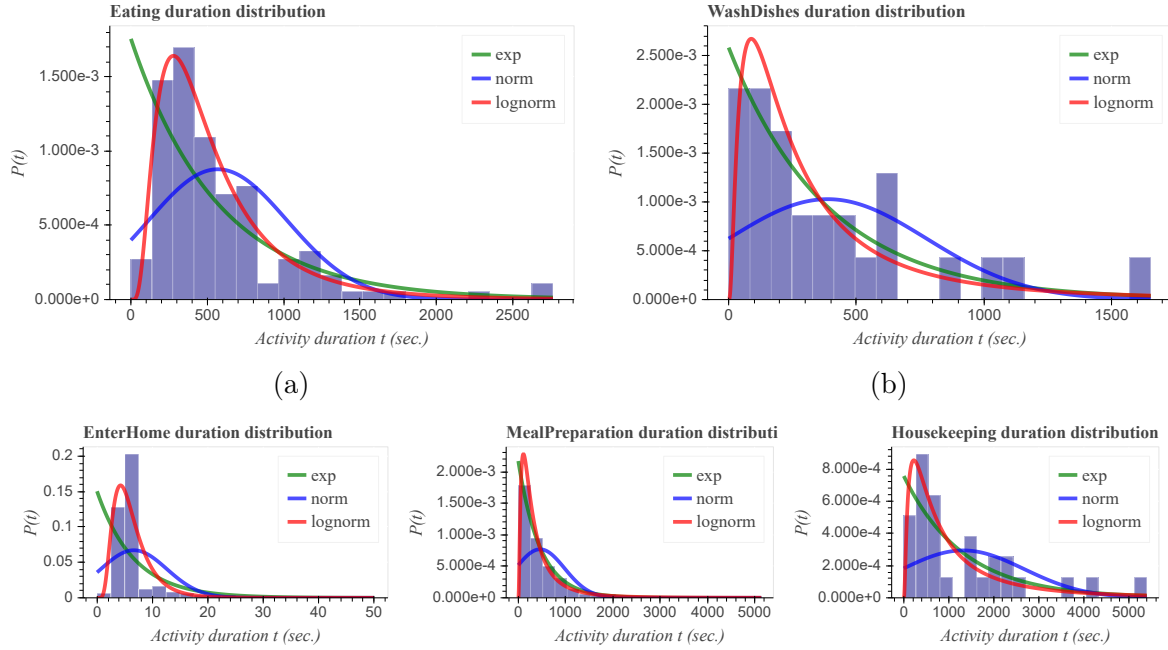


Figure 3.8: Duration of activities house keeping (a), eating (b), and other various activities for 60 days from the CASAS aruba smart home database

Activity	Exponential	Normal	Log-normal
Dress (a)	0.000373	0.000823	<b>0.00036</b>
WashBreakfastDishes (b)	0.00167	0.00227	<b>0.00154</b>
WatchTV	<b>1.54e-05</b>	3.39e-05	1.91e-05
CookDinner	0.000175	<b>0.000142</b>	0.000212
BedToiletTransition	0.000479	0.000375	<b>0.000255</b>
EatDinner	5.01e-05	8.97e-05	<b>4.35e-05</b>
EatLunch	0.000282	9.8e-05	<b>7.5e-05</b>
EveningMeds	0.00187	0.00204	<b>0.00155</b>
LeaveHome	<b>7.62e-06</b>	1.05e-05	1.18e-05
MorningMeds	0.00488	0.00309	<b>0.00226</b>
Phone	7.9e-05	0.000174	<b>5.89e-05</b>
Sleep	9.95e-06	6.42e-06	<b>6.4e-06</b>
PersonalHygiene	0.000212	0.000193	<b>0.000139</b>
WashLunchDishes	<b>0.000674</b>	0.000954	0.000723
Toilet	0.000602	<b>0.000251</b>	0.000538
WorkAtTable	3.92e-05	4.08e-05	<b>3.89e-05</b>

Table 3.3: Wasserstein distance between activity duration histograms and different probabilistic distributions for various activities for home hh103.

Activity	Exponential	Normal	Log-normal
<b>EatDinner (a)</b>	8.82e-05	0.000199	<b>7.23e-05</b>
<b>Relax (b)</b>	7.12e-05	9.38e-05	<b>6.13e-05</b>
CookDinner	<b>8.95e-05</b>	0.000194	0.000111
Dress	0.000241	0.000721	<b>0.000174</b>
EatBreakfast	0.000404	0.000523	<b>0.000319</b>
EnterHome	0.00273	0.00566	<b>0.00166</b>
Eat	0.000409	0.000434	<b>0.000402</b>
Groom	0.00052	0.000722	<b>0.000502</b>
EveningMeds	0.00272	0.00219	<b>0.00132</b>
MorningMeds	0.0042	0.0027	<b>0.00181</b>
PersonalHygiene	0.000202	<b>0.000131</b>	0.000183
TakeMedicine	<b>0.000838</b>	0.000907	0.000951
SleepOutOfBed	2.14e-05	3.26e-05	<b>2e-05</b>
WashDinnerDishes	<b>0.00012</b>	0.000237	0.00017
WashDishes	0.000241	0.000288	<b>0.000223</b>
Work	<b>8.97e-05</b>	0.000185	0.000103

Table 3.4: Wasserstein distance between activity duration histograms and different probabilistic distributions for various activities for home hh109.

Activity	Exponential	Normal	Log-normal
<b>Eating (a)</b>	5.49e-05	0.000147	<b>5.03e-05</b>
<b>WashDishes (b)</b>	0.000126	0.000258	<b>0.000101</b>
EnterHome	0.0113	0.0185	<b>0.0104</b>
Housekeeping	<b>4.04e-05</b>	9.65e-05	4.32e-05
MealPreparation	5.82e-05	0.000103	<b>5.23e-05</b>

Table 3.5: Wasserstein distance between activity duration histograms and different probabilistic distributions for various activities for home aruba.

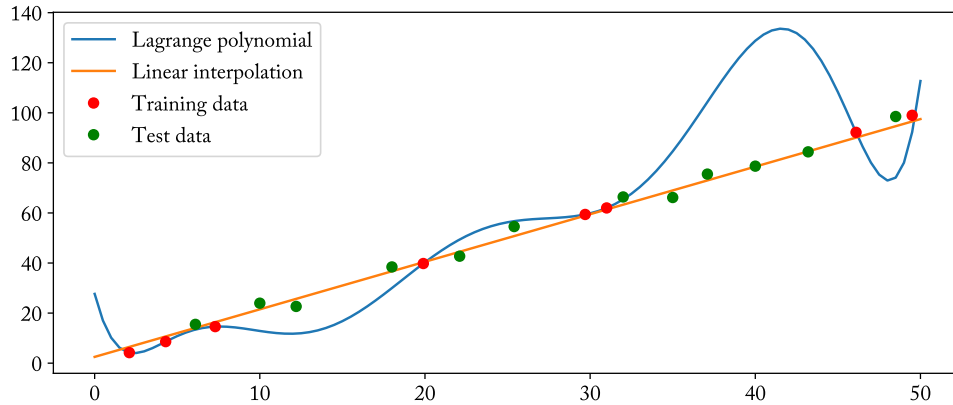


Figure 3.9: Example of overfitting: the linear regression offer a better representation of the data than the Lagrange polynomial even if it fit less properly the training data.

- Previously stated domain condition  $\mu - 3\sigma > 0$  is not always respected. More than half of the observed activities in smart home hh103, almost every activity in smart home hh109, and every activity of smart home aruba do not respect this condition. More specifically, activities dress and wash breakfast dishes from hh103 smart home (figure 3.7 (a, b)), eat dinner and relax from hh109 smart home (figure 3.7 (a, b)) and activities eating and wash dishes from aruba smart home (figure 3.8 (a, b)) are some clear examples of spread out normal distributions. This is a major problem as it means the model gives a significant probability to an event which cannot physically happen, i.e. a negative duration.
- Wasserstein distance for normal distribution often offer higher results than other tested distributions (in bold), meaning that it is not the most efficient law to use. In particular, the log-normal distribution is the most representative distribution for 11 activities out of 16 for hh103 and hh109 smart homes, and 4 activities out of 5 for aruba smart home. In the case where the log-normal distribution does not possess the lowest wasserstein distance, it still offer competitive results, for instance for activity wash lunch dishes in smart home ( $7.23e - 4$  against  $6.74e - 4$  for exponential distribution) or activity take medicine for smart home hh109 ( $9.51e - 4$  against  $8.38e - 4$  for exponential distribution). Actually, the normal distribution is even almost always less efficient than exponential and log-normal distribution;

Finally, log-normal distributions offer satisfying results for every situation, no matter the smart home or the observed activity. Contrary to normal law, log-normal distribution is defined on  $\mathbb{R}^+$  making it more consistent with the type of data observed. Moreover, for most activities, log-normal often offer the best Wasserstein distance, or one of the best, meaning log-normal is one of the best tested distributions to model activity duration.

The efficiency of the log-normal distribution is not a coincidence.

As stated before, the duration of actions composing an activity is not likely to be independent are they possess common factors, such as inhabitant's tiredness, attention or health status. However, activity duration can instead be seen as a mean duration influenced these factors, meaning activity duration is not a sum anymore but a product of these independent factors.

$$duration(activity_i) = \overline{duration(activity_i)} \times \prod_i f_i$$

where  $duration(activity_i)$  is the duration of  $activity_i$ ,  $\overline{duration(activity_i)}$  is the expected duration of this same activity, and  $f_i$  are various positive factors influencing the activity duration, for instance the tiredness of the inhabitant, his health status, his haste, his level of concentration, etc.

Moreover, a variant of the central limit theorem called multiplicative central limit theorem, or Gibrat's law [Samuels, 1965], states that the geometric mean of  $n$  independent positive random variables  $X_i$  tends to follow a log-normal distribution, assuming all  $X_i$  possess finite variance.

This theorem can be seen as the central limit theorem applied to the logarithm of a product of independent positive variables  $X_i$ :

$$Y = \prod_i X_i$$

$$\log(Y) = \log\left(\prod_i X_i\right) \text{ (assuming all } X_i \text{ are positive)}$$

$$\log(Y) = \sum_i \log(X_i)$$

If  $X_i$  are independent positive variables,  $\log(X_i)$  are also independent variables, meaning  $\log(Y)$  respects the central limit theorem and tends to follow a normal distribution. Consequently,  $Y$  follows a log-normal distribution.

This observation makes sense to the log-normal distribution to model activity duration. Consequently, log-normal distribution is less likely to produce overfitting.

#### Distribution parameters computation

STA model allows the use of any distribution.

However, as stated before and illustrated in figures 3.6, 3.7, 3.8, log-normal distribution offer relevant and satisfying results for most of the monitored activities, no matter the smart home topology, equipment or inhabitant.

Moreover, the efficiency of the log-normal distribution can be explained by the corollary of the central limit theorem. Consequently, log-normal distribution is very not likely to overfit the data.

In the remainder of this thesis, log-normal distribution will be considered for any activities, even if other distributions may be punctually used for specific activities.

Log-normal distribution can be modeled by the mean and standard deviation of the logarithm of duration. In particular, if  $\mu$  and  $\sigma$  are respectively estimations of the expectation and standard deviation of the log of duration:

$$\mu = \frac{1}{n} \sum_{i=1}^n \log(d_i), \sigma = \frac{1}{n-1} \sum_{i=1}^n (\log(d_i) - \mu)^2 \text{ (Bessel's correction)}$$

with  $n$  length of the data, then  $e^\mu$  and  $e^\sigma$  are the shape parameters used as log-normal distribution parameters. Bessel's correction corrects the bias in the estimation of the data variance [So, 2008].

### 3.3 Training phase duration assessment

In order to build a STA model depicting the life habits of the smart home inhabitant, his behavior must be observed during a training phase of a few days long. Duration of this training phase is a key factor to ensure a good representativeness of the model. If this training phase is too short, the model is insufficiently trained and does not efficiently represent the global behavior of the inhabitant. On the other hand, if the

training phase is too long, the assumption 5 attesting that the observed behavior is representative of the usual behavior of the inhabitant becomes more difficult to hold and the model quality might be impacted.

In most existing works considering behavior modeling, training phase is generally a few days long, but no more details are provided.

In this section, this question is explored in more details and a methodology to determine when the model is sufficiently trained is proposed.

Another way to state the problem is to find the moment when observing the inhabitant behavior does not provide more information about his routine. That is, finding the moment when the life habits model does not evolve anymore.

To assess if the life habits model is still evolving during the training phase, it is proposed to generate a new life habits model after each day of observation and to compare the obtained model with the previously generated ones. If the two models are different, it means the observation of this day brings new information about the life habits of the inhabitant. Otherwise, it means we did not learn anything about the inhabitant life habits. If the model does not evolve for a few days long, it signifies that the model has converged and the training is over.

### Activity ordering

Concerning the activity ordering feature, a commonly used tool to compare probabilistic model is the perplexity.

Perplexity is a commonly used measure in the language model community. It estimates the distance between two distributions  $D$ . These distributions can be empirical  $D_{\text{empirical}}$ , i.e. extracted from a database, or theoretical  $D_{\text{model}}$ , i.e. expressed by a model. Perplexity can be used to compare a model with an empirical distribution, or to compare two models in regards to an empirical distribution. To compute perplexity, entropy is required and is defined below, in consistence with definition introduced in [Vidal et al., 2005a]:

**Definition 3.9** *Let  $S$  denotes a sample of event sequences  $S = [w_1, \dots, w_n]$  where each  $w_i \in [[1, \dots, n]]$  is an event sequence. The entropy  $\hat{\chi}$  of  $S$  in regards to a PFA  $\langle A, P \rangle$  is defined by:*

$$\hat{\chi}(S, \langle A, P \rangle) = -\frac{1}{|S|} \sum_{w \in S} \log P(w | \langle A, P \rangle)$$

**Definition 3.10** *Perplexity  $PP$  of a sample  $S$  against PFA  $\langle A, P \rangle$  is given by:*

$$PP(S | \langle A, P \rangle) = 2^{\hat{\chi}(S, \langle A, P \rangle)}$$

*which can also be written:*

$$PP(S | \langle A, P \rangle) = \left[ \prod_{w \in S} P(w | \langle A, P \rangle) \right]^{-\frac{1}{|S|}}$$

### 3.3. Training phase duration assessment

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To compute perplexity and entropy, the norm of  $S$  denoted  $|S|$  is required. Two definitions can be used:

- The norm by string, which corresponds to the number of sequences in the sample  $|S| = n$ ;
- the norm by symbol, which corresponds to the sum of the length of each sequence composing the sample  $|S| = \sum_{i \in [1, n]} |w_i|$ . This norm is often preferred [Jelinek, 1997].

Entropy can be understood as the quantity of modification which has to be applied on the model  $\langle A, P \rangle$  to be used instead of the original distribution  $D_{empirical}$  to generate the sample  $S$  [Vidal et al., 2005a]. Perplexity, on the other hand, is the inverse of the geometric mean of the probability within the model of the sample sequences.

Perplexity and entropy might sometimes diverge when the tested sample  $S$  possesses a sequence which cannot be fired by the model. To avoid this situation, the probability can be smoothed: null probabilities are replaced by an infinitesimal value to still be able to compare entropy of different models. Several smoothing strategies exist. In this section, null probabilities are replaced by 1% of the minimum value a probability transition might take, that is  $\frac{1}{100 \times N_{event}}$  with  $N_{event}$  the total number of activities carried out during the training phase. This way, it ensures that a model which cannot fire a given test sequence will possess a lower entropy than a model which can.

Let consider an inhabitant carrying his everyday life in his smart home. The performed activities are recognized and enlisted in an activity event sequence  $w$  for  $n$  days.  $w_i$  designates the list of activities carried out the  $i^{th}$  day. For each day of observation  $i \in [[1, n]]$ , a model  $STA_i$  is generated from the concatenated sequences  $[w_1, \dots, w_i]$ . Then, the perplexity of full event sequence  $w$  against each generated  $STA_i$  is computed. The perplexity is expected to decrease at each iteration, as after each day the inhabitant life habits are better modeled. If the perplexity converges, it indicates the inhabitant life habits have been fully modeled and further training is not required anymore. Otherwise, additional training is required.

#### Activity duration

Concerning activity duration, a similar approach is proposed by comparing the distributions from model  $STA_i$  with the final distributions in model  $STA_n$ . If the model has been sufficiently trained, distribution from the  $i^{th}$  model should be similar to the last  $n^{th}$  model.

Wasserstein distance introduced in section 3.2.3 is a commonly used metrics to compare probability distributions. The lower the Wasserstein distance, the more the distributions are similar.

Wasserstein distance is expected to decrease after each day of observation, and to converge once the life habits have been completely identified, meaning the training phase is over. In the same manner that entropy for activity ordering, if the Wasserstein distance did not converge, additional training is required.

### Case study

As each dwelling and inhabitant is different, the required training duration might vary from a smart home to another. Consequently, the proposed methodology has to be applied on each of them. In particular, entropy, perplexity and Wasserstein distances can be computed on the flight to immediately stop the training phase as soon as the model is considered as representative enough.

However, in order to test the proposed methodology, and in order to have a first order of magnitude of the needed training phase length, a first short case study is proposed. It focus on the ARUBA smart home database, part of the CASAS project. In this smart home, a single individual carries out his everyday activities for 90 days. Observed activities are meal preparation, eating, wash dishes, relax, leave home, bed to toilet transition and work. 2662 activities were carried out by the inhabitant during this period.

Results for activity ordering is depicted in figure 3.10, and for activity duration in figure 3.11.

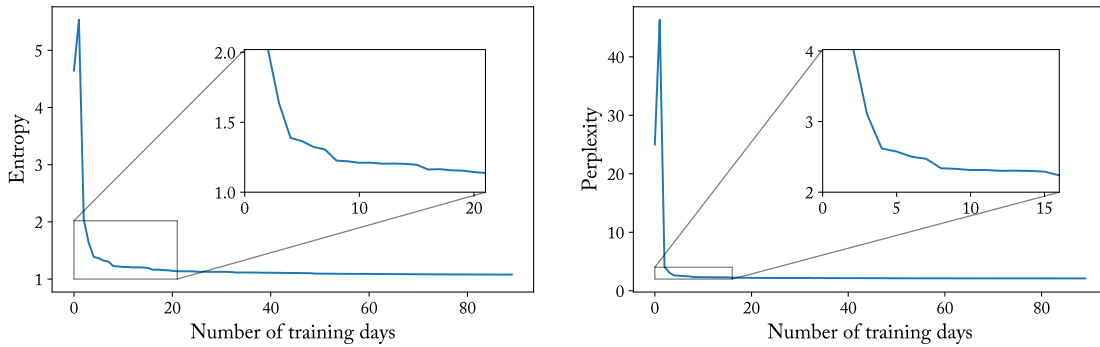


Figure 3.10: Evolution of entropy and perplexity for models generated each day for 90 days.

Concerning activity ordering, it can be seen that entropy and perplexity both converge very quickly. After only one week, the usual routine of the inhabitant is globally well understood and, after 20 days, both entropy and perplexity are stable and do not evolve anymore. These results tend to testify that 2 to 3 weeks of observation is enough to get the life habits of an individual.

Regarding the activity duration feature in figure 3.10, most activities also converge after a similar duration of 10 to 20 days. Meal-related activities, on the other hand, require more time to converge. Meal preparation and wash dishes activities both converge after 40 days of training. The fact that these activities require more time to be fully modeled is actually not that surprising as they cluster breakfast, lunch and dinner activities which can be carried out with very different duration. However, even in this critical scenario, the duration required for training is still bearable.

This case study offers an order of magnitude of the training phase duration for a single smart home inhabitant. A training phase of 10 to 20 days is actually sufficient to get the life habits of this specific inhabitant. Some activities might require more time, but worse-case scenarios do not exceed 40 days long training. This observation

### 3.4. Application to a public database

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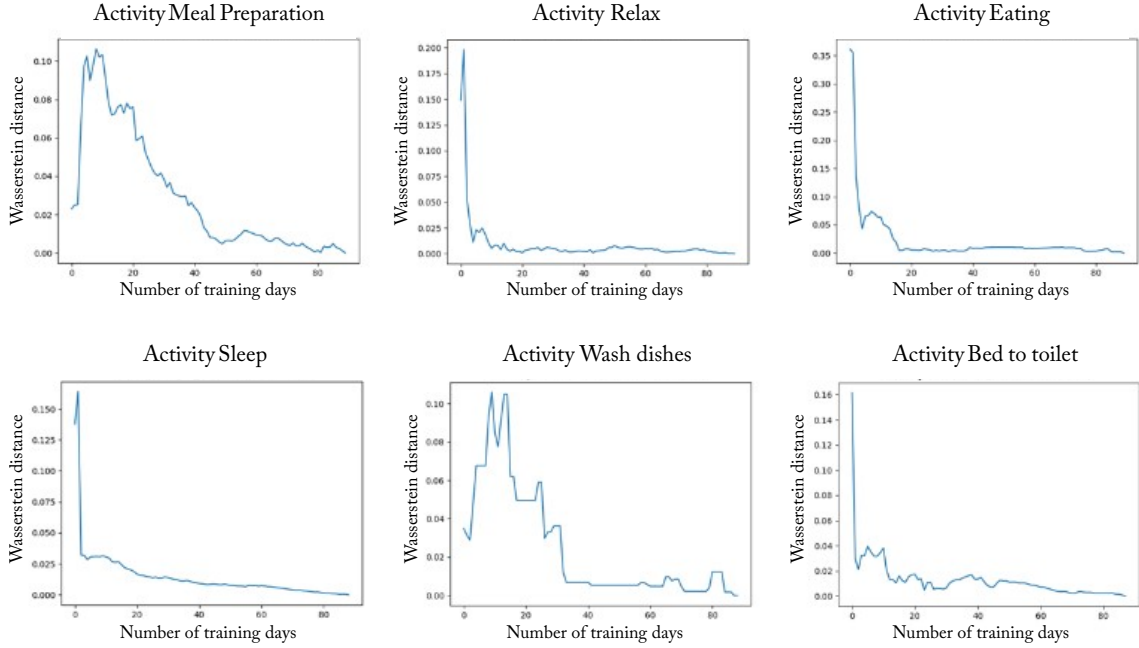


Figure 3.11: Evolution of the Wasserstein distance for most activities for 90 days.

is reassuring regarding the assumption 5 about unsupervised training data. Inhabitant behavior might possess some anomalies, but their number is expected to be low thanks to regular check-ups with medical staff during the training phase. Such hypothesis is easier to hold true if the training phase duration is limited.

However, as each inhabitant and smart home is different, this duration might varies. For each equipped smart home, the entropy, perplexity and Wasserstein computation have to be carried out in order to assess the training duration. This study is in particular performed for case studies presented in section 3.4.

## 3.4 Application to a public database

In order to assess the relevancy of the proposed model, several case studies are proposed. They are based on the databases presented in chapter 2 section 2.4.

### 3.4.1 DOMUS smart home

DOMUS database proposes to observe the behavior of 6 different users for 10 days. In this section, only model of user 1 and user 2 are exploited.

Methodology proposed in section 3.3 is applied in order to evaluate the training phase duration. Results are presented for user 1 in figures 3.12 and 3.13, and user 2 in figures 3.14 and 3.15.

Regarding user 1, the perplexity and entropy seems to both converge after 5 days. It might attest for a strong life habits regarding the activity ordering feature the inhabitant always follow, and which is rapidly captured by the model. Results for the activity duration feature however draw another conclusion. Only the activity wake

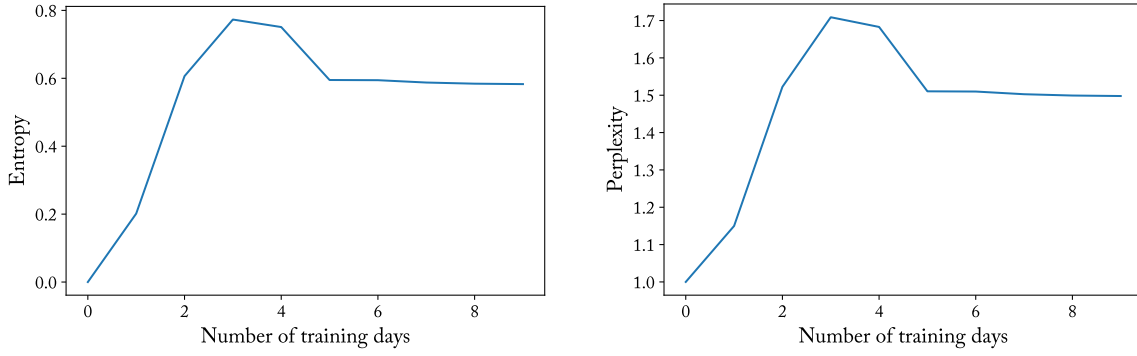


Figure 3.12: Evolution of entropy and perplexity from day 1 to day 10 for DOMUS smart home, user 1.

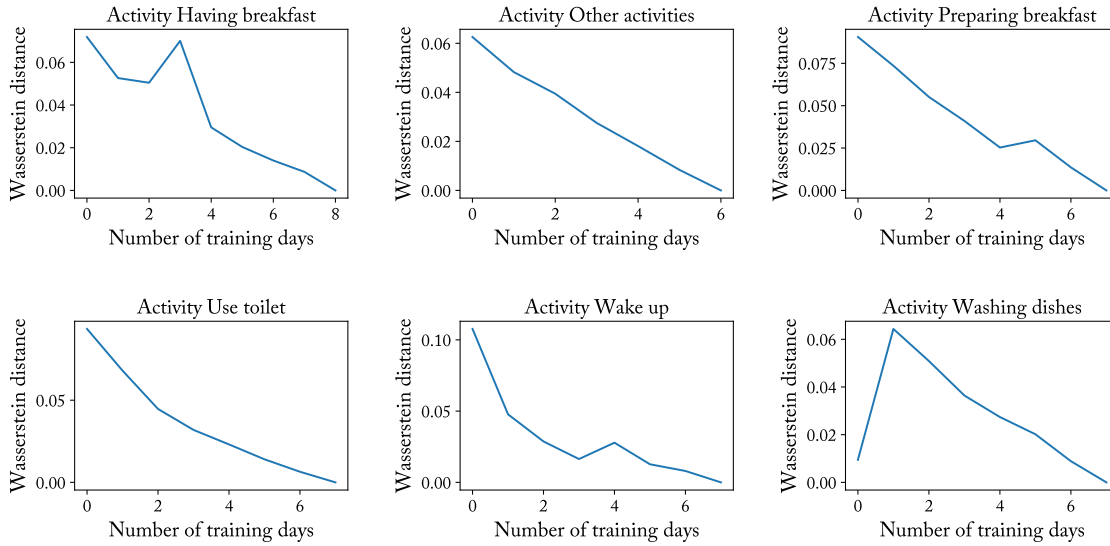


Figure 3.13: Evolution of the Wasserstein distance for every DOMUS smart home monitored activities carried out by user 1 for 10 days.

up seems to be sufficiently observed for training. Every other activity do not seem to converge after 10 days. Additional observation is required.

Concerning user 2, entropy and perplexity both stop to evolve after the 6th day, which seems to attest that 6 days of observation for this feature. For activity duration, activities having breakfast, use toilet and washing dishes seems to converge, even if a longer training would be required to confirm it. The three other activities does not have converged at all and testify for the need of more training.

As no more data is available, models will be generated on these sole 10 days. However, in a perfect case scenario, more training would be necessary for activity duration. This scenario is in fact explored in the second case study.

For each user, a model depicting his life habits is generated according to methods presented in this chapter.

These models are displayed in figure 3.16. They have been generated using Python

### 3.4. Application to a public database

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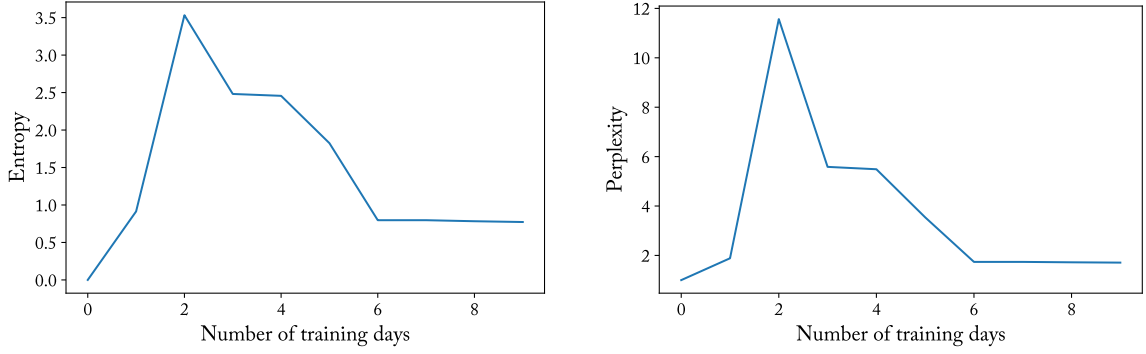


Figure 3.14: Evolution of entropy and perplexity from day 1 to day 10 for DOMUS smart home, user 2.

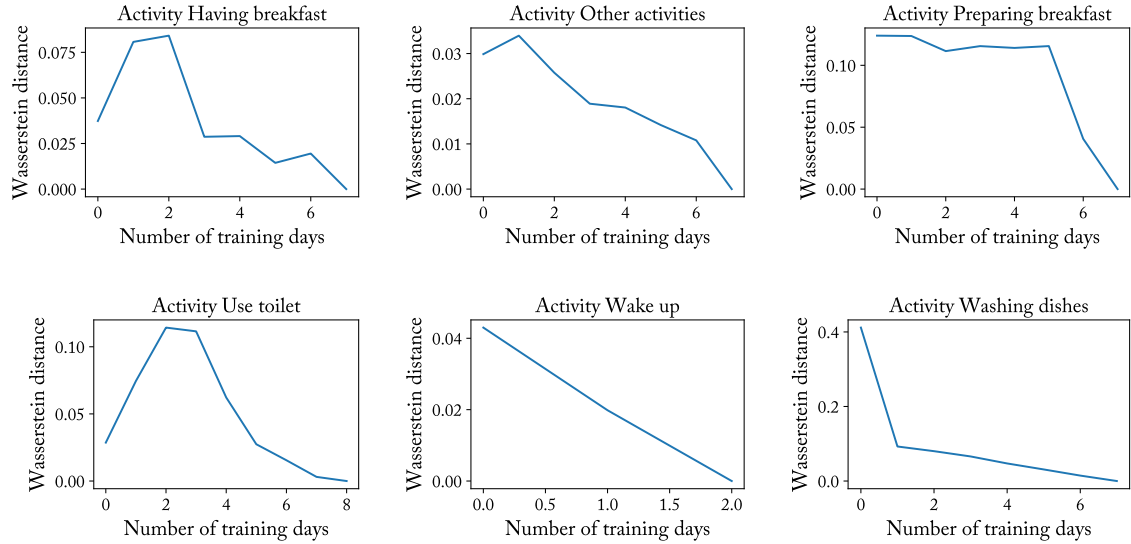


Figure 3.15: Evolution of the Wasserstein distance for every DOMUS smart home monitored activities carried out by user 2 for 10 days.

3.6 with GraphViz library. Median of activity duration  $e^\mu$  is in seconds. These models depict what is the morning routine of each of the experimenters, and noticeable differences are observed.

Concerning activity ordering, likelihood is a powerful tool to compute probability for each sequence of events to occur and therefore know life habits pattern of the inhabitant. For user 1, the word of length 6 the most probable to occur is [Other activities, Wake up, Use toilet, Preparing breakfast, Having breakfast, Washing dishes] with a likelihood of 11.16%. His morning routine is very likely to correspond to this order. Authors in [Saives et al., 2015] also exploited this database to extract the usual routine of the inhabitant. However, they use manual labeling which is time consuming and not scalable to the large amount of smart home which are expected to be equipped in the near future. They applied their methodology to the same user 1 and obtained the same morning routine, which tends to testify the correctness of our automatic approach.

User 2 has the same pattern, but with a much lower likelihood (3.97%) and some other patterns such as [Wake up, Use toilet, Preparing breakfast, Having breakfast, Washing dishes, Use toilet] appear with a similar likelihood (2.20%). Consequently, the models attest that user 2 behavior is more diverse than user 1. This observation confirms the relevancy of the assumption 6 (potential multi-class behavior). It also confirms the reason why entropy and perplexity rapidly converge for user 1, as his life habits are well-defined.

The models also allow for activity duration observation. In the presented example, user 1 activities related to breakfast are longer than user 2. The median time is equal to 199s and 579s for preparing and having breakfast activities for user 1, while user 2 requires 118s and 311s with similar shape parameters. Other activities roughly possess the same duration. Consequently, users 1 and 2 are likely to possess different eating patterns.

DOMUS database confirms the relevancy of the proposed approach. On the one hand, the obtained life habits which can be extracted from the model are consistent with manual inspection of other authors. Moreover, obtained models differ from a user to another despite acting in the same dwelling with the same equipment monitoring the same activities during the same period of the day. It attests for the need for model able to extract the personal life pattern of an individual, rather than relying on life habits most people are expected to follow. It also evidences that the proposed methodology is able to extract these personal life habits.



### 3.4.2 Hh103 CASAS smart home

Smart home hh103 from the CASAS project follows the everyday life of the inhabitant for 60 days. Methodology proposed in section 3.3 is applied in order to know the necessary training phase duration. Results for entropy and perplexity is illustrated figure 3.17, while results for activity duration are displayed figure 3.18.

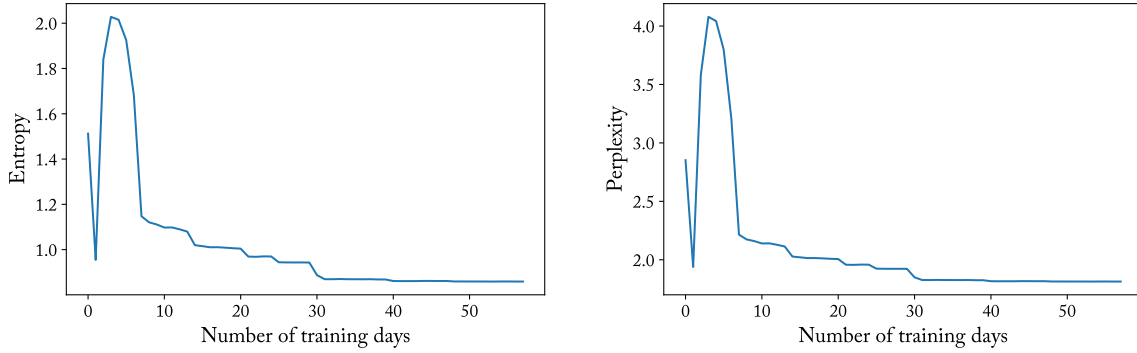


Figure 3.17: Evolution of entropy and perplexity from day 1 to day 60.

The evolution of the entropy and the perplexity attests for a training phase of 40 days long to obtain satisfying model.

Regarding activity duration, some activities such as eat breakfast or cook dinner are sufficiently observed after 20 days while some other activities such as eat lunch, sleep or bed to toilet transition require 40 days of observation.

Consequently, a 40 days long training phase is chosen. The following days will be used for activity anomaly detection in next chapter.

As the number of observed activities is consequent, the obtained model is particularly leafy. It is depicted in figure 3.20. To offer a clearer overview of the inhabitant life habits, a trimmed model is proposed for illustration instead. In this model, every transition with a probability lower than 15% is not depicted. It corresponds to behaviors which happened less than once per week, and which consequently are not likely to belong to the usual routine of the inhabitant. Moreover, the initial state is not represented neither for the sole sake of readability.

Trimmed model is depicted in figure 3.19. In the same way as previous case study, model has been generated using Python 3.6 and GraphViz library with activity duration median time expressed in seconds.

From this model, several conclusions can be drawn.

Concerning activity ordering, it can be seen that the inhabitant possesses very clear life habits. Sleep activity is almost always followed by personal hygiene activity before taking his breakfast. Between each meal, the inhabitant usually leaves his home and/or carries out personal hygiene activity. Meal related activities are often carried out in the specific order cook - eating - wash dishes, testifying for a very organized lifestyle. Consequently, a first conclusion which can be drawn from these observations is that the inhabitant is not likely to suffer from cognitive impairment.

Finally, inhabitant sleep patterns is often disturbed by toilet activities as he is expected to interrupt his sleep roughly 2 times per night.

Concerning activity duration, some comparisons can be made with the DOMUS database previously explored. In particular, it can be seen that meal related activities are notably longer with hh103 inhabitant compared to DOMUS experimenters, attesting for different eating patterns.

Moreover, all meals share a very similar median time of roughly 17 to 19 minutes. Many individuals have very short breakfast as they are dissatisfied to eat early in the morning just after waking up. As the hh103 inhabitant has a breakfast duration comparable to other meals, it attests for a rich breakfast, which is often associated with a healthier lifestyle [Smith, 1998].

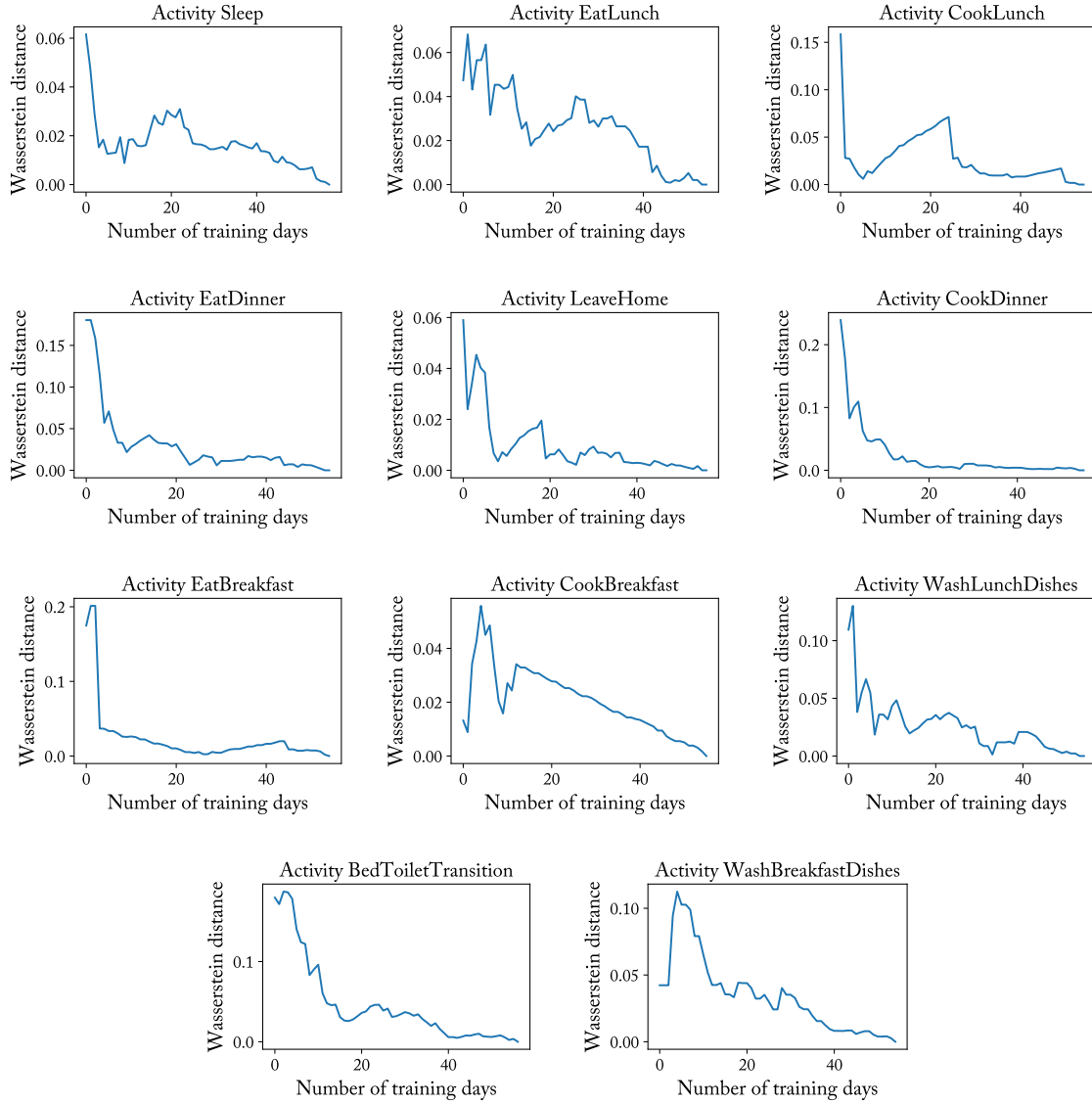


Figure 3.18: Evolution of the Wasserstein distance for every hh103 smart home monitored activities for 60 days.

### 3.4. Application to a public database

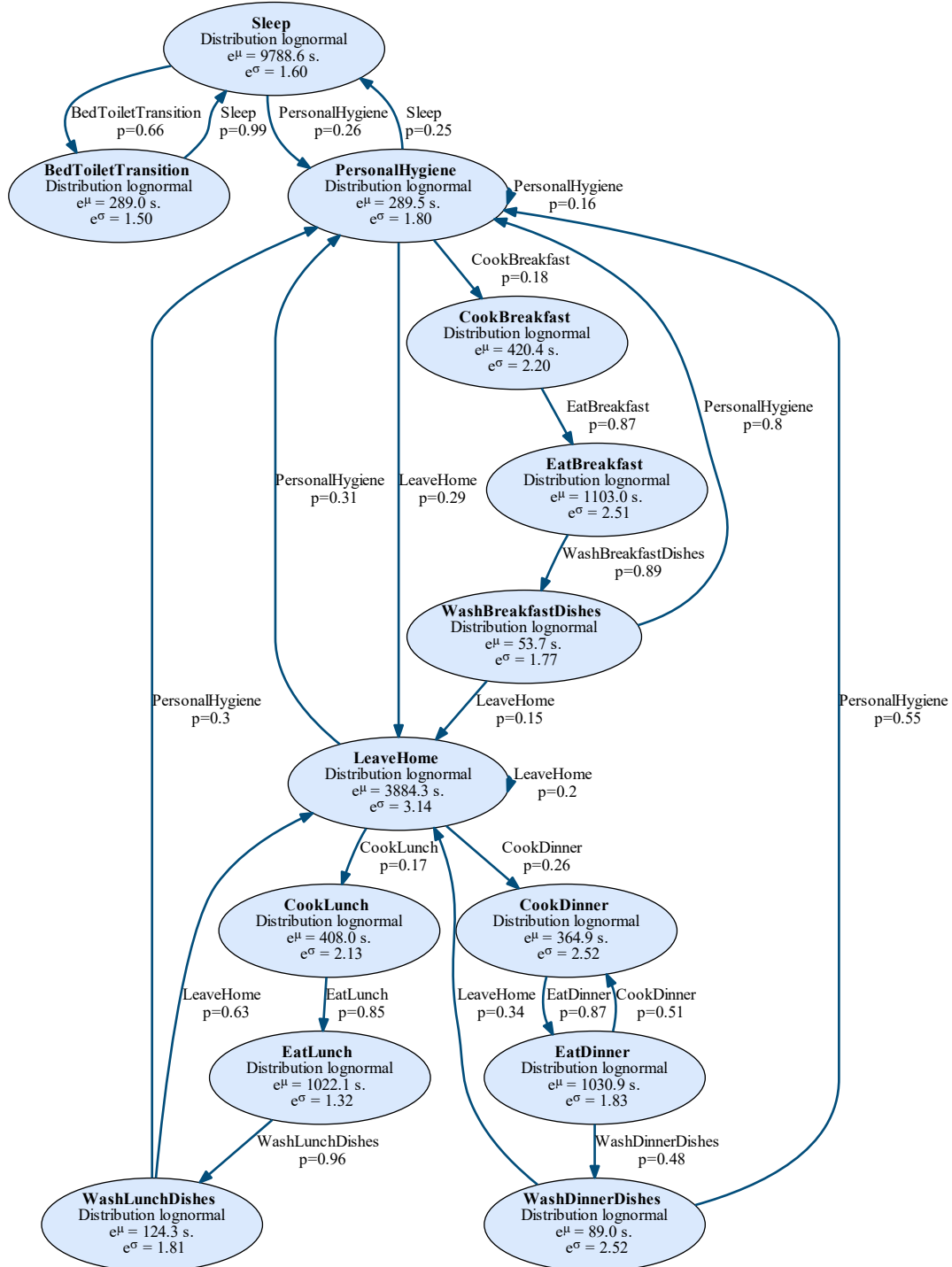


Figure 3.19: Trimmed STA representing the life habits of smart home hh103 inhabitant.

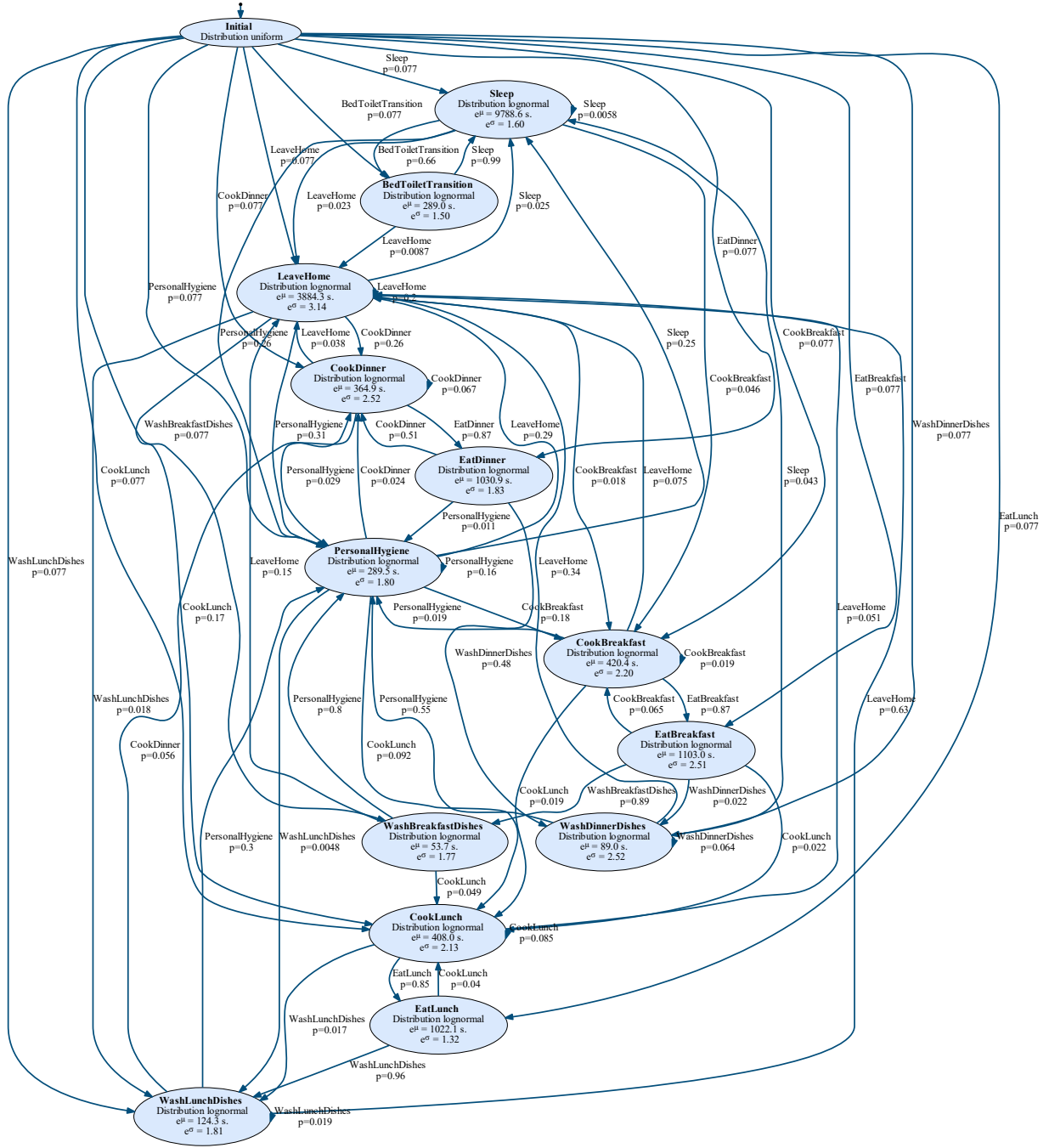


Figure 3.20: Life habits model of smart home hh103 inhabitant

## 3.5 Conclusion

Most of the individuals possess personal life patterns they tend to follow. These patterns offer an interesting overview of his health status to medical staff. Moreover, when someone suffers from a disease, these life patterns are influenced.

As each person possesses personal and unique behavior, a methodology extracting the habits of a smart home inhabitant by observing his behavior is required. This extraction is particularly challenging regarding the objective, i.e. offering insightful information to medical teams and easing communication with them, and the characteristics of human behavior, which can sometimes be indeterministic and plural.

To answer this needs, Stochastic Timed Automaton (STA) is proposed with an automatic generation procedure. An STA is composed of a structure which is automatically generated to ensure an envelope model, i.e. a model where any activity sequence can occur. Then, the probabilities associated to transitions and to location delays representing respectively the activity ordering and duration behavior features of the inhabitant are generated after a training phase. In particular, the probabilistic distributions able to satisfactorily model activity duration are explored, and the wide-coverage of the log-normal distribution is discussed.

The duration of the training phase is critical as a too short training leads to a poorly trained model unable to express the routine of the inhabitant, while a too long training phase is more likely to possess anomalies and disturb the training phase. Therefore, a procedure to assess if the training has been sufficiently long is also introduced.

Generation procedure and training duration assessment were both applied to two different cases study to attest of their efficiency. In both cases, the obtained models offer a clear overview of the life patterns of the individual. They also highlight the need for individual model as two different inhabitants executing the same activities in the same smart home still generates widely different models.

The next chapters exploit this model in order to detect behavioral deviations. Chapter 4 focus on anomaly, i.e deviation occurring at a specific time and for a short duration, while chapter 5 considers long-term deviation which slowly deteriorates the health and the routine an individual.

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# CHAPTER 4

## Anomaly detection in human behavior

---

*"Ce ne sont pas tant les règles que leurs exceptions qui sont importantes."*  
- Gary Kasparov -

### Abstract

When an individual gets sick, his behavior is most often impacted and modified. This chapter proposes a methodology to detect such behavior changes in regard to the activity ordering and duration features. If an anomaly is detected, the medical staff is informed about the deviation. Proposed methodology is applied on two case studies to be the most representative of real-life scenarios.

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### Contents

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<b>Introduction . . . . .</b>	<b>80</b>
<b>4.1 Anomaly detection framework . . . . .</b>	<b>80</b>
<b>4.2 Activity ordering anomalies . . . . .</b>	<b>81</b>
4.2.1 Symptoms and diseases which may influence activity ordering	81
4.2.2 Distance between observed behavior and life habits . . . . .	82
<b>4.3 Activity duration anomalies . . . . .</b>	<b>86</b>
4.3.1 Symptoms and diseases which may influence activity duration	86
4.3.2 Distance between observed duration and expected behavior .	87
<b>4.4 Application on smart home databases . . . . .</b>	<b>90</b>
4.4.1 Limits of existing databases and artificial data generation . .	90
4.4.2 DOMUS smart home . . . . .	90
4.4.3 Hh103 CASAS smart home . . . . .	94
<b>4.5 Conclusion . . . . .</b>	<b>97</b>

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# Introduction

A behavioral anomaly is a short-term modification of the inhabitant behavior which happens at specific moments and for a short time [Kaddachi et al., 2018]. An anomaly can have various causes such as a blunder -the inhabitant spilled water because of his clumsiness-, or more serious reasons such as a fall, a faint, or a disease. For instance, weakness symptoms may impact physical activities as the inhabitant becomes less able to carry them, while episodes of confusion due to cognitive impairments highly disrupt the order in which the inhabitant performs his everyday tasks.

Detecting these anomalies is particularly useful for medical staff. Most existing works about health monitoring consider vital signs, but many diseases affect the behavior of an individual first. Detecting these disruptions offer relevant information to medical staff as this type of information is normally hardly accessible for them while enabling early detection of critical diseases.

In order to offer relevant information to medical staff, features of human behavior were reviewed in chapter 2. Activity ordering and duration were identified as particularly interesting features as they cover most diseases the frail people might suffer while offering selective enough information to refine medical prognosis. Consequently, anomaly detection regarding these two features are explored in this chapter.

## 4.1 Anomaly detection framework

Figure 4.1 depicts the scope of this chapter and its positioning within the whole framework.

A smart home inhabitant carries out his everyday life in his home (1). However, no information about his health status is available now. The inhabitant might be healthy and have a behavior consistent with his life routine, or he might be sick and act differently than usual. The objective of this chapter is precisely to assess his health status by observing his behavior. Just like the training phase, the inhabitant triggers sensor events (2) which are used by existing activity recognition algorithms to feed an activity event database (3).

These events are compared to the inhabitant life habits model (4) generated during the training phase in chapter 3. If the observed behavior fits the model, it means the inhabitant continues to carry out his life as usual. Otherwise, a behavioral anomaly is detected (5) and sent to the medical team (6). Depending on the amplitude, the nature, and the frequency of the detected anomalies, medical staff can refine their prognosis, adapt their medical monitoring, or call for an appointment or emergencies in more critical scenarios.

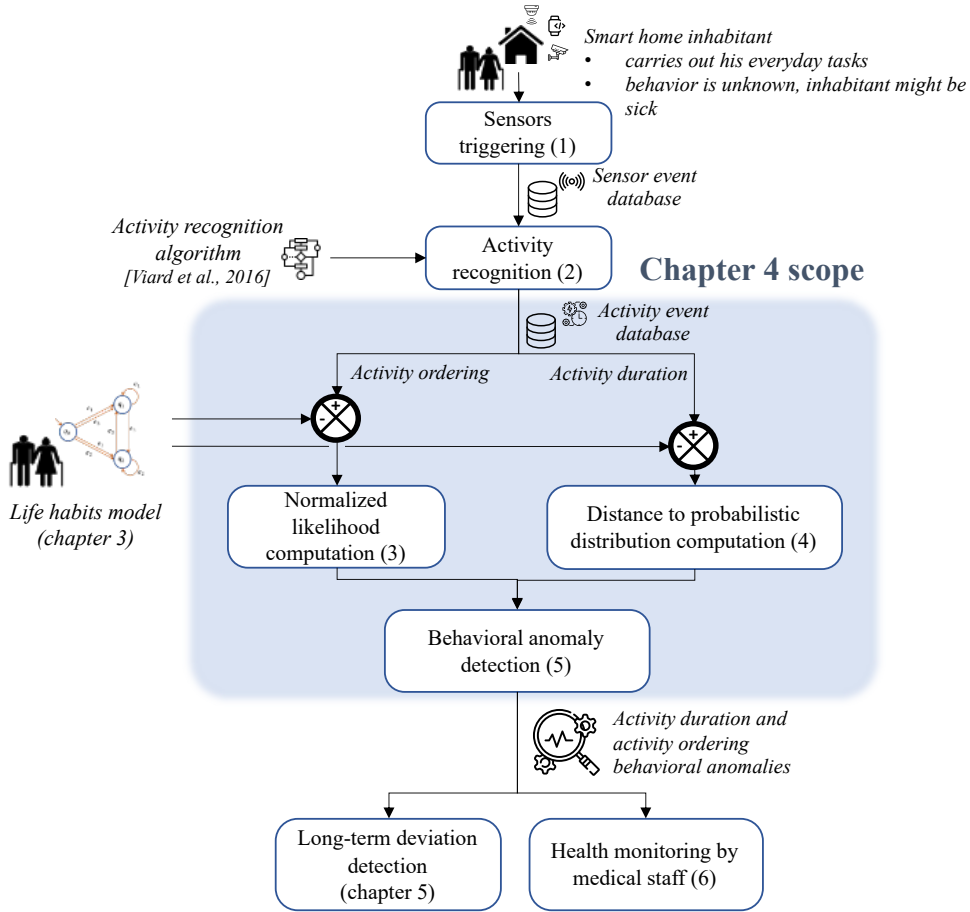


Figure 4.1: Proposed framework for behavioral anomaly detection.

## 4.2 Activity ordering anomalies

### 4.2.1 Symptoms and diseases which may influence activity ordering

As stated in subsection 2.1.1, activity ordering is a human behavioral feature which is influenced when the inhabitant suffers from sundowning syndrome, episodes of confusion, and wandering. Sundowning syndrome denotes an episode of confusion which typically happens at the end of the day to people suffering from dementia, while wandering represents moments when the inhabitant is lost in his own home and move from a room to another or carries out activities in a random way and order [Cankurtaran, 2014].

These symptoms are typical of various cognitive diseases and decline, such as Alzheimer's diseases or Mild Cognitive Impairments (MCI) for example. The objective of medical staff in this scenario is to evaluate the amplitude of the confusion episode. It can be evaluated by observing how long the episode lasts, i.e. how many activities are detected as anomalous, and by observing their frequency: daily, weekly, etc.

Activity ordering might also be influenced by specific diseases which force the inhabitant to miss or carry additional activities. Urinary Tract Impairment (UTI) is a

common example many elderly will suffer in their life, and affect the activity ordering feature because of additional bathroom activities. Meal disorder is another example of symptom which may affect activity ordering. Diagnostics of such health problem can be done by observing which activities disturb the activity ordering feature.

### 4.2.2 Distance between observed behavior and life habits

The objective of this section is to offer a metric to compute a distance between a newly observed sequence of activities and the STA model depicting the usual life habits of the inhabitant. If this distance exceeds a given threshold, an anomaly is detected and medical staff is informed. Several metrics already exists in the literature. They are reviewed in next subsections.

In this section, for the sole sake of readability, PFA model  $\langle A, P \rangle$  is considered instead of the STA model  $\langle A, P, \mu \rangle$ , as only the probabilities associated with transitions are insightful for the activity ordering feature.

#### Existing metrics

A first possibility is to examine if the test sequence  $w$  possess a valid fireable path  $\theta$  in the model. If not, it means the observed sequence has never been observed during the training phase, and is consequently considered as an anomaly. On the other hand, if such a valid path exists, it means the sequence is consistent with the model. This method has been explored for diagnosis of industrial systems in [Klein et al., 2005], [Roth et al., 2009].

However, this approach is not consistent with the assumption 5. Observed behavior during the training phase is unsupervised and may possess punctual anomalies, for example due to external disturbances. Consequently, a valid path in the STA does not necessarily mean the observed behavior corresponds to the usual routine of the inhabitant. A more refined method is required.

Other tools adapted for PFA are discussed in [Vidal et al., 2005a]: Likelihood and perplexity. They exploit the probabilities associated to transitions to determine if a given sequence is consistent with a model.

Likelihood  $P$  of a sequence  $w$  has been introduced in definition 3.8. It represents the probability that the tested model  $\langle A, P \rangle$  generates a given sequence:

$$P(w|\langle A, P \rangle) = \sum_{\theta \in \Theta_A(w)} (P(\theta|\langle A, P \rangle))$$

Perplexity, on the other hand, has been introduced in definition 3.10. It represents a cost to pay in order to use the model  $\langle A, P \rangle$  instead of the original distribution to generate the tested sequence sample  $S$ :

$$PP(S|\langle A, P \rangle) = 2^{\hat{\chi}(S, \langle A, P \rangle)}$$

with  $\hat{\chi}(S, \langle A, P \rangle)$  the entropy.

$$\hat{\chi}(S, \langle A, P \rangle) = -\frac{1}{|S|} \sum_{w \in S} \log P(w|\langle A, P \rangle)$$

As perplexity and entropy compare distributions, they offer relevant results only when comparing a sample of roughly the same size as the sample used for model training. In our case, STA model was trained from a few weeks long training sample, meaning perplexity and entropy are not adapted to evaluate daily behavior, or to evaluate the behavior of a part of a day.

Likelihood represents the probability that the model generates the tested sequence. It can be interpreted as the probability that the observed behavior fit the usual life habits, and is consequently well-suited for our objective. However, it also possesses two drawbacks.

First, likelihood score depends on the length of the tested sequence.

Let  $w_n = [e_1, \dots, e_n]$  be a sequence of events and  $w_{n+1} = [e_1, \dots, e_n, e_{n+1}]$  the concatenation of  $w_n$  and event  $e_{n+1}$ . Likelihood of sequence  $w_{n+1}$  is:

$$P(w_{n+1}|\langle A, P \rangle) = \sum_{\theta_{n+1} \in \Theta_A(w_{n+1})} P(\theta_{n+1}|\langle A, P \rangle)$$

By generation, each path  $\theta_{n+1}$  in  $\Theta_{\langle A, P \rangle}(w_{n+1})$  can be expressed as a path  $\theta_n$  in  $\Theta_{\langle A, P \rangle}(w_n)$  followed by a transition generating  $e_{n+1}$ .

$$\forall \theta_{n+1} \in \Theta_{\langle A, P \rangle}(w_{n+1}), \exists \theta_n \in \Theta_{\langle A, P \rangle}(w_n), t_{n+1} \in \delta_{\langle A, P \rangle} | \theta_{n+1} = \theta_n.t_{n+1}$$

where  $\theta_n.t_{n+1}$  denote the path  $\theta_n$  followed by transition  $t_{n+1}$ .

Consequently, number of valid paths in  $\Theta_{\langle A, P \rangle}(w_{n+1})$  is necessarily fewer or equal to the number of valid path in  $\Theta_{\langle A, P \rangle}(w_n)$ , and their probability is necessarily lower:

$$\begin{aligned} P(w_{n+1}|\langle A, P \rangle) &= \sum_{\theta_{n+1} \in \Theta_A(w_{n+1})} P(\theta_{n+1}|\langle A, P \rangle) \\ &\leq \sum_{\theta_n \in \Theta_A(w_n)} P(\theta_n|\langle A, P \rangle) \times P(t_{n+1}|\langle A, P \rangle) \text{ as } |\Theta_A(w_{n+1})| \leq |\Theta_A(w_n)| \\ &\leq \sum_{\theta_n \in \Theta_A(w_n)} P(\theta_n|\langle A, P \rangle) \text{ as } P(t_{n+1}|\langle A, P \rangle) \leq 1 \\ &\leq P(w_n|\langle A, P \rangle) \end{aligned}$$

with  $t_{n+1} \in \delta_{\langle A, P \rangle}$  such as  $\theta_{n+1} = \theta_n.t_{n+1}$

Consequently, if a sequence of activity  $w$  possesses a low likelihood score, two different reasons might be imputed: either the sequence does not fit the model, meaning the inhabitant had an unusual behavior, or the length of the sequence is important and mechanically induces a low likelihood. This situation is problematic as it means a low likelihood score does not allow to conclude on the health status of the inhabitant.

Secondly, as the sum of probabilities of outgoing transitions of each state must be equal to 1, likelihood of a sequence might be mechanically low if the life habits of the inhabitant are diverse, which may happen according to the assumption 6 (multi-class behavior). An example of this situation is given in figure 4.2. Inhabitant 1 possesses a clear life pattern corresponding to the sequence  $[e_{WakeUp}, e_{Breakfast}, e_{Toilet}, e_{Leave}, e_{WakeUp}]$

## 4.2. Activity ordering anomalies

while inhabitant 2 possesses two major habits corresponding to sequences  $[e_{Wakeup}, e_{Breakfast}, e_{Toilet}, e_{Leave}, e_{Wakeup}]$  and  $[e_{Wakeup}, e_{Toilet}, e_{Leave}, e_{Wakeup}]$ . The paths corresponding to these sequences are highlighted in the figure.

Likelihood of sequence  $w = [e_{Wakeup}, e_{Breakfast}, e_{Toilet}, e_{Leave}]$  is equal to 0.225 for inhabitant 1 and 0.1125 for user 2. The lower likelihood for inhabitant 2 does not mean the sequence does not correspond to his life habits, but is due to the variety of his life routines.

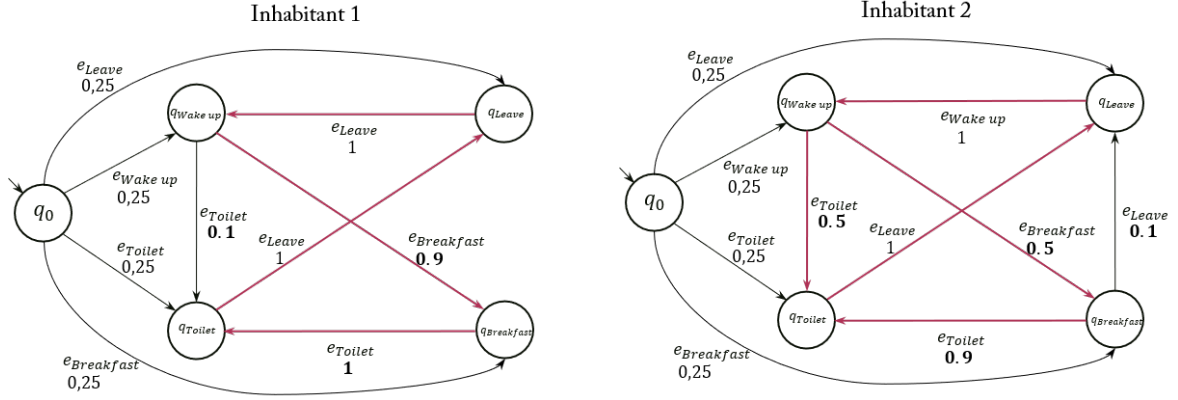


Figure 4.2: Examples of life habits model for two inhabitants. Transitions corresponding to the sequences with the highest likelihood are highlighted.

Thus, a low likelihood score does not give clear information about the tested sequence as it can be both due to an unusual behavior or to a usual behavior of an individual with diverse life habits.

To solve these two problems, normalized likelihood initially introduced in [Viard et al., 2016] is proposed.

### Normalized likelihood

The objective is to offer a distance between a sequence and a model reflecting if the tested sequence corresponds to a usual routine of an inhabitant. As likelihood based distance depends on the length of the sequence and the variety of the life habits, a low score does not allow to conclude on the consistence of the observed behavior in regards to the usual life habits, and consequently about the health status of the inhabitant.

A more suitable metric adapted from the likelihood is the normalized likelihood, defined below:

**Definition 4.1** *Normalized likelihood is the probability that a model  $\langle A, P \rangle$  generates a test sequence of events  $w$  divided by the likelihood of the most probable path of same length:*

$$||P(w|\langle A, P \rangle)|| = \frac{P(w|\langle A, P \rangle)}{\max_{v \in \Sigma^{|w|}} P(v|\langle A, P \rangle)}$$

with  $P(w|\langle A, P \rangle)$  likelihood defined in definition 3.8, and  $\Sigma^{|w|}$  the set of all sequences of length  $|w|$ .

By normalizing with the most probable path of same length, the metric is not dependent anymore of the length of the tested sequence. Moreover, the most common life habit always get a score of 1, and other sequences are evaluated relatively to this main life habits, negating the drawback of likelihood concerning multi-class behavior.

Consequently, a high normalized likelihood necessarily attests of the consistence between the observed sequence and the usual life habits, while a low normalized likelihood evidences the inconstancy between the sequence and the life habits model.

If we consider a second time the examples illustrated in figure 4.2, the likelihood and normalized likelihood of the main life habit of inhabitant 1  $[e_{Wakeup}, e_{Breakfast}, e_{Toilet}, e_{Leave}, e_{Wakeup}]$  and the main life habits of inhabitant 2  $[e_{Wakeup}, e_{Breakfast}, e_{Toilet}, e_{Leave}, e_{Wakeup}]$  and  $[e_{Wakeup}, e_{Toilet}, e_{Leave}, e_{Wakeup}]$  are given in table 4.1 It can be seen that the likelihood score does not allow to know if the sequences are consistent with the usual routine of the users, while normalized likelihood is unambiguous and clearly state that the tested sequences either corresponds to the most observed life habits or is a very common behavior.

		Likelihood	Normalized likelihood
User 1	$[e_{Wakeup}, e_{Breakfast}, e_{Toilet}, e_{Leave}, e_{Wakeup}]$	0.225	1
User 2	$[e_{Wakeup}, e_{Breakfast}, e_{Toilet}, e_{Leave}, e_{Wakeup}]$	0.1125	1
	$[e_{Wakeup}, e_{Toilet}, e_{Leave}, e_{Wakeup}]$	0.125	0.56

Table 4.1: Likelihood and normalized likelihood of main life habits of users 1 and 2.

### Computational complexities

Normalized likelihood is a very efficient metric, but its computation can be challenging for large models. As it requires to find the valid path with the highest likelihood for normalization, it may lead to combinatorial explosion.

With  $C_{||L||}$  the complexity of the normalized likelihood computation,  $C_L$  the complexity of the likelihood and  $C_M$  the complexity of the computation of the maximum value of the likelihood for a given length, we have:

$$C_{||L||} = C_L + C_M$$

With the forward algorithm [Rabiner, 1989], likelihood computation reaches a polynomial complexity.

$$C_L = O(card(Q_A)^2 \times |w|)$$

with  $card(Q_A)$  number of states in the STA structure  $A$ . Finding the most probable sequence within a model require to compute the likelihood of every possible sequence of length  $|w|$ , leading to:

$$C_M = O(card(\Sigma_A)^{|w|} \times C_L) = O(card(\Sigma_A)^{|w|} \times card(Q_A)^2 \times |w|)$$

The complexity is consequent. However, it can be greatly reduced by using some specific techniques and model simplification.

On the one hand, complexity of likelihood computation is highly impacted if the model is deterministic. From each state, there can be one unique fireable transition no matter the occurred event, leading to a constant complexity ( $O(1)$ ). Therefore, complexity is reduced to:

$$C_{L_{deterministic}} = O(|w|)$$

Regarding maximum likelihood computation, existing works [Viard, 2018] explored model reduction by removing events which are associated to transitions with lower probabilities. This method greatly reduces the number of transition to explore between two states, but is not rewarding in our case as there is only a unique transition between two states by generation.

On the other hand, use of dynamic programming can widely reduce complexity by using the forward algorithm and prefix memorization to avoid multiple computation of the same probabilities. This simplification has been described in [Viard, 2018] and [Vidal et al., 2005a]. This way, the computation complexity of the most probable sequence is defined by:

$$C_M = O(card(\Sigma_A)^{|w|} \times card(Q_A)^2)$$

removing the linear component  $|w|$  from the complexity.

In conclusion, in the case of a deterministic PFA on which dynamic programming is applied, complexity of the normalized likelihood computation is:

$$C_{||L||_{deterministic}} = O(|w| + card(\Sigma_A)^{|w|})$$

The complexity is greatly reduced, but is still consequent. However, the maximum probability computation part which is the most impacting in the complexity ( $O(card(\Sigma_A)^{|w|})$ ) can be run offline for various length  $|w|$  once the model is built while the likelihood computation only possesses a linear complexity ( $O(|w|)$ ), meaning that despite its complexity, normalized likelihood can be computed online.

## 4.3 Activity duration anomalies

Activity duration is represented through probabilistic distribution associated to delays within states. Any distribution can be used, but the versatility and good representativeness for most public databases of log-normal has been stated in chapter 3. Consequently, this section will consider log-normal distribution as the default choice. However, results and methods presented here can be extended to any distributions.

### 4.3.1 Symptoms and diseases which may influence activity duration

Activity duration is influenced by numerous different symptoms and diseases. Most trouble threatening the physical health status of an individual requires the inhabitant

to spend more time to achieve his tasks. This is the case for mobility problems, physical weakness, fatigue, inactivity, and general decline in ADL execution. Moreover, health issues concerning specific activities might influence their duration as well. Sleep impairment and eating disorder may result in shorter activities than expected, while UTI might increase bathroom duration.

The activity duration feature covers a large number of health problems. However, this feature is selective enough to give medical staff relevant information in order to refine their prognosis. Each health problem impacts a different set of activities. For instance, physical weakness impact most activities, while sleep impairment mainly affects sleep duration and eating disorder obviously impacts meal related activities.

Moreover, the type of temporal deviation also informs about potential responsible symptoms. For instance, an increase of sleep duration might attest of weakness and fatigue symptoms, while a decrease is more likely to be provoked by sleep impairment symptoms.

### 4.3.2 Distance between observed duration and expected behavior

#### Existing solutions and limits

Evaluating a distance between an observed duration and a model describing the expected behavior in order to detect outliers has already been explored for fault detection and diagnostic of industrial systems. Most of these works considered time thresholds which can correspond directly to the minimum and maximum duration observed during a training phase [Pandalai and Holloway, 2000], or be generated from a distribution built over the training data. Most of the time, training data is assumed to be normally distributed [Das and Holloway, 2000], but some authors considered more elaborated distribution, such as skewed normal distribution [Schneider et al., 2012].

Detecting anomalies in the behavior of a smart home inhabitant thanks to time threshold corresponding to the minimum and maximum observed duration during the training phase is a straightforward strategy. However, it is not consistent with the work assumption 5 defined in chapter 3. During the training phase, inhabitant behavior is unsupervised meaning that, even if most of his behavior is consistent with his usual life routine, some anomalies may happen. This assumption invalidates the use of such thresholds.

Moreover, the use of thresholds generates a label output: either the observed behavior is within the thresholds and is considered normal, or it exceeds them and is considered abnormal. Label output does not give additional information about the amplitude of an anomaly. Finally, it is impossible to select a specific abnormal event except by modifying model parameters. As these anomalies have to be analyzed by medical staff to identify possible responsible diseases, label output is not well-suited.

On the other hand, evaluating the consistence between the observed activity and the duration distribution generated in chapter 3 is the most natural way to proceed. It offers a score output, which enables analysts to have more precise information about the anomaly amplitude and type. Moreover, anomalies can be sorted and the thresholds

used to identify if a behavior is abnormal can easily be modified, easing the analysis process.

Detecting anomalies is only the first part of the health status evaluation. Once an anomaly has been detected, its nature, amplitude and frequency have to be evaluated by medical staff to identify a list of possible health problems causing the observed deviation. This evaluation is not part of this work. This chapter aims at offering the tools so that medical staff have access to relevant information to be able to determinate the health status of a frail individual in his home.

#### Distance to a probabilistic distribution

When considering distribution to identify if an observed behavior is normal or abnormal, most works consider normal distribution [Azefack et al., 2019, Forkan et al., 2015, Das and Holloway, 2000]. As stated in chapter 3, normal distribution is often a relevant choice if the observed phenomenon validates the central limit theorem. However, it has been shown that activity duration is not likely to respect the required hypothesis. Instead, activity duration is very likely to follow a corollary of this theorem, which can be called the *multiplicative* central limit theorem. Duration of an activity is the product of various, independent factors, depending for instance of the health, tiredness, urge or level of concentration of the inhabitant. In this case, activity duration tends to follow log-normal distribution.

First is introduced anomaly detection when the expected behavior is normally distributed. In a second part, an adaptation of this method is proposed to consider log-normal distribution.

Let consider normally distributed training data  $d_i$ ,  $i \in [1, n]$  with  $n$  the number of observations. Parameters  $\mu_N$  and  $\sigma_N$  of the experimental normal distribution  $N(\mu_N, \sigma_N)$  are computed from the  $d_i$ :

$$\mu_N = \frac{1}{n} \sum_{i=1}^n d_i; \sigma_N = \frac{1}{n-1} \sum_{i=1}^n (d_i - \mu_N)^2 \text{ (Bessel's correction)}$$

It is possible to compute a distance between a new observed duration  $d_{observed}$  and this distribution by computing the distance  $\tau_N$  with the expected mean  $\mu_N$ , and to express it in a number of standard deviation  $\sigma_N$ :

$$\tau_N(d_{observed}) = \frac{d_{observed} - \mu_N}{\sigma_N}$$

The more important the distance is, the more the observed duration differs from the distribution. In particular, if this distance reaches a given threshold, an anomaly may be identified. The value of this threshold depends on the expected amount of anomalies to observe. For instance, if 99.74% of observations are expected to fit the distribution, an anomaly is detected when time distance exceeds 3 or  $-3$ . Similarly, a threshold of 2 or  $-2$  stands for 95.44% of the expected observation.

Figure 4.3 illustrates correspondence between expected quantity of normal observation and corresponding threshold.

This distance can easily be adapted to consider log-normal distribution. Let consider that training data  $d_i$  follows a log-normal distribution  $Lognormal(\mu_{LogN}, \sigma_{LogN})$ .  $\mu_{LogN}$  and  $\sigma_{LogN}$  are computed as follows:

$$\mu_{LogN} = \frac{1}{n} \sum_{i=1}^n \log(d_i) ; \sigma_{LogN} = \frac{1}{n-1} \sum_{i=1}^n (\log(d_i) - \mu_{LogN})^2 \text{(Bessel's correction)}$$

With such parameters,  $\mu_{LogN}$  and  $\sigma_{LogN}$  are respectively the mean and the standard deviation of the logarithm of the data. It implies that  $e^{\mu_{LogN}}$  and  $e^{\sigma_{LogN}}$  are respectively the median and the *multiplicative* standard deviation of the data.

In that case, previously introduced distance  $\tau_N$  can be adapted to consider log-normal distribution. Let consider  $\tau_{LogN}$  the distance between an observation  $d_{observed}$  and the expected log-normal distribution. We have:

$$\tau_{LogN} = \frac{\log(d_{observed}) - \mu_{LogN}}{\sigma_{LogN}}$$

Similarly that  $\tau_N$ , thresholds are defined depending on the expected proportion of normal behavior to observe. If 99.74% of observations are expected to fit the distribution, an anomaly is detected when time distance exceeds 3 or  $-3$ , etc.

Figure 4.3 illustrates the computation of these distances, and the similarity between normal and log-normal distribution.

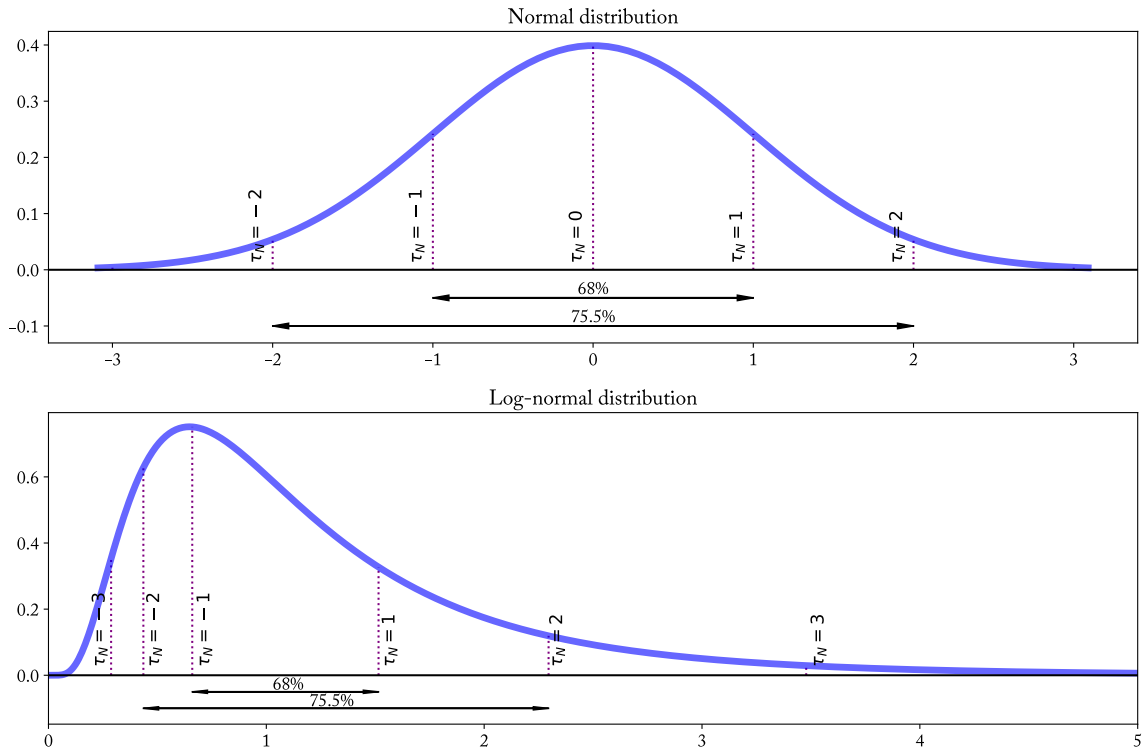


Figure 4.3: Relation between  $\tau_N$  and  $\tau_{LogN}$  distances with the observation expectation ranges.

It should be noted that a significant distance  $\tau_{LogN}$  does not necessarily mean the observed behavior is an anomaly. For instance, there is 0.26% chance that the expected distribution generates a data with a distance  $\tau_{LogN}(d_{observed}) = 3$ . This situation is very unlikely but may happen. It attests for the need for further exploration and investigation for medical staff to know if the observed behavior is an actual anomaly and if it expresses a health problem.

## 4.4 Application on smart home databases

### 4.4.1 Limits of existing databases and artificial data generation

To test the presented methodology, a labeled database of a sick inhabitant is necessary. To the best of our knowledge, there is no public database of this sort. Therefore, it is proposed to artificially build scenarios depicting symptoms evolution to be the most representative of real life observation. Moreover, artificial generation allows to test various situations, including worst-case scenarios to challenge the proposed method.

### 4.4.2 DOMUS smart home

Three scenarios are proposed: In the first scenario, the inhabitant carries out its activity as usual. His behavior corresponds to the life habits expressed by the model previously generated, meaning the order in which his activities is executed corresponds to the most probable activity event sequence within the model, and activity duration is generated from the distributions in the model.

In the second scenario, the inhabitant suffers from a loss of appetite. Loss of appetite is an important feature for medical staff to observe as it often mirrors the health status of a patient [Chalmers et al., 2019]. The activity ordering feature is unaffected, but meal related activities have shorter duration than usual. To simulate this alteration, meal-related activity duration is generated accordingly to the model and multiplied by a random positive factor  $f \in [0, 1]$ .

Finally, scenario 3 depicts an inhabitant suffering from urinary tract infection which is a common disease in the older population [Enshaeifar et al., 2019]. The routine of the inhabitant is modified by additional activities "Use toilet" randomly occurring during the day. However, activity duration is not modified.

Details about these scenarios and their artificial generation are given in table 4.2.

Activity duration is generated by the random variate function from the Scipy library on Python 3.6. Each scenario is ten days long.

## Application and results

Results for each scenario are depicted in figure 4.4. The list of activities index is stated in figure 4.3. Activity ordering is evaluated by computing normalized likelihood for each activity in relation to the previous occurred event. For instance, in scenario 1 the second event "Use toilet" follows activity "Wake up". It consequently possess a likelihood of 15.3% ( $17\% \times 90\%$ ) and a normalized likelihood of 90% ( $\frac{17\% \times 90\%}{17\% \times 100\%}$ ). Activity duration is evaluated according to section 4.3. If an activity evaluation reaches a threshold defined

Table 4.2: Activity sequence and duration for each simulated scenario.

	Scenario 1	Scenario 2	Scenario 3
<b>Symptom and disease</b>	Good Health	Loss of appetite	Urinary Tract Infection
<b>Generated activity sequence</b>	Usual life routine: [Wake up, Use Toilet, Preparing Breakfast, Having Breakfast, Washing dishes, Other activities]	Usual life routine: [Wake up, Use Toilet, Preparing Breakfast, Having Breakfast, Washing dishes, Other activities]	Usual life routine with one to three additional "Use toilet" activity randomly carried out every day
<b>Generated activity duration</b>	Randomly generated according to STA distribution	Activity Preparing and Having breakfast duration are multiplied by a random factor $f \in [0, 1]$ . Other duration are randomly generated according to STA distribution	Randomly generated according to STA distribution

by the medical staff, an anomaly is detected. For this case study, threshold of 15% for activity ordering which roughly correspond to a behavior which happened less than once per week, and  $2\sigma$  for activity duration,

For scenario 1, as the sequence of activity tested is consistent with the usual life routine of the inhabitant, normalized likelihood fluctuates between 78% and 100% and no anomaly is detected. Considering activity duration, most are included in  $[-1, 1]$  (green area) meaning the observed behavior is perfectly normal. Only activity "Use toilet" the first day is slightly shorter than expected, and activities "Use toilet" and "Preparing Breakfast" are longer than expected respectively the 4th and 9th day. Yet, these deviations' amplitude are not more than  $2\sigma$  (-1.93, 1.96 and 1.89), and are consequently considered as benign.

Concerning scenario 2, normalized likelihood is the same as activities are executed is the same order. However, duration study highlights a more disturbed behavior. In particular, activity "Preparing breakfast" is shorter than expected the 2nd, 3rd, 4th, 6th, 7th, 8th, and 9th day (respective distances are -3.39, -1.74, -2.32, -1.937, -4.26, -1.76, -7.24) On the other hand, activity "Having breakfast" is shorter than expected every day except day 10 (-1.15, -3.89, -1.39, -2.70, -1.98, -1.05, -6.05, -5.90, -3.90). These anomalies are sent to medical staff. As the deviations' amplitudes are severe and repeated several days in a row, a health problem can be deduced. The behavior deviation only concerns meal-related activities, thus eating disorder can be expected. Additionally, as the activity duration study reveals that these activities are shorter than expected, the loss of appetite is the privileged scenario. Other activities are punctually longer or shorter than expected ("Washing dishes" the 1st day, and "Other activity" the 7th day), but as these deviations appear once and have a low amplitude (below  $2\sigma$ ), they do not signify a massive change in inhabitant routine.

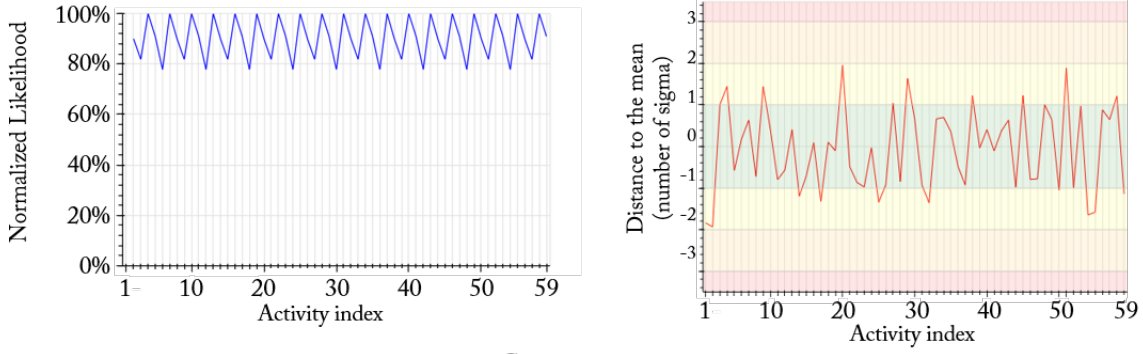
Finally, scenario 3 possess a more chaotic normalized likelihood which testifies a change in activity ordering. By observing more closely the activities, it appears that the sequences which possess a low normalized likelihood are ["Use toilet", "Use toilet"] (0%) 5 times, ["Having breakfast", "Use toilet"] (9.1%) 4 times, ["Use toilet", "Having breakfast"] (0%) 3 times, ["Preparing breakfast", "Use toilet"] (0%) 3 times, ["Washing dishes", "Use toilet"] (11.1%) 3 times, ["Use toilet", "Washing dishes"] (11.1%) 5 times, and ["Other activities", "Use toilet"] (0%) 2 times. As "Use toilet" appears in all of

these sequences, it can then be concluded that the inhabitant may suffer from a urinary problem. Yet, it should be noted that normalized likelihood offer no information about activity frequency. Medical staff has no information if activity "Use toilet" is executed more or less often than expected. Activity duration seems to be consistent with the usual life habits as no activity deviates from the expected behavior, except for activity "Use toilet" the 5th and 8th day (-2.30 and -2.17 respectively) and "Other activity" the last day (2.29). Yet, as these deviations are of different natures and not recurrent, they are not likely to express a health problem.

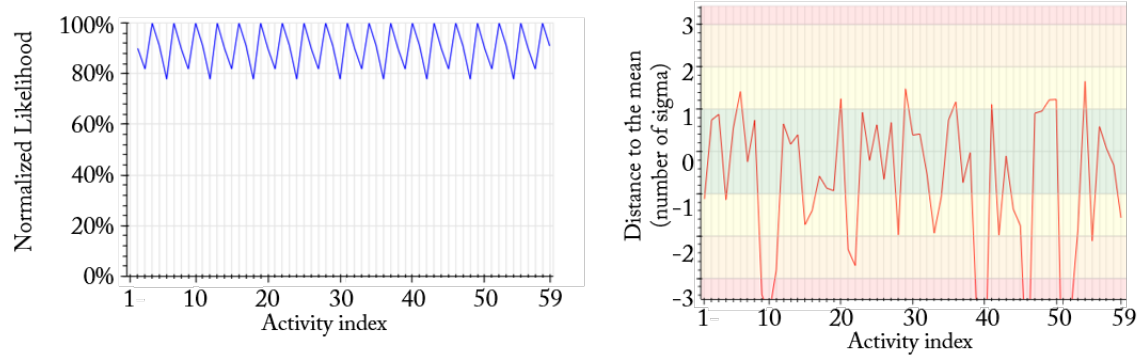
Table 4.3: List of index and associated activity

Scenario 1 & 2 Index - Activity		Scenario 3 Index - Activity	
1, 7, 13, 19, 25, 31, 37, 43, 49, 55	Wake up	1, 10, 19, 27, 34, 41, 48, 55, 63, 70	Wake up
2, 8, 14, 20, 26, 32, 38, 44, 50, 56	Use Toilet	2, 3, 5, 7, 11, 12, 13, 15, 20, 24, 25, 28, 31, 35, 40, 42, 45, 49, 53, 56, 58, 61, 64, 67, 71, 72, 77	Use Toilet
3, 9, 15, 21, 27, 33, 39, 45, 51, 57	Preparing Breakfast	4, 14, 21, 29, 36, 43, 50, 57, 65, 73	Preparing Breakfast
4, 10, 16, 22, 28, 34, 40, 46, 52, 58	Having Breakfast	6, 16, 22, 30, 37, 44, 51, 59, 66, 74	Having Breakfast
5, 11, 17, 23, 29, 35, 41, 47, 53, 59	Washing dishes	8, 17, 23, 32, 38, 46, 52, 60, 68, 75	Washing dishes
6, 12, 18, 24, 30, 36, 42, 48, 54	Other activities	9, 18, 26, 33, 39, 47, 54, 62, 69, 76	Other activities

### Scenario 1



### Scenario 2



### Scenario 3

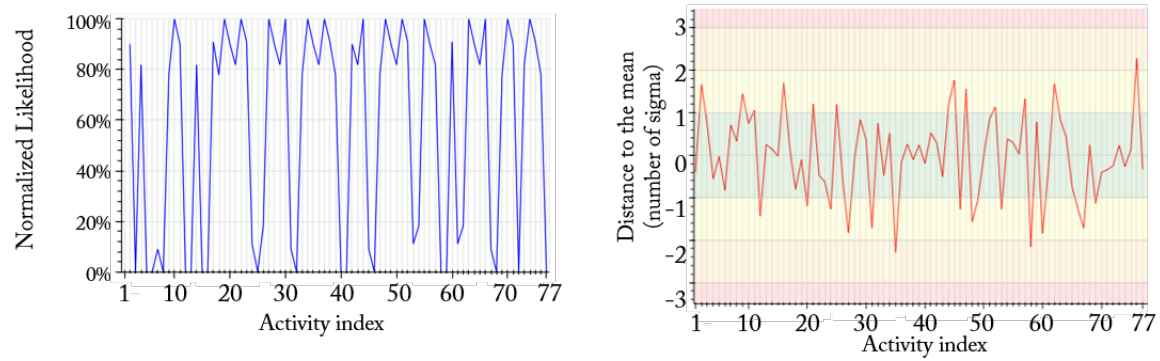


Figure 4.4: Normalized likelihood (left) and time distance (right) of each activity for each scenario.

### 4.4.3 Hh103 CASAS smart home

The hh103 smart home database offers to observe the behavior of its inhabitant for 60 days. The first 40 days are used for model generation. To test the anomaly detection methodology, the 10 following days are used through two scenarios.

In the first scenario, the 10 days are directly used without any artificial modifications. It is expected to observe a mainly sane behavior with potential scarce anomalies, according to assumption 5 (unsupervised behavior).

In scenario 2, a more challenging situation is proposed by combining several types of anomalies impacting various activities. In this scenario, the inhabitant is suffering from a cold or influenza, which triggers fatigue, eating disorder and weakness symptoms.

Sleep duration and personal hygiene duration are increased, as the inhabitant is tired and requires more time to carry usual activities, while meal related activities duration is reduced due to loss of appetite individuals usually experience when they are sick. Moreover, some random activities Leave Home are removed as the inhabitant become too tired to walk outside and prefer to stay at home.

Table 4.4 illustrates the two scenarios and the anomalies artificially generated. In total, 13 activities "Leave Home" have been removed.

Table 4.4: Activity sequence and duration for each scenario.

	Scenario 1	Scenario 2
Symptom and disease	Original behavior	Cold, influenza
Activity ordering feature	Days 40 to 50 from hh103 database unmodified	Days 40 to 50 from hh103 database where each "Leave Home" activity has 50% chance to be removed.
Activity duration feature	Days 40 to 50 from hh103 database unmodified	Days 40 to 50 from hh103 database where "Sleep" activities durations are multiplied by a random factor $f_{Sleep} \in [1, 2]$ , "Personal hygiene" activity duration by $f_{hygiene} \in [1, 1.5]$ and cooking and eating activities by $f_{meal} \in [0, 1]$ .

## Application and results

Results for both scenarios are depicted in figure 4.5 and 4.6. If the normalized likelihood is below 14%, which roughly corresponds to a behavior observed less than once per week, an anomaly is detected. The same way, for activity duration, if a time distance exceeds the  $-3$  or  $3$  threshold, an anomaly is raised. Table 4.5 displays the index of each activity for both scenarios. It can be observed that 8 leave home activities were removed in the scenario 2.

Regarding the first scenario, most of the observed behavior is considered as usual. A few anomalies still occur and are highlighted by red circles on the figure. Normalized likelihood delivers a score below 14% three times. The anomalies correspond respectively to activity sleep followed by activity cook breakfast, activity personal hygiene followed by activity cook lunch and wash lunch dishes followed by cook dinner. These anomalies appear due to missing activities personal hygiene or leave home.

## CHAPTER 4. Anomaly detection in human behavior

Scenario 1		Scenario 2	
Index - Activity		Index - Activity	
1, 3, 5, 22, 24, 44, 46, 65, 67, 83, 85, 105, 107, 109, 111, 129, 131, 133, 148, 150, 173, 175	Bed to Toilet Transition	1, 3, 5, 18, 20, 39, 41, 57, 59, 75, 77, 94, 96, 98, 100, 117, 119, 121, 136, 138, 158, 160	Bed to Toilet Transition
2, 4, 6, 21, 23, 25, 43, 45, 47, 64, 66, 68, 82, 84, 86, 104, 106, 108, 110, 112, 128, 130, 132, 134, 147, 149, 151, 172, 174, 176	Sleep	2, 4, 6, 17, 19, 21, 38, 40, 42, 56, 58, 60, 74, 76, 78, 93, 95, 97, 99, 101, 116, 118, 120, 122, 135, 137, 139, 157, 159, 161	Sleep
10, 17, 20, 26, 31, 41, 42, 48, 50, 54, 62, 63, 72, 87, 91, 103, 113, 115, 116, 120, 127, 138, 146, 157, 158, 163, 171, 177, 181, 183, 184	Personal Hygiene	10, 14, 16, 22, 27, 36, 37, 43, 44, 48, 54, 55, 61, 73, 79, 83, 92, 102, 104, 109, 115, 123, 127, 134, 140, 144, 145, 150, 156, 162, 166, 168	Personal Hygiene
11, 15, 18, 19, 30, 32, 36, 49, 55, 76, 92, 102, 114, 121, 139, 145, 159, 164, 170, 182	Leave Home	15, 26, 103, 105, 128, 146, 167	Leave Home
7, 27, 69, 88, 135, 152, 154, 178	Cook Breakfast	7, 23, 62, 80, 124, 141, 163	Cook Breakfast
8, 28, 70, 89, 136, 153, 155, 179	Eat Breakfast	8, 24, 63, 81, 125, 142, 164	Eat Breakfast
9, 29, 71, 90, 137, 156, 180	Wash Breakfast Dishes	9, 25, 64, 82, 126, 143, 165	Wash Breakfast Dishes
12, 33, 51, 73, 93, 94, 117, 160	Cook Lunch	11, 28, 45, 65, 84, 106, 147	Cook Lunch
13, 34, 52, 74, 95, 118, 161	Eat Lunch	12, 29, 46, 66, 85, 107, 148	Eat Lunch
14, 16, 35, 53, 75, 96, 119, 162	Wash Lunch Dishes	13, 30, 47, 67, 86, 108, 149	Wash Lunch Dishes
37, 39, 56, 58, 77, 79, 97, 99, 122, 124, 140, 142, 165, 167, 169	Cook Dinner	31, 33, 49, 51, 68, 70, 87, 89, 110, 112, 129, 131, 151, 153	Cook Dinner
38, 40, 57, 59, 78, 80, 98, 100, 123, 125, 141, 143, 166, 168	Eat Dinner	32, 34, 50, 52, 69, 71, 88, 90, 111, 113, 130, 132, 152, 154	Eat Dinner
60, 61, 81, 101, 126, 144	Wash Dinner Dishes	35, 53, 72, 91, 114, 133, 155	Wash Dinner Dishes

Table 4.5: List of index and associated activity for hh103 case study.

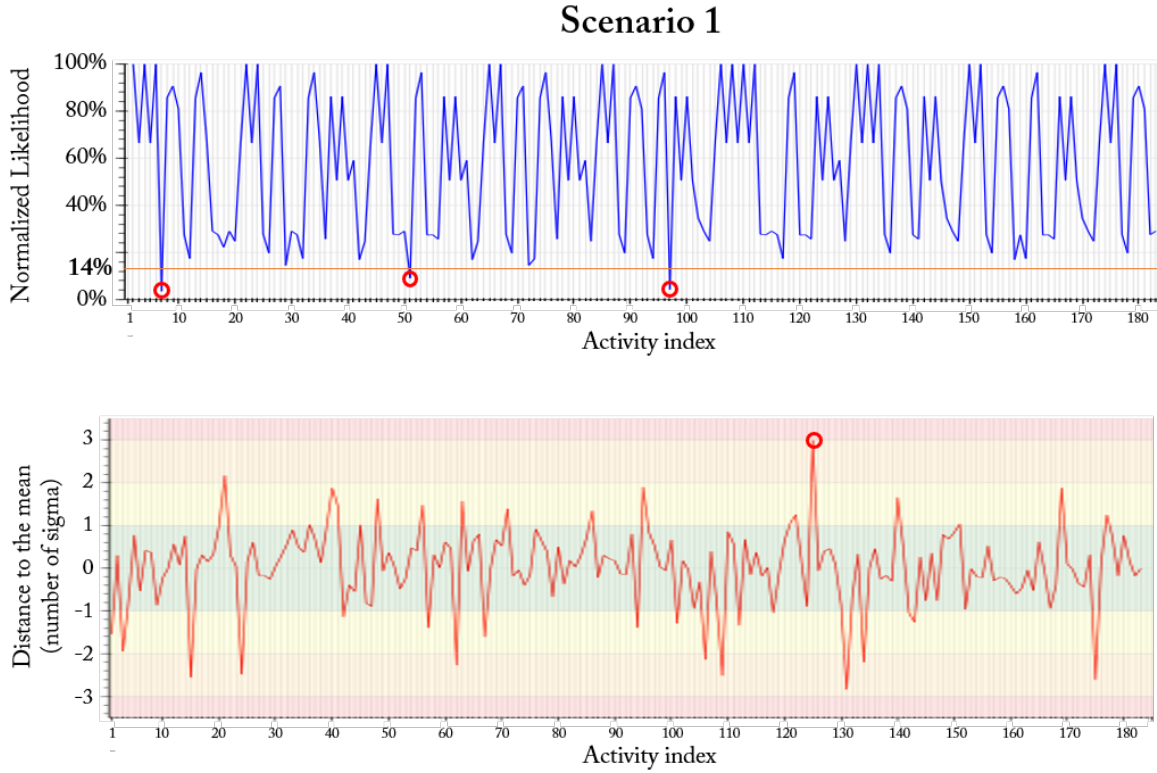


Figure 4.5: Normalized likelihood and time distance for scenario 1 of hh103 case study.

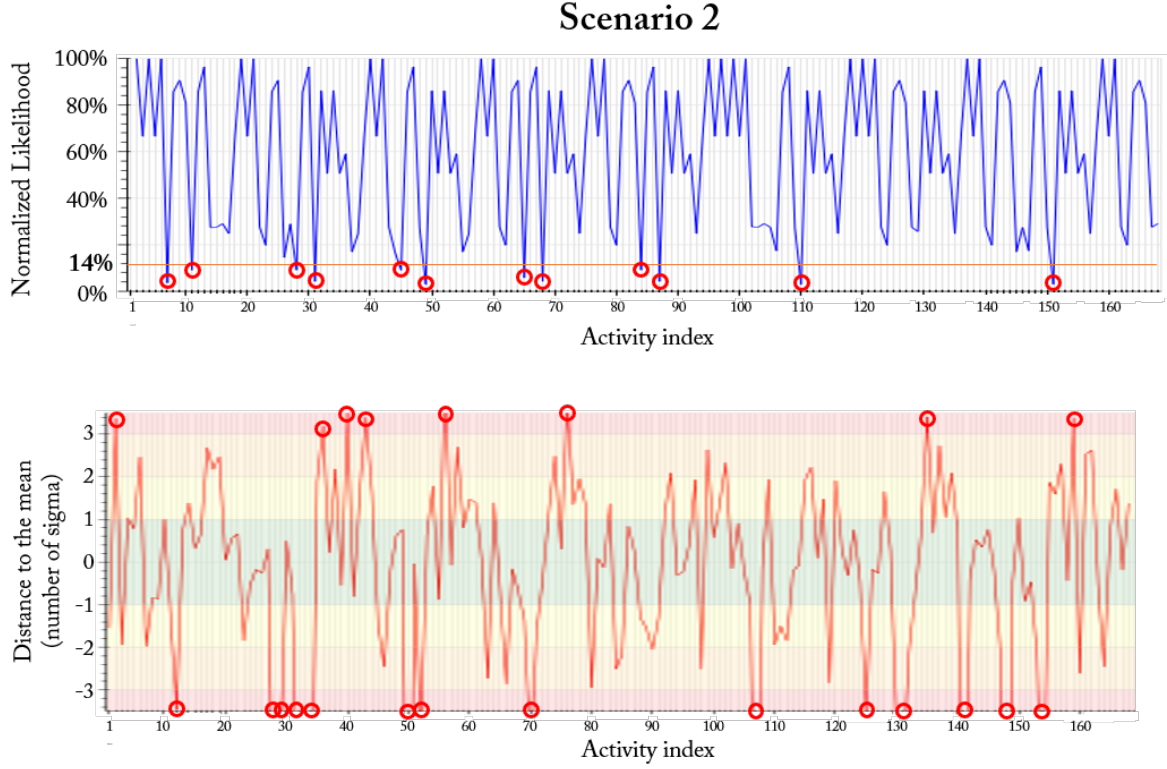


Figure 4.6: Normalized likelihood and time distance for scenario 2 of hh103 case study.

On the other hand, activity duration possesses a unique anomaly the 6th day as activity eat dinner is longer than usual.

From these observations, two conclusions can be drawn:

- The observed behavior seems to be sane as anomalies are scarce and affects different activities. However, it is not possible to declare if the proposed diagnosis is correct or not as the database is unlabeled and no information about the health status of the inhabitant is accessible;
- These results still confirm the relevancy of assumption 5 (unsupervised behavior). The observed behavior is supposed to be mainly sane and might possess punctual anomalies, which is indeed the case.

Regarding the second scenario, the 13 removed "Leave Home" activities trigger additional anomalies regarding the normalized likelihood. Twelve low likelihood scores are raised, meaning 9 out of the 13 removed activities led to a detectable anomaly as 3 anomalies were already present in the original behavior. Low likelihood score sequences are ["Sleep", "CookBreakfast"] once (3.4%), ["PersonalHygiene", "CookLunch"] four times (8.9%), ["WashLunchDishes", "CookDinner"] three times (4.2%), ["PersonalHygiene", "CookDinner"] three times (2.8%), and ["WashBreakfastDishes", "CookLunch"] once (5.7%).

It is difficult to identify the common cause of these anomalous sequence as the activity "LeaveHome" appears in none of them. Nevertheless, a closer inspection to the

life habits model show that this activity is missing in the sequences. This observation alone is, however, too limited to assess the health status of the inhabitant. Inhabitant might be tired because of sleep disturbance leading to reduced physical activity, or might be suffering from mobility problems which discourage him to go outside. The inhabitant may also suffer from weakness due to common disease, or might even suffer from episode of confusion. Inspection of the activity duration is necessary to refine the prognosis.

Regarding the activity duration feature, numerous meal related activities possess abnormally short duration. Activities "CookBreakfast", "EatBreakfast" and "CookLunch" raise an anomaly once, while "EatLunch" raise an anomaly four times, "CookDinner" three times and "EatDinner" 6 times, for a total of 16 anomalies.

On the other hand, several activities possess longer duration than expected: activity "Sleep" 6 times and "PersonalHygiene" twice.

The reduced duration of meal-related activity tends to testify that the inhabitant is not simply suffering from mobility problems or episodes of confusion, but rather from general weakness symptoms or physical decline. As the sleep activities are also longer than usual, the weakness symptoms is privileged.

The cause of these symptoms, however, is not identified. At this state, it is clear that the inhabitant is suffering from a disease which tire him, but it is not possible to not which one yet. It could be a cold or influenza, but might also be an infection, or other type of disease. It is up to the medical staff to complete the prognosis thanks to the inhabitant medical record, or after a medical appointment.

The proposed approach was still able to detect early signs of the disease and to send refined enough information to medical staff to get a satisfying prognosis.

## 4.5 Conclusion

A modification in an individual's health status often triggers a modification in his behavior. For example, if someone gets a cold, he is likely to be tired and to spend more time sleeping. If he is suffering from cognitive impairment, he might be subject of episodes of confusion where his behavior becomes erratic. Observing the behavior of an individual and detecting these changes can offer a relevant overview of his health condition. To that end, his behavior is compared to the previously generated model depicting the inhabitant's life habits. If the observed behavior does not fit the model, it means his behavior changed, which might attest for an alteration of his condition.

It should be noted that this chapter objective is to offer relevant information to medical staff in order to help their diagnosis. The inhabitant's health condition evaluation from these anomalies require their expertise and is not part of this work.

Two features within human behavior were identified as critical: activity ordering and duration. To evaluate the first feature, the newly observed sequence of activity is compared to the STA. There already are existing metrics fulfilling this aim. However, they fail to consider the plurality of the human behavior and might offer numerous false negatives. Consequently, normalized likelihood is introduced as it is able to consider models with multiple paths with high probability.

Considering the activity duration feature, the time the inhabitant spent to carry a specific activity is compared to the distribution expressing the expected usual activity duration. Distance to normal distribution is commonly used by existing works. As log-normal distribution is considered in our model instead, an adaptation of this distance is proposed.

To test proposed methodology, artificial database is proposed as, to the best of our knowledge, there is no existing labeled database of a sick smart home inhabitant. The data is generated to be the most representative of a ill person and to simulate challenging scenarios. The case studies offer satisfying results as the anomalies are correctly detected and a limited list of health problems causing the anomalies can be identified.

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# CHAPTER 5

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## Long term deviation detection

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*"Pour réussir, il ne suffit pas de prévoir. Il faut aussi improviser."*  
- Isaac Asimov, *Fondation, Partie 5 : Les Princes Marchands* -

### Abstract

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Anomaly detection is relevant to identify brutal changes in the inhabitant's behavior due to short-term diseases, such as influenza or a cold. However, most of the elderly will suffer from diseases which will provoke a slow decline of their behavior, such as frailty or cognitive impairments. To answer this need, long-term deviation detection is introduced through data forecasting in order to assess trends and potential future anomalies within behavior. The methodology is applied on several case studies to highlight its versatility and efficiency even in the most critical scenarios.

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### Contents

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<b>Introduction . . . . .</b>	<b>100</b>
<b>5.1 Medical motivation and needs . . . . .</b>	<b>100</b>
5.1.1 Symptoms and health trouble associated to long term behavioral deviation . . . . .	100
5.1.2 Objective and proposed framework . . . . .	101
<b>5.2 Long term deviation detection . . . . .</b>	<b>101</b>
5.2.1 Industrial system predictive maintenance . . . . .	101
5.2.2 Existing data forecasting methods . . . . .	103
5.2.3 Choice of a model . . . . .	109
<b>5.3 Case study . . . . .</b>	<b>115</b>
5.3.1 Artificial data generation . . . . .	115
5.3.2 Results . . . . .	116
5.3.3 Hh103 smart home . . . . .	118
<b>5.4 Conclusion . . . . .</b>	<b>123</b>

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# Introduction

Anomaly detection introduced in previous chapter is a powerful tool to offer medical staff additional information to help diagnosis of various health troubles which affect the behavior of an individual before affecting his vital signs.

However, some other diseases trigger long-term behavioral deviations, i.e. changes in behavior which continuously increase over time. Frailty or Parkinson's disease are some examples of typical degenerative diseases which affect the elderly and modify their behavior on the long term. Anomaly detection is inadequate to detect such health problems as it requires a long period of time before the behavior reaches alarming threshold, while early detection is often critical for such diseases. Moreover, it is difficult for medical staff to diagnose such diseases just by observing the behavioral anomalies as there is no way to distinguish those due to a long evolution to those which happened abruptly due to a fall for instance.

Consequently, this chapter offers adapted tools to detect the earliest possible slow decline in the behavior of an individual and ease their prognosis. The objective is to detect trends within the behavior of an individual to alarm potential future anomalies before they occur. When a potential future anomaly is detected, the information is sent to medical staff with the nature of the anomaly and its expected date, assessing for its criticality. Depending on these parameters, medical staff can carry out a more knowledgeable check-up in order to diagnose early signs of a potential degenerative disease.

## 5.1 Medical motivation and needs

### 5.1.1 Symptoms and health trouble associated to long term behavioral deviation

Long term behavioral deviations are caused by degenerative diseases which slowly degrade the health status of the sufferer. These degenerative diseases include cognitive impairment, such as Alzheimer or Parkinson's diseases, and diseases provoking physical declines such as frailty. The elderly are the main sufferers of these kinds of affection, and many of them will have to face at least one of them.

Physical and most cognitive degenerative diseases affect the activity duration feature. Due to the decline of the physical capabilities of the sufferer, the time he spends on physically challenging hobbies will reduce, such as exercising or leaving his home. On the other hand, time spent on the required tasks of everyday life, such as meal preparation or hygiene activities, might increase as it becomes harder and harder for the inhabitant to carry them.

Consequently, evolution of activity duration is a major information to assess if the inhabitant is suffering of a degenerative disease.

On the other hand, activity ordering is particularly useful to detect episode of confusion, i.e. period of time the inhabitant possesses an irrational behavior regarding

his usual life habits. Episodes of confusion are mainly due to cognitive decline impairments. Degradation of the health status of an individual suffering from such affection will provoke an increase of the frequency of such episode. However, it will not increase the level of irrationality of the episodes. Contrary to activity duration which can be more important as the disease becomes more and more critical, activity ordering is an all-or-none feature. Either the observed behavior is rational, or it is not. Consequently, anomaly detection already allows the earliest detection of these symptoms.

Therefore, this chapter will only consider the activity duration feature of the inhabitant's behavior.

### 5.1.2 Objective and proposed framework

Similarly as previous chapter, the inhabitant continues to carry out his everyday life as usual. His health status is unknown, meaning he can be healthy, slightly sick, or he might be suffering from a degenerative disease.

These activities are compared to the expected life habits STA generated in the training phase. From this comparison, future potential anomaly is assessed thanks to trend analysis and data forecasting methods detailed in this chapter. If an anomaly is forecast, the information is sent to medical staff with the expected anomaly type, concerned activity, and expected anomaly date. With this information, medical staff is able to assess the existence and potential criticality of the decline. Depending on their conclusion, they can organize a medical check-up to diagnose the earliest possible the degenerative the inhabitant might suffer.

## 5.2 Long term deviation detection

Early detection of potential health problems by observing evolution of the behavior of the inhabitant can be seen as an analog problem of predictive maintenance problematic. In industrial systems, some equipment may slowly degrade due to erosion and usury. Being able to detect when a component is about to crash or malfunction is particularly critical in order to maximize efficiency of a system. Consequently, this section introduces a quick survey of existing predictive maintenance tools in order to propose an adapted solution for our problematic.

### 5.2.1 Industrial system predictive maintenance

In industry, system fault is a critical problem which can lead to production shutdown, system damage, and in severe case operator safety endangerment. System maintenance offer tools to avoid these situations. There exists different maintenance strategies. They can be classified into three different categories [Carvalho et al., 2019]:

- Corrective maintenance (also called Run-to-Failure maintenance) is the most straightforward maintenance strategy as it simply aims at repairing or replacing a component when it is detected as faulty. This strategy is rudimentary and requires to stop the process to intervene and repair, which can be costly.

- Preventive maintenance aims at performing and optimizing a maintenance schedule to anticipate system failures. Number of maintenance operations has to be minimized to reduce maintenance costs, but have to be performed enough to replace a potential defective equipment before faulty behavior.
- Finally, predictive maintenance uses predictive tools and continuous monitoring to determine in advance when intervention is necessary. It allows early detection of defects which greatly reduce number of critical faults and situations.

A good maintenance strategy aims at minimizing maintenance costs while reducing the intervention time and improving the lifetime of equipment.

Corrective maintenance strategies only detect when a component is faulty, which does not allow methods to optimize its use and its lifespan.

Predictive maintenance strategies reduce to a minimum the amount of maintenance operations and enable early detection of faults, offering the best performances. Due to the new opportunities offered by Industry 4.0 technologies, these strategies are more and more explored [Carvalho et al., 2019].

In the context of medical monitoring, corrective maintenance strategy would consist in a patient calling for a medical appointment when he suffers of symptoms. Preventive maintenance would be regular check-ups to determinate if the health status of the patient is worsening or not. Predictive maintenance can be considered as the continuous monitoring of the inhabitant to detect potential trends in his behavior or vital signs and predict future health problems.

Consequently, predictive maintenance is explored in more details to get techniques which suit our work assumptions.

### **Predictive maintenance existing methods**

Existing solutions within predictive maintenance can be ordered in three categories:

- Knowledge-based approaches exploit the theoretical knowledge on the observed phenomenon to build a model describing its behavior. The model parameters can be updated while observing the system evolution over time to be the most accurate possible. These approaches can be very efficient if we possess theoretical knowledge about the system or phenomenon observed. This is not our case as estimating the health status of an inhabitant by observing his behavior is currently inaccessible.
- Statistical approaches exploit mathematical background and wide databases of past observations to estimate if a component is working properly. Smart home inhabitant's behavior monitoring is a recent topic. To the best of our knowledge, no existing database offer to observe a patient behavior suffering from various diseases. Consequently, these approaches are not well-suited to our case. However, this field could be explored in a few years when more smart home inhabitant's behavior databases will be available.

- Finally, machine learning approaches are also developed. They offer to exploit the data to extract components and relationship within it. These approaches often offer interesting results, and sometimes even outperform statistical approaches [Baptista et al., 2018].

Machine learning approaches are adapted to our case as we possess data related to the health status of the inhabitant (the activity time distance  $\tau$ ) but possess no mathematical background or theoretical knowledge to manually extract the interesting components and patterns within it. It is a very vast topic which covers numerous techniques and mathematical models.

The choice of a machine learning technique highly relies on the objective we want to achieve, and consideration about the input data: its quantity, labeling, number of variables, if they possess anomalies, potential constraints on the type of model -for instance considering black box approach-, etc.

Objective of this chapter is to detect long-term deviations in the inhabitant behavior regarding the activity duration indicator. As data is unlabeled and might possess anomalies (assumption 5), most classification approaches are not adapted. Input data is a time series, i.e. a series of data point in time order, and we want to detect critical behavior before their apparition. In this context, data forecasting is a very natural and efficient kind of technique to use.

Data forecasting aims at exploiting the features within a time series and knowledge in the domain to forecast their future values. As it allows to detect the presence of a potential health problem before it becomes too severe, this approach enables preemptive actions for medical staff which is a critical advantage as stated in previous section 5.1. It also gives clear information to medical staff by indicating which activity is influenced by a long-term deviation, what kind of deviation is happening, i.e. if the activity is getting longer or shorter than usual to be executed, and in how much time the behavior is expected to be anomalous. This information offer a clear overview of the health status of the inhabitant and help for the medical prognosis.

As it offers many advantages when applied to medical field, data forecasting has already been explored by some works for vital signs monitoring. For instance, [Khalil and Sufi, 2008] explored exponential smoothing forecasting method to monitor heart rate and blood pressure in order to detect early signs of tachycardia and fibrillation. [Forkan et al., 2015] also uses exponential smoothing to monitor numerous vital signs and detect problematic situations before they become critical. Figure 5.1 illustrates an example of body temperature monitoring and forecasting.

To the best of our knowledge, no existing work proposes to applied data forecasting to behavioral related data.

## 5.2.2 Existing data forecasting methods

Data forecasting methods can be classified into two categories: qualitative forecasting and quantitative forecasting. Qualitative forecasting (also called judgmental forecasting) proposes approaches for forecasting of data for which there is no historical data available. Examples of domains where qualitative forecasting is adapted are launch

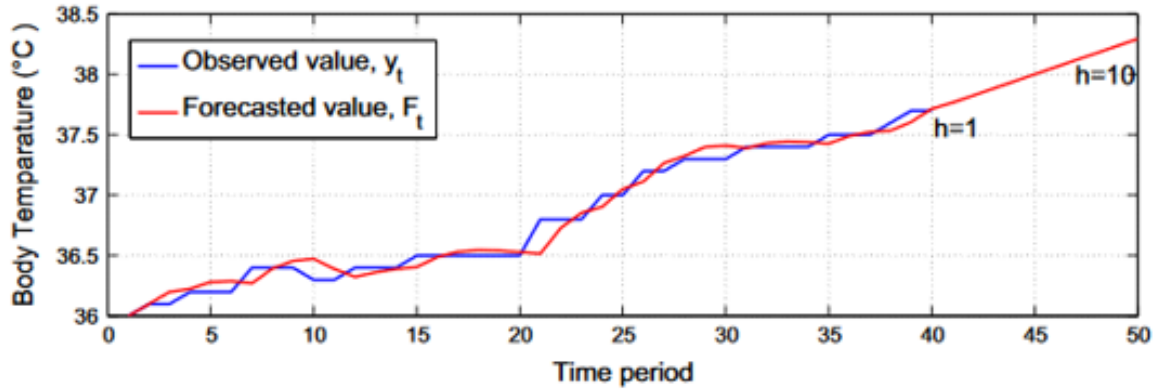


Figure 5.1: Exponential smoothing applied to body temperature to detect potential trends and fever symptoms after the 40th time period [Forkan et al., 2015].

of new products or markets and some specific political decisions. Quantitative approaches, on the other hand, require past data or other related data to forecast future values under the assumption that future data depends on the past.

**Assumption 8** *The behavior of an individual depends, even slightly, of its previous behavior.*

This assumption obviously holds for inhabitants suffering from slow decline behavior, as their behavior is more and more affected. Subsection 5.2.3 also explores this assumption for healthy behaviors, and attests for its relevancy.

With this assumption, quantitative approaches are the most adapted techniques to our problem. Within quantitative approaches, two techniques are widely used [Hyndman and Athanasopoulos, 2018]: Exponential smoothing and ARIMA. Exponential smoothing models the features within the data, such as trends or seasonality, by smoothing equations. ARIMA model aims at forecasting future values of time series by exploiting the autocorrelation within the data. Autocorrelation is the correlation between a data and its lagged value.

Both of these methods works on times series. Time series is a sequence of data taken at successive equally spaced points in time. Consequently, data pre-processing is required in order to obtain a unique value each day for each activity. If an activity has been carried out several times the same day, the duration is added in order to obtain a unique value. The distribution associated to each activity is updated in order to still offer relevant activity duration evaluation.

Exponential smoothing and ARIMA are both introduced in next subsection. Then, smart home databases are explored to determine which technique is the most adapted for behavior monitoring.

### Exponential smoothing

Exponential smoothing is a simple but one of the most successful forecasting methods. It aims at describing up to three components of a time series: the level, the potential trend and the potential seasonality. The level is the smoothed value of the time series,

while the trend is a slow increase or decrease in the data and seasonality is a pattern within the data which repeat with a fixed period, for instance a weekly or monthly period. Several models are available depending on the components we want to observe.

Figure 5.2 proposes examples of time series with trends and seasonality.

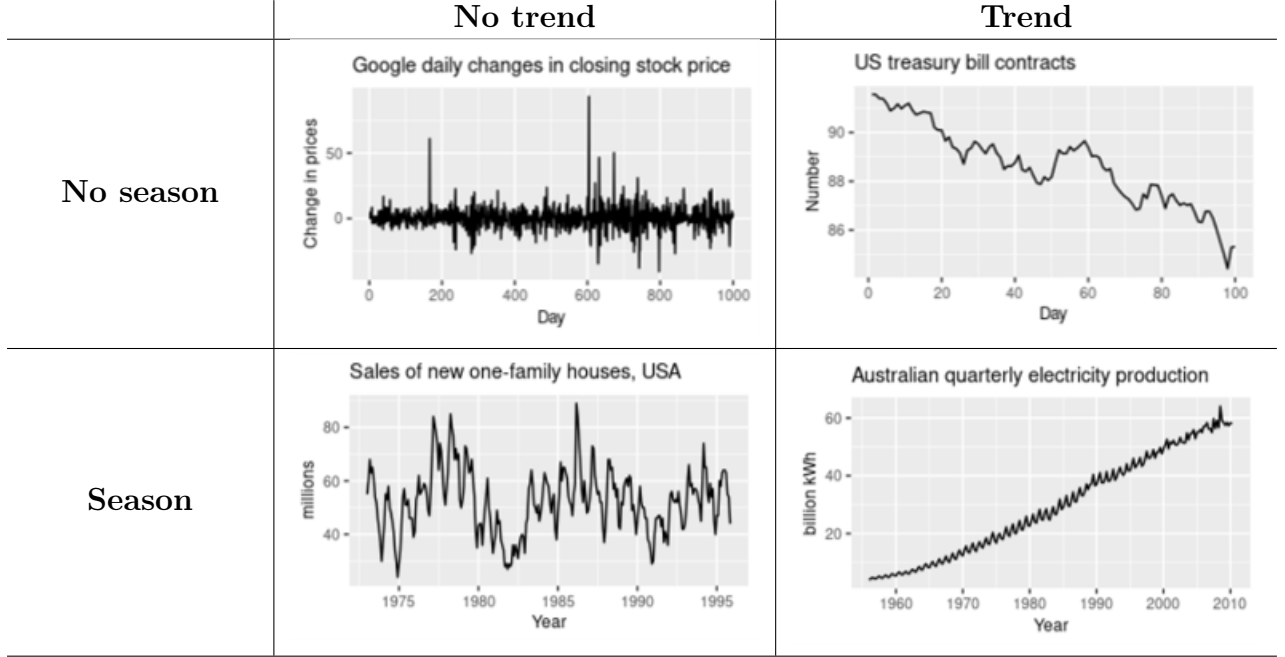


Figure 5.2: Example of time series with and without trend and seasons [Hyndman and Athanasopoulos, 2018].

Each of these components are described as weighted averages of past observations, where the weights are reducing exponentially when the observation become older [Gardner Jr, 1985]. In consequence, the basic smoothing equation for level can be written as:

$$\text{Level equation: } l_t = \alpha y_t + (1 - \alpha)l_{t-1}$$

where  $l_t$  is the level of the series at time  $t$  and  $\alpha \in [0, 1]$  is the smoothing parameter.

Trend equation estimates the trend  $b_t$  of the series at time  $t$ . If there is a trend within the data, the level equation is also slightly modified as follow:

$$\text{Level equation: } l_t = \alpha y_t + (1 - \alpha)(l_{t-1} + b_{t-1})$$

$$\text{Trend equation: } b_t = \beta(l_t - l_{t-1}) + (1 - \beta)b_{t-1}$$

with  $\beta \in [0, 1]$  the trend smoothing parameter.

In some cases, the trend can be damped to make the predicted trend converge to 0. It is useful for forecasting data where infinite growth is not realistic, such as in economy fields. This is not necessary in our case as activity duration is modeled by log-normal distribution. The distance  $\tau_{LogN}$  might infinitely decline, meaning the activity duration converges to 0, and might infinitely grow if the inhabitant get sicker and sicker.

Finally, if the data is seasoned, season equation can be used. Two methods are available, depending if it is expected that the season amplitude grows with the trend (multiplicative) or is independent (additive).

Both scenarios are described below:

### Additive method

$$\text{Level equation: } l_t = \alpha(y_t - s_{t-m}) + (1 - \alpha)(l_{t-1} + b_{t-1})$$

$$\text{Trend equation: } b_t = \beta(l_t - l_{t-1}) + (1 - \beta)b_{t-1}$$

$$\text{Season equation: } s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1 - \gamma)s_{t-m}$$

### Multiplicative method

$$\text{Level equation: } l_t = \alpha \frac{y_t}{s_{t-m}} + (1 - \alpha)(l_{t-1} + b_{t-1})$$

$$\text{Trend equation: } b_t = \beta(l_t - l_{t-1}) + (1 - \beta)b_{t-1}$$

$$\text{Season equation: } s_t = \gamma \frac{y_t}{(l_{t-1} + b_{t-1})} + (1 - \gamma)s_{t-m}$$

with in both cases  $m$  the season period length,  $\gamma$  the season smoothing parameter.

From these components, it is possible to forecast the  $h$  next values of the times series  $\hat{y}_{t+h|t}$ . Forecast value is the sum (respectively the product) of the level, trend and season defined in the previous equation in the case of the additive method (respectively the multiplicative method).

$$\text{Forecast equation: } \hat{y}_{t+h|t} = \begin{cases} l_t + hb_t + s_{t+h-m(k+1)} & \text{if additive method} \\ (l_t + hb_t)s_{t+h-m(k+1)} & \text{if multiplicative method} \end{cases}$$

with  $k = \text{int}(\frac{h-1}{m})$  so the forecast depends on the last observed season and with the convention that  $b_t = 0$  (respectively  $s_{t+h-m(k+1)} = 0$  or 1) if there is no trend equation (respectively no season equation for additive method or multiplicative method). It can be noted that if season equation is not used, additive and multiplicative method offer the same forecast.

To forecast future values, estimating the smoothing parameters vector  $\theta = (\alpha, \beta, \gamma)$  and the initial states vector  $X_0 = (l_0, b_0, s_0, \dots, s_{-m+1})$  is required. Several methods are available [Hyndman et al., 2002]. The most straightforward method consists in minimizing the Mean Squared Error (MSE):

$$\hat{\theta}_{MSE}, \hat{X}_{0_{MSE}} = \arg \min \sum_{i=1}^N \epsilon_i(\theta, X_0)^2 = \arg \min \sum_{i=1}^N (y_i - \hat{y}_i(\theta, X_0))^2$$

Other methods consider the assumption that the error  $\epsilon_i$  is normally distributed:

$$\epsilon_t \sim N(0, \sigma)$$

It is then possible to find the parameters which minimize the residual variance  $\sigma^2$ . An approximation of the likelihood can also be computed, in order to find the parameters which maximize it.

### Auto-regressive models

Auto-regressive models, on the other hand, aim at describing the autocorrelation within the data, i.e. the correlation between the time series and its lagged values. ARIMA model is one of the most successful, as it combines auto-regression (AR), differencing (Integrative I) and moving-average (MA) to express each value of the time series as a linear combination of the previous ones [Hyndman and Athanasopoulos, 2018].

This subsection presents ARIMA model. To define the method, ARMA model has to be defined first and is introduced below.

Let  $y_t \in \mathbb{R}$  be a times series of length  $N$  with  $t$  an integer index. The  $ARMA(p, q)$  model is then given by:

$$y_t - a_1 y_{t-1} - \dots - a_p y_{t-p} = \epsilon_t + \theta_1 \epsilon_{t-1} + \dots + \theta_q \epsilon_{t-q}$$

where  $\{a_i\}_{i \in [1, \dots, p]}$  is the set of the  $p$  order AR (Auto Regressive) coefficients,  $\{\theta_i\}_{i \in [1, \dots, q]}$  are the  $q$  order MA (Moving Average) coefficients, and  $\epsilon_t$  is the error-term associated to  $y_t$ . The  $p$  order AR can be seen as how far in the past is the autoregression, i.e. for how many days an activity duration will influence the following days. The  $q$  order MA (Moving Average) coefficients, on the other hand, can be thought of as the size of the weighted moving average of the past forecast errors. It represents how much a forecast error will influence the next forecasts.

By considering the backward shift operator  $B$  with  $B^m y_t = y_{t-m}$ , the previous model can be written:

$$\Phi_p(B)y_t = \Theta_q(B)\epsilon_t$$

where

$$\begin{aligned}\Phi_p(B) &= 1 - a_1 B - a_2 B^2 - \dots - a_p B^p \\ \Theta_q(B) &= 1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q\end{aligned}$$

ARMA model aims at describing correlation within time series. It implies two prerequisites for its use:

- The time series have to possess autocorrelations which can be expressed by the model. The quality of the prediction relies on these correlations. Subsection 5.2.3 explore existing databases and highlights the existence of such correlation in most activity duration.
- Data has to be stationary, which means data does not depend on time.

This chapter objective is to detect and measure potential trends in behavior. A trend is a slow increase or decrease of the time series over time. Consequently, activity duration is very unlikely to be stationary, and the second prerequisites is not fulfilled. As ARMA model cannot be directly applied to our time series, it is proposed to make the time series stationary by differencing it before applying the ARMA model. Differencing can be done by subtracting successive values in the time series  $y'_t = y_t - y_{t-1} = (1 - B)y_t$ . More generally speaking,  $y_t^{(d)} = (1 - B)^d y_t$ .

Thus is defined the  $ARIMA(p, d, q)$  model:

$$\Phi_p(B)(1 - B)^d y_t = \Theta_q(B)\epsilon_t$$

## 5.2. Long term deviation detection

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To estimate the coefficients of this model,  $d, p, q$  orders must be chosen, then coefficients  $a_{i \in \{1, \dots, p\}}$  and  $\theta_{i \in \{1, \dots, q\}}$  have to be evaluated. Maximum Likelihood Estimation is the most used technique for their evaluation. It consists in finding the vector parameters  $\theta = (a_1, \dots, a_p, \theta_1, \dots, \theta_q, \sigma^2)'$  which maximizes the likelihood function:

$$\hat{\theta}_{MLE} = \arg \max_{\theta \in \Theta} L(\theta|y)$$

with  $\Theta$  parameter space and the likelihood function being, under the assumption that the error-term  $\epsilon_t$  follow a Gaussian white noise  $N(0, \sigma^2)$ :

$$L(\theta|y) = \frac{1}{\sqrt{(2\pi)^n \det(\Gamma_n)}} e^{-\frac{1}{2} Y^T \Gamma_n^{-1} Y}$$

with  $\Gamma(\theta) = E(yy')$  the  $N \times N$  covariance matrix of  $y$  depending on  $\theta$ .

Instead of the likelihood, the log-likelihood is often used as it eases computation and converges to the same optimum:

$$\log L(\theta|y) = -\frac{1}{2} [N \log(2\pi) + \log |\Gamma(\theta)| + y' \Gamma(\theta)^{-1} y]$$

In practice, optimizing the likelihood is equivalent to minimizing the sum of squared errors (SSE):

$$SSE = \sum_{i=1}^n \epsilon_i^2$$

Considering ARIMA orders  $p, d, q$ , they can be estimated by data inspection and auto-correlative, partial-correlative and stationary estimation. Yet, these tools often require manual inspection and decision-making, while long-term behavioral deviation affects numerous smart home inhabitants, whose each activity must be inspected.

Another automatic method exists. All models with orders  $p, q \in [[0, 7]]$ , as it is not expected to have more than a week-long auto-correlation, and  $d \in [[0, 2]]$ , as higher differencing are very unlikely to produce more stationary data, are generated. This generation process is only a few seconds long. Then the model minimizing the Akaike Information Criterion (AIC) is selected. AIC is an efficient tool for model selection as it estimates the trade-off between goodness of fit and the complexity of the model, allowing to avoid overfitting.

$$AIC = 2k - 2 \log L$$

with  $k = p + q + 1$  the number of parameters of the model and  $\log L$  the maximum value of the log-likelihood function defined earlier. A model with a high  $AIC$  possesses an important number of parameters and offers a low likelihood, which means the model is inefficient to represent the data. On the other hand, a low  $AIC$  score means that the model possesses a high likelihood even if the number of parameters is low, attesting for its relevance. Consequently, from all the generated ARIMA models is selected the one with the lowest  $AIC$ .

### 5.2.3 Choice of a model

Auto-correlation  $r_k$  expresses the correlation between each  $i^{th}$  and  $(i - k)^{th}$  values of a time series:

$$r_k = \frac{\sum_{i=k+1}^N (y_i - \bar{y})(y_{i-k} - \bar{y})}{\sum_{i=1}^N (y_i - \bar{y})^2}$$

with  $N$  length of the time series,  $k \in \mathbb{N}$ ,  $y$  the observed times series with  $y_i$  its  $i^{th}$  value and  $\bar{y}$  its mean.

A significant value for  $r_k$  means the  $i^{th}$  value of the time series highly depends of the  $(i - k)^{th}$  value. If every multiple of  $k$  possesses significant values, it might attest for the existence of a season of period  $k$  within the data.

Both exponential smoothing and ARIMA models offer interesting results. As they consider different components, the choice of a method over the other relies on the features within the data we want to represent. ARIMA model exploits the autocorrelation within the data to forecast next values of the time series. If the data possesses auto-correlations, ARIMA can give relevant values. Otherwise, exponential smoothing may give more interesting results if the data possess trends or seasonality.

To know which method is the most adapted, it is proposed to explore public smart home databases presented in section 1.3 and to evaluate the existence of autocorrelation and seasonality. If there is autocorrelations within the data, it attests for the relevancy of ARIMA model. Otherwise, exponential smoothing is more appropriate, and seasonality will be considered depending if they exist in the data.

Smart homes hh103, hh109 and aruba are considered as they offer long enough behavior observation to draw first conclusions -60 days for hh smart homes and 90 days for aruba-. Applied methodology is illustrated in figure 5.3.

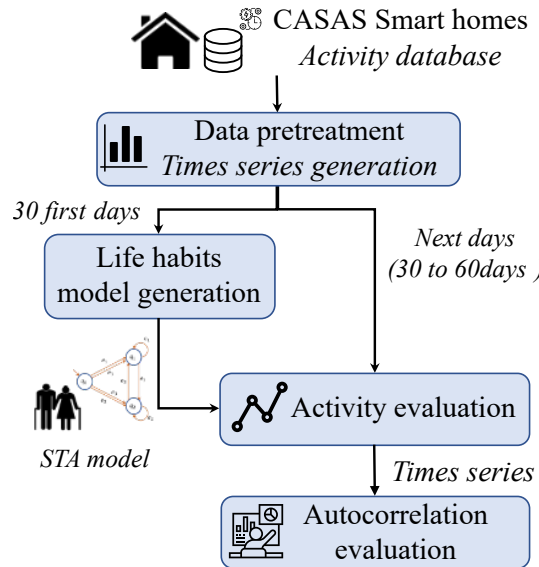


Figure 5.3: Proposed methodology to assess existence of autocorrelation within human behavior.

While the inhabitant carries out his everyday life, his activities are recorded in an activity databases thanks to activity recognition algorithms. In order to generate time series, data pretreatment is applied. Duration of several instances of the same activities carried out the same day is added in order to obtain a unique activity duration each day. For instance, if the inhabitant carried out the activity "PersonalHygiene" from 8:01:38 to 8:11:02, from 12:45:51 to 12:48:59 and from 20:01:24 to 20:05:11, then the activity duration for this day is unique and is 16min 19sec. Having one unique value per day is necessary in order to make seasonality and autocorrelation study relevant.

Proceeding this way produces times series which encompasses two different features: activity duration and activity number. Indeed, if an activity is carried out more often than usual, the total duration on the whole day would increase as well. However, both of these features monitor the same symptoms: decline in ADL, weakness, inactivity, UTI, sleep and diet disturbances, and fatigue. The coverage of each feature in regard to the symptoms of interest is reminded in figure 5.4.

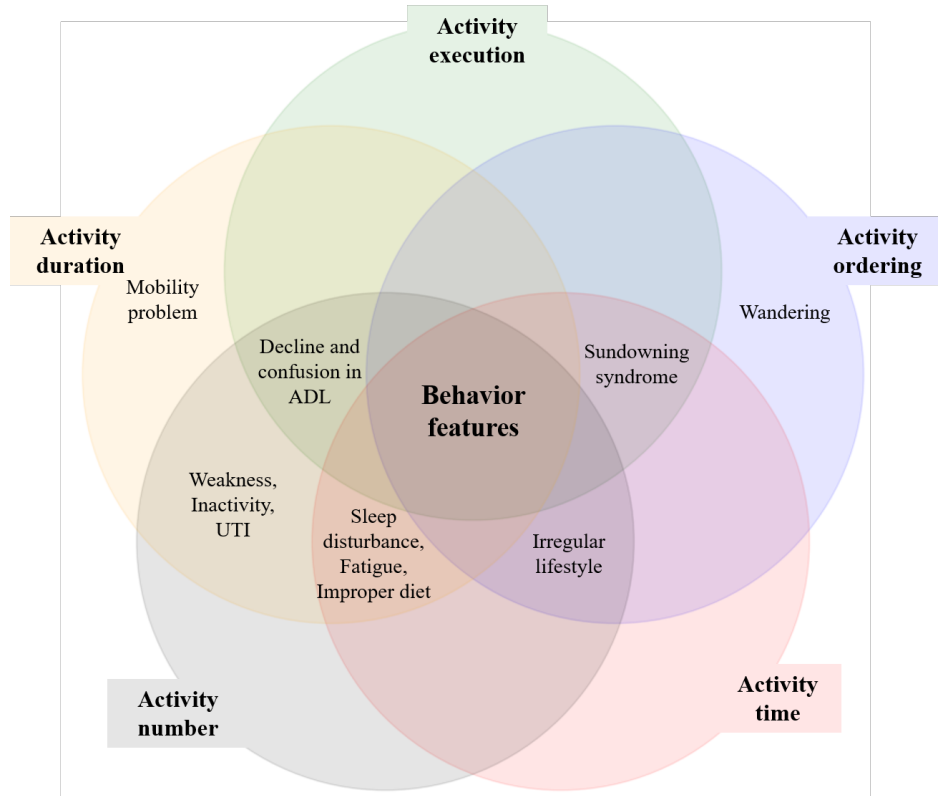


Figure 5.4: Relation between the five identified behavioral features and the symptoms they can detect.

The only symptoms not already covered by activity duration is irregular lifestyle. Consequently, the influence of daily data generation on the symptoms detectable is moderated.

For each database, the first 30 days are used to generate the life habits model conforming to the protocol defined in chapter 3. Training phase is 30 days long has it has been defined as a long enough period for most smart homes (section 3.3).

With the following days -30 days for hh smart homes, 60 days for aruba smart

home-, activity duration is evaluated conforming to methodology presented in chapter 4. This way, a time series for each activity is generated, where each value corresponds to the activity duration for a day. Autocorrelations within this time series are then computed and studied.

## Results and conclusion

Results for some activities are depicted in correlograms figure 5.5 5.6 and 5.7.

A correlogram plot the autocorrelation  $r_k$  versus  $k$  the time lags. It also displays the confidence band by a blue area between the  $\pm 2/\sqrt{N}$  thresholds with  $N$  the length of the time series. If an autocorrelation score  $r_k$  is beyond this limit, it is considered strong.

Most activities possess autocorrelations interesting to exploit. In particular, every activity possesses strong negative  $r_1$  or  $r_2$  scores. When considering human behavior, these values make sense. When an inhabitant spends a lot of time on a specific activity, he is more likely to spend less time on it the next day, and inversely the day after. For instance, if the inhabitant spent slept a lot a given day, he is less likely to sleep a lot the day after as he is rested. Consequently, the inhabitant might be more tired and sleep longer the day after, and so on. The same reasoning can be applied to other activities, especially meal related activities. This situation results in significant negative  $r_1$  and  $r_2$  values for most activities.

On the other hand, some specific activities possess strong  $r_7$  score, meaning time spent of the activity depends on the time spent on it the week before. This is the case for activities wash dishes in aruba smart home (figure 5.5 (c)), breakfast-related activities for hh103 smart home (figure 5.6 (a)), and most meal-related activities or sleep activity for hh109 smart home (figure 5.7 (a) and (b)). However, for these activities, the  $r_{14}$  score is not significant enough to attest for the existence of a weekly season.

Finally, some other activities possess other relevant autocorrelation values, such as the  $r_8$  score for activity bed to toilet and wash dishes for aruba smart home (figure 5.5 (a) and (c)),  $r_3$  score for the activity work from the same database (figure 5.5 (d)), or  $r_4$  score for eat dinner for smart home hh103 (figure 5.6 (b)).

They correspond to specific habits in the individual which are tricky to explain, but these correlations do exist and can be exploited to offer relevant forecasting.

Regarding the results obtained for various smart homes, as every observed activities possess significant autocorrelation score, ARIMA is a relevant choice for data forecasting in our case.

However, exponential smoothing may also give relevant results for activities possessing seasons, or activities without or with low auto-correlation score.

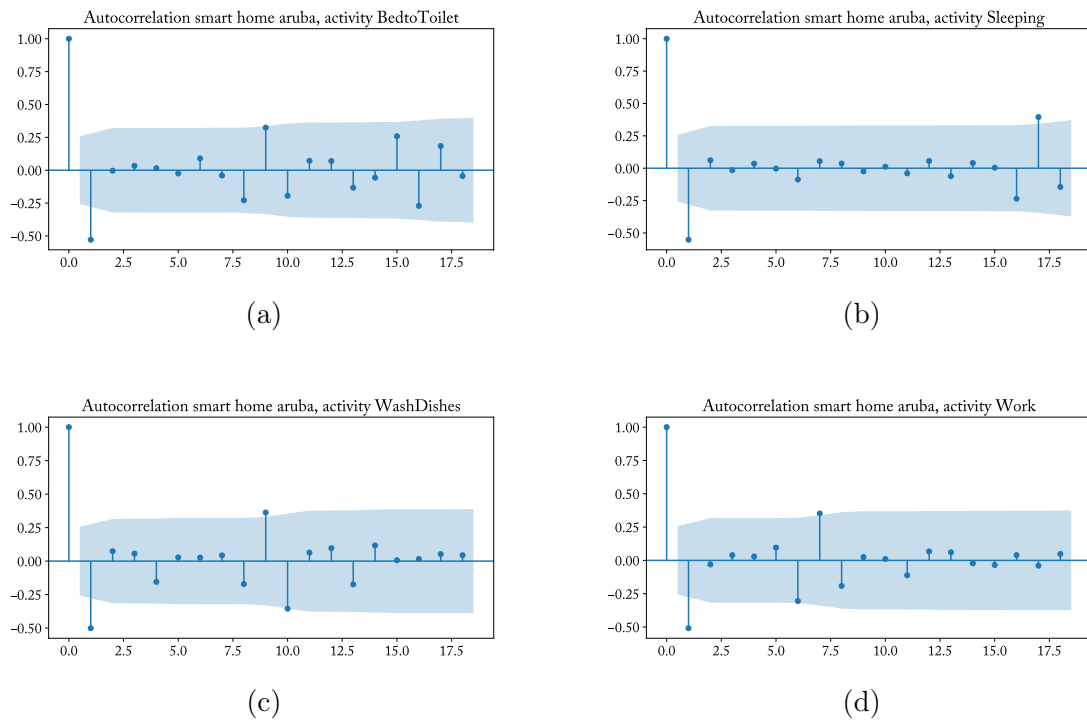


Figure 5.5: Autocorrelation score for various activities for aruba smart home: Bed to toilet (a), sleeping (b), wash dishes (c) and work (d)

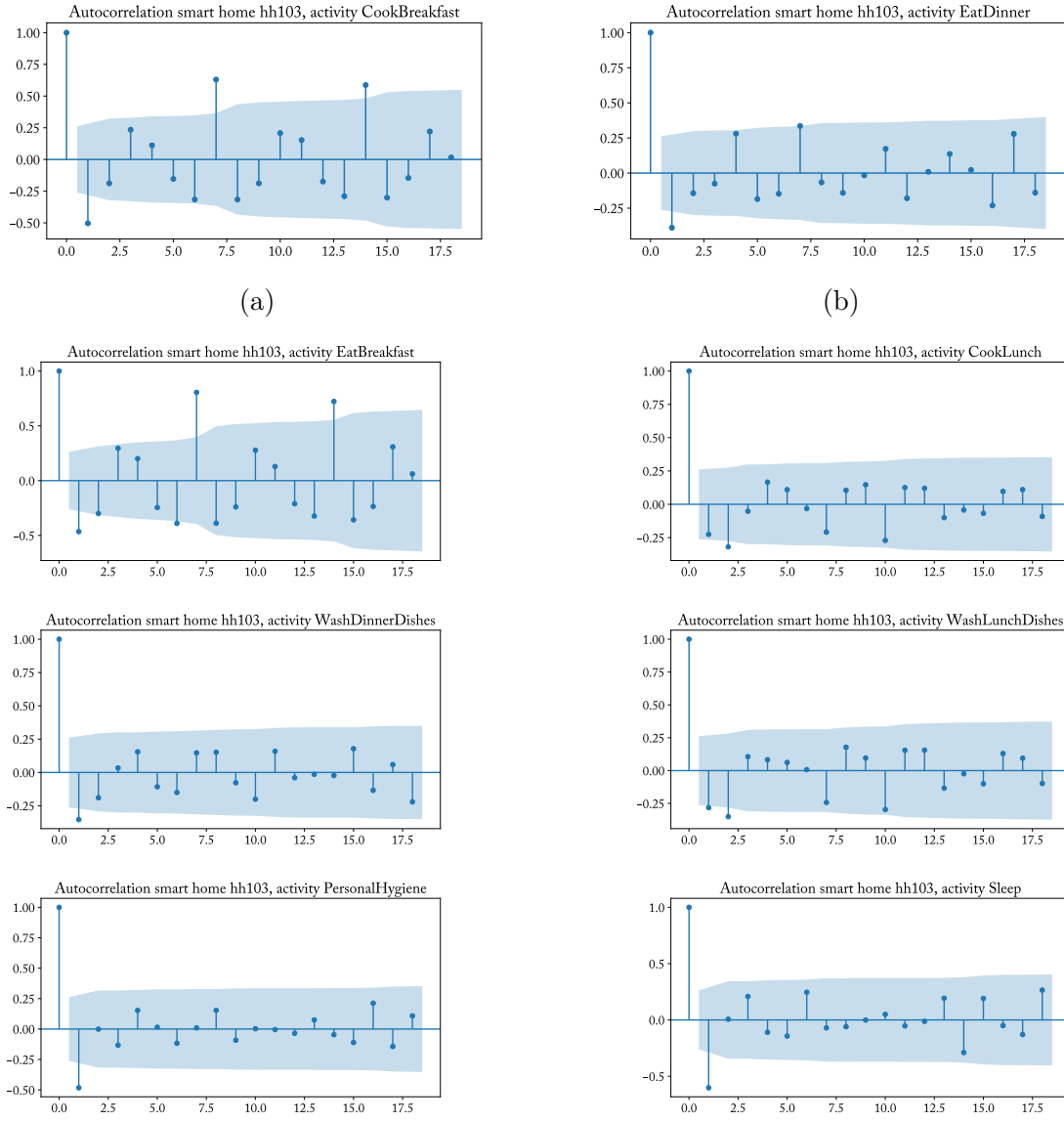


Figure 5.6: Autocorrelation score for activities cook breakfast (a), eat dinner (b), and other various activities for hh103 smart home.

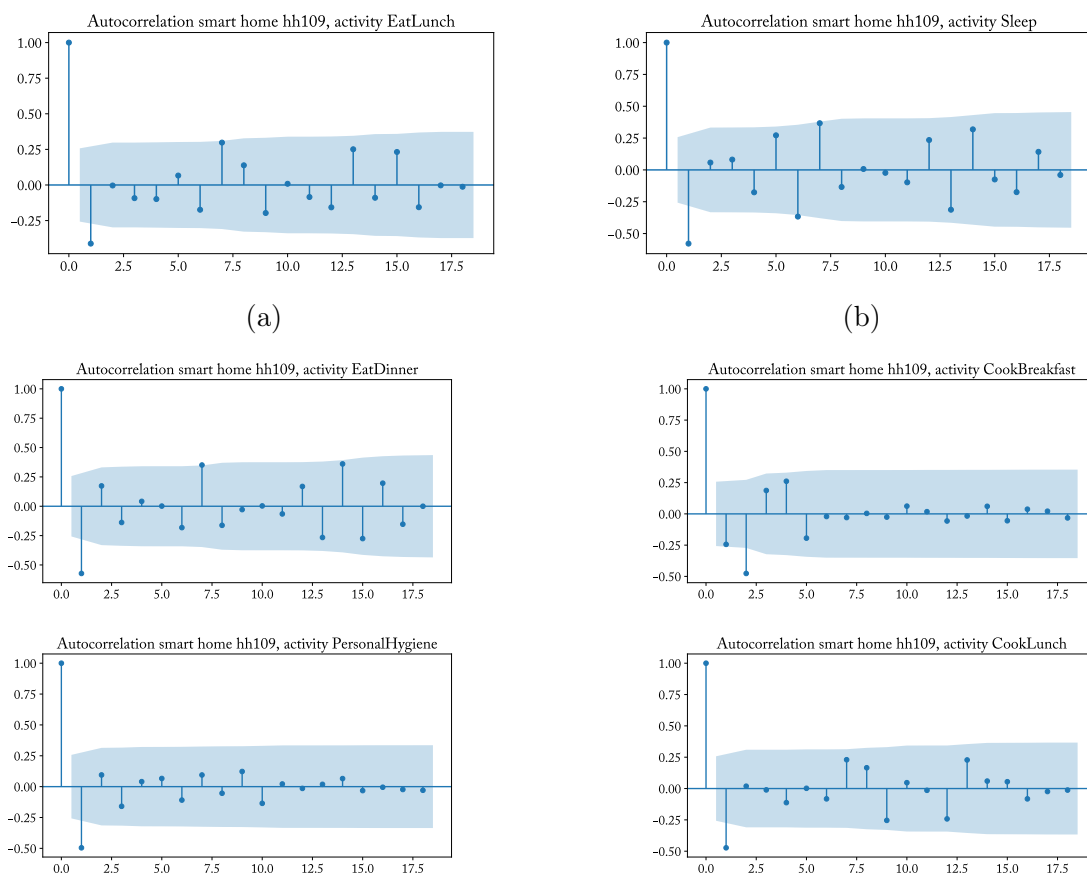


Figure 5.7: Autocorrelation score for activities cook breakfast, sleep, and other various activities for hh109 smart home.

### 5.3 Case study

To validate the proposed approach for long-term deviation detection, methodology is applied on a healthy and a sick behavior. As stated earlier, to the best of our knowledge, there is no labeled database of sick inhabitants. Consequently, artificial data generation is proposed instead. It allows testing various scenarios, including the most challenging.

#### 5.3.1 Artificial data generation

To be the most realistic possible, a health problem most elderly will meet in their life is chosen: frailty. Frailty is a decline in the physical state of an individual which alters their endurance and capability. It may result in disability, hospitalization, and in some severe cases death. Early symptoms of frailty include weight loss, weakness, and low physical activity. In general, these symptoms evolve slowly, from being hardly noticeable to having a major impact on the inhabitant behavior. Early detection can help to reduce the process, and in some cases to reverse it [Tsipouras et al., 2018].

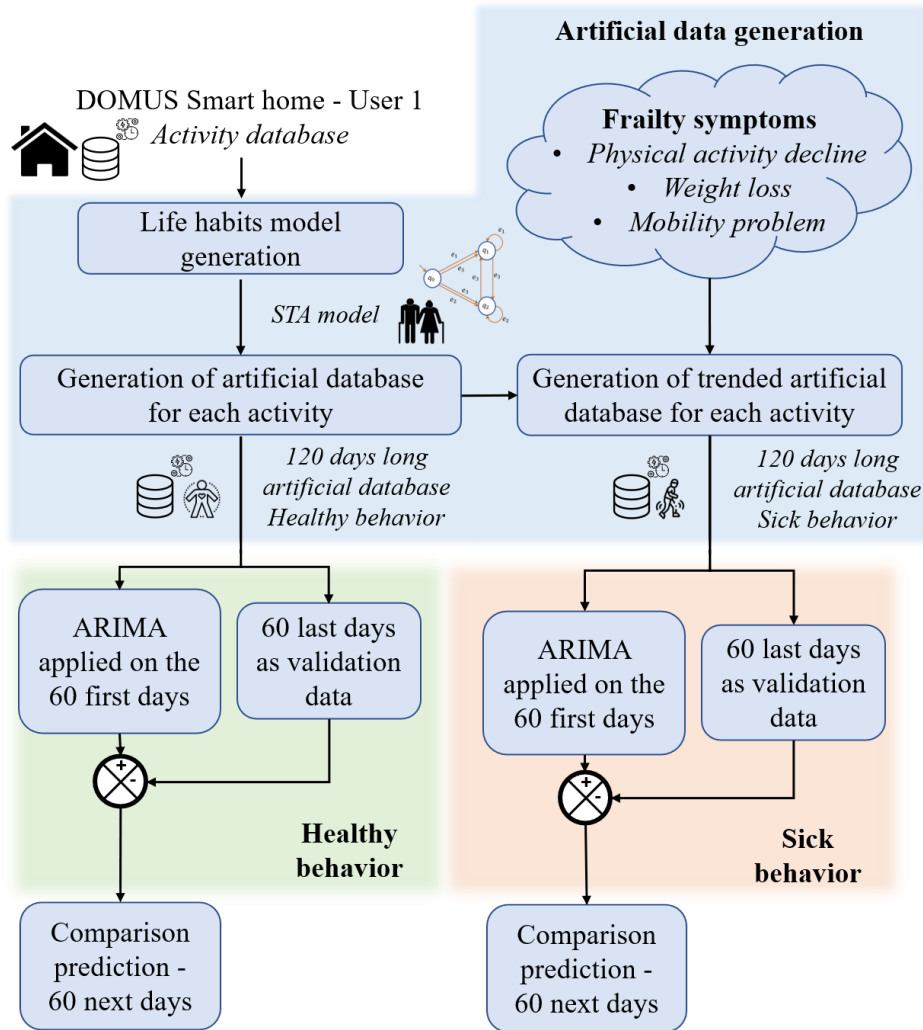


Figure 5.8: Methodology for healthy and sick behavior generation.

Consequently, protocol illustrated figure 5.8 is proposed. First, inhabitant life habits model is generated from the 10-days long DOMUS database. Only user 1 is considered. From this model, 120 days of data are artificially generated for each activity. Each activity duration is created according to the probabilistic distribution defined in the STA model. This generation provides time series which are not likely to possess auto-correlation. It is the worst-case scenario for the ARIMA method as this method heavily relies on auto-correlation to offer relevant results. The first 60 days are used for ARIMA training, while the next 60 days are used as validation data.

These 120 days long data are also duplicated and modified to simulate a sick behavior: Meal related activities duration is reduced leading to weight loss, while duration of most other physical activities is increased due to slow walking speed and difficulties to carry out physical efforts. Time series is modified by adding a linear trend  $-\frac{3t}{120}$  to "Having breakfast" activity and  $\frac{3t}{120}$  for other activities, with  $t$  time series index  $t \in [[1, 120]]$ . These trends simulate a slow decline in inhabitant behavior leading to noticeable anomalies after 120 days. Then, the same methodology is applied.

### 5.3.2 Results

Results for activities "Wake up", "Having breakfast" and "Other activities" are depicted in figures 5.9 and 5.10 for healthy behavior (left) and sick behavior (right). As data possess low auto-correlation, ARIMA forecasting only give information about the trends within the data, which is enough to assess the health status of the inhabitant.

Considering healthy behavior data, time distance sometimes reaches important value the first 60 days, which means behavioral anomalies are detected. For instance, activity "Having breakfast" is particularly short ( $t = -2.92$ ) the 44th day. However, these anomalies are scarce and are not repeated, which seems to attest they are due to normal randomness in human behavior rather than medical problems. Additionally, data forecasting does not evidence for the existence of trend in behavior as no time distance above 3 or below -3 is forecast. Consequently, this behavior is considered healthy. This prognostic is confirmed by the next 60 days of data as no anomaly is detected.

Regarding trended data, some anomalies are sometimes detected the first 60 days. For instance, activity "Wake up" is especially long ( $t = 3.49$ ) the 54th day, while activity "Having breakfast" is short the 44th and 60th days. As their number of occurrences is low, this does not testify for the presence of a medical problem. Nevertheless, due to trends in behavior, ARIMA forecasting highlights possible anomalies in the future. Activities "Wake up" and "Other activities" are expected to have most of their duration beyond the  $3\sigma$  limit around day 120 and 140, while the majority of duration of activity "Having breakfast" may be below the  $-3\sigma$  around day 140. This information attests of the existence of a slow evolution in the current behavior of the inhabitant. These forecasts are consistent with the artificial trend and the validation data as future anomalies are detected after the 80th day, whose number become concerning after the 100th day.

This case study highlights the relevance of the proposed approach as slow decline was detected the 60th day, while anomaly detection alone could detect the existence of a potential medical problem only after the 100th day. Additionally, data forecasting

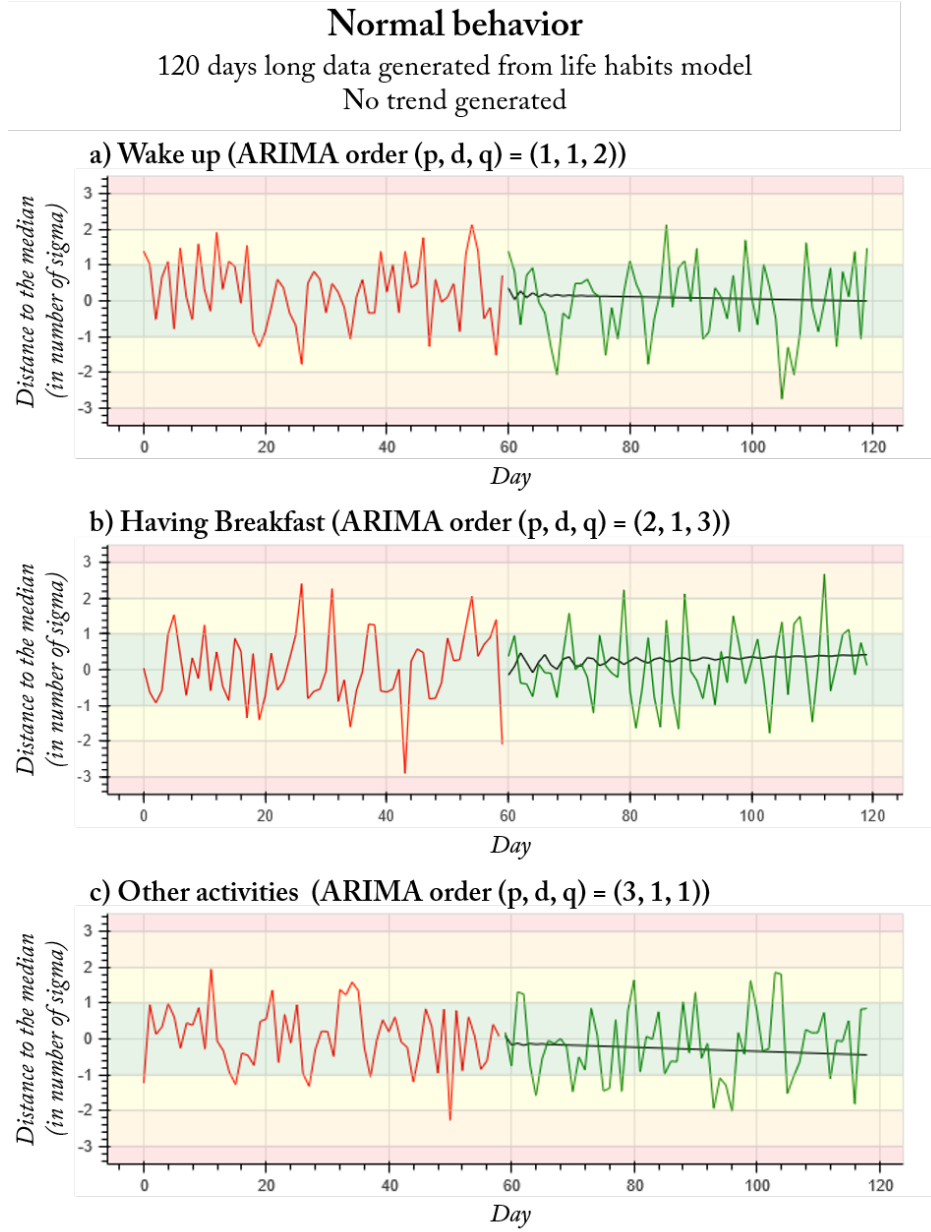


Figure 5.9: Prediction for activities Wake up, Having breakfast and Other activities for original artificial data (a, b, c). First 60 days are training data in red, last 60 days are validation data in green, ARIMA forecasting in black.

testifies for the existence of slow evolution in the behavior, while anomalies alone cannot distinguish a behavioral change due to brutal changes to those resulting from a long-term deviation. Moreover, as it successfully detected slow declines in a worst case scenario, case study attests of the proposed methodology resilience. Thanks to this information, medical staff will be able to have early and more precise information about the health status of the patient, which will ease the medical prognosis.

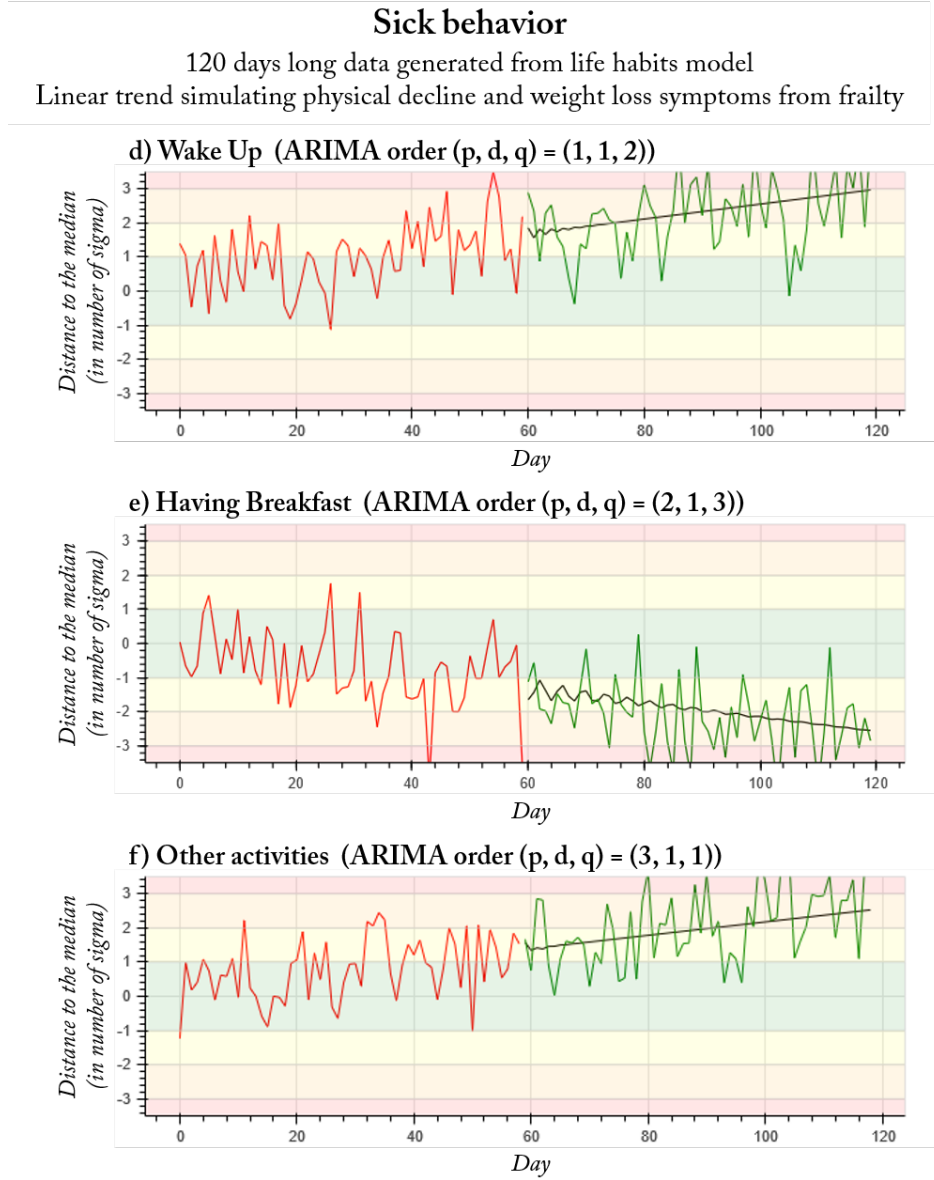


Figure 5.10: Prediction for activities Wake up, Having breakfast and Other activities for artificially trended data (d, e, f). First 60 days are training data in red, last 60 days are validation data in green, ARIMA forecasting in black.

### 5.3.3 Hh103 smart home

#### Case study protocol

Another case study is proposed using the hh103 smart home. This database proposes 60 days of data which is enough for testing long-term deviations. Previous case study confirm the relevancy of proposed methodology even on worst-case scenarios, i.e. data possessing no autocorrelation. The case study proposed in this subsection offer to test the approach on a real database.

As previous subsection, two scenarios are proposed: first, the methodology is ap-

plied on the original inhabitant behavior. No modification of any sort is applied, except the protocol for time series generation introduced in subsection 5.2.3 in order to possess a unique duration per day. No information about the health status of the inhabitant is accessible. However, according to assumption 5 (unsupervised behavior), it is expected to obtain a non-trended behavior, meaning the inhabitant is healthy.

In the second scenario, it is proposed to artificially introduced trends representative of sleep disruption and fatigue symptoms in order to test their detection and the relevancy of long-term deviations detection compared to anomaly detection for such medical problems.

In this second scenario, sleep disruption is modeled by increasing the night's activities, such as bed to toilet transitions, leading to a decrease and less qualitative sleep time.

On the other hand, this situation leads to overall tiredness of the inhabitant who consequently carries fewer physical activities. This is modeled by a decrease of the duration of activity leave home.

As the database is 60 days long, it is proposed to model the deviation through a linear trend  $\pm \frac{3}{60}$ . This way, it is expected to detect an anomalous at the end of the 60-day-long case study

The first 30 days are used as training data for the ARIMA model. Then, ARIMA forecasting is compared to the 30 following days used as validation data.

## Results

Results for long-term deviations detection are illustrated in figure 5.11 for original data and figure 5.12 for sick behavior.

Regarding the original behavior, it can be seen monitored activities possess no or low trends, testifying for an inhabitant in good health. In detail, sleep activity possesses no trend, showing the sleep pattern of the inhabitant is not evolving on time. However, it can be observed that an anomaly is detected the 40th day, where the activity duration is way shorter than expected. It can be due to the inhabitant sleeping somewhere else, leading to an undetected sleep activity. This anomaly has not been forecast by the ARIMA model, which is perfectly normal as no information within the first 30 training days could lead to such a conclusion. This situation highlights the fact that anomaly detection presented in chapter 4 and long-term deviation detection introduced in this chapter are complementary approaches which allow to detect different types of behavioral deviations.

Regarding bed to toilet transition activity, a slight increasing trend is detected. Its amplitude is yet too low to be concerning, but it still shows that the behavior of the inhabitant is slowly evolving.

Finally, leave home activity also possesses an anomaly the forecasting method was not able to predict. It can also be observed that the ARIMA method offer a more fitting forecasting. It can be due to strong autocorrelations within this specific activity, leading to a better quality model.

Regarding the sick behavior, several conclusions can be drawn. For each activity, the trend is correctly detected as the forecast indicate anomalous behavior in 53 days

(activity sleep), 47 days (activity bed to toilet) and 49 days (activity leave home). The early detection for bed to toilet transition is explained by the already existing trend in the original behavior which adds up to the artificial one.

Consequently, from the 30th day, the health status of the inhabitant is known. It is particularly efficient as the behavioral anomalies only appeared between the days 40 and 50, meaning long-term deviation is able to assess the health status of the inhabitant a few weeks before focusing on anomaly detection alone.

This information is sent to medical staff. The sleep duration decrease and bed to toilet transition duration increase clearly state for a change in the sleep pattern of the inhabitant. The leave home duration decrease can be interpreted as a consequence of these disruptions, testifying that the inhabitant becomes more and more tired and unable to carry out physical activities. It can also be linked to a general physical decline of the inhabitant. Nevertheless, the causes of this decline can be multiple. It can be due to an infection disrupting inhabitant sleep, a simple change in his life habits, or more serious cognitive problem causing agitation at night time.

Closer inspection by medical staff is necessary to identify exactly the potential causes of these deviations, for instance after examination of his medical records or through a medical appointment. This work does not aim to draw a prognosis in place of the caretakers, but rather offer them additional tools to help them detecting the earliest possible specific troubles and information to help establishing a prognosis.

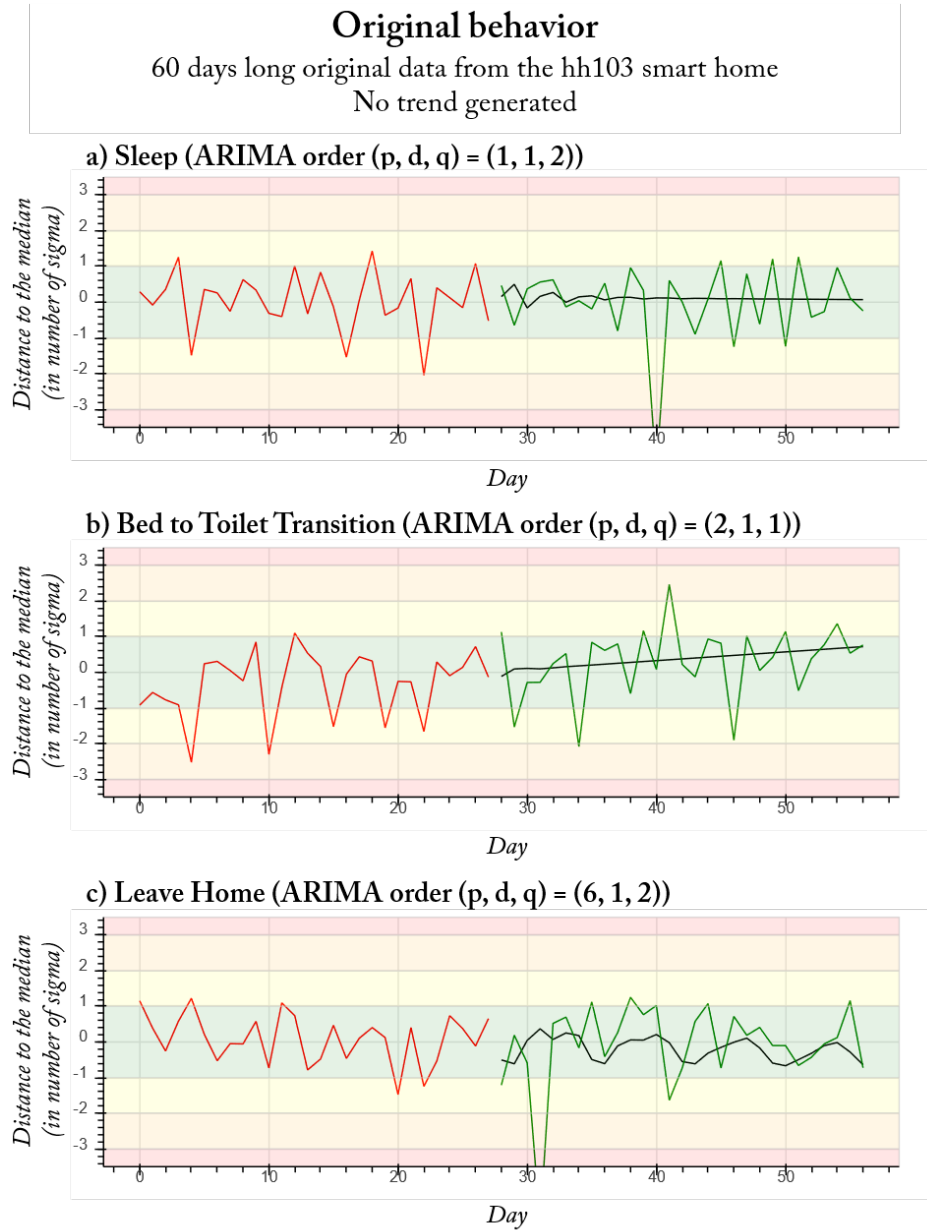


Figure 5.11: Prediction for activities Sleep, Bed to Toilet transition and Leave home for original data (a, b, c). The first 30 days are training data in red, last 30 days are validation data in green and ARIMA forecasting is in black.

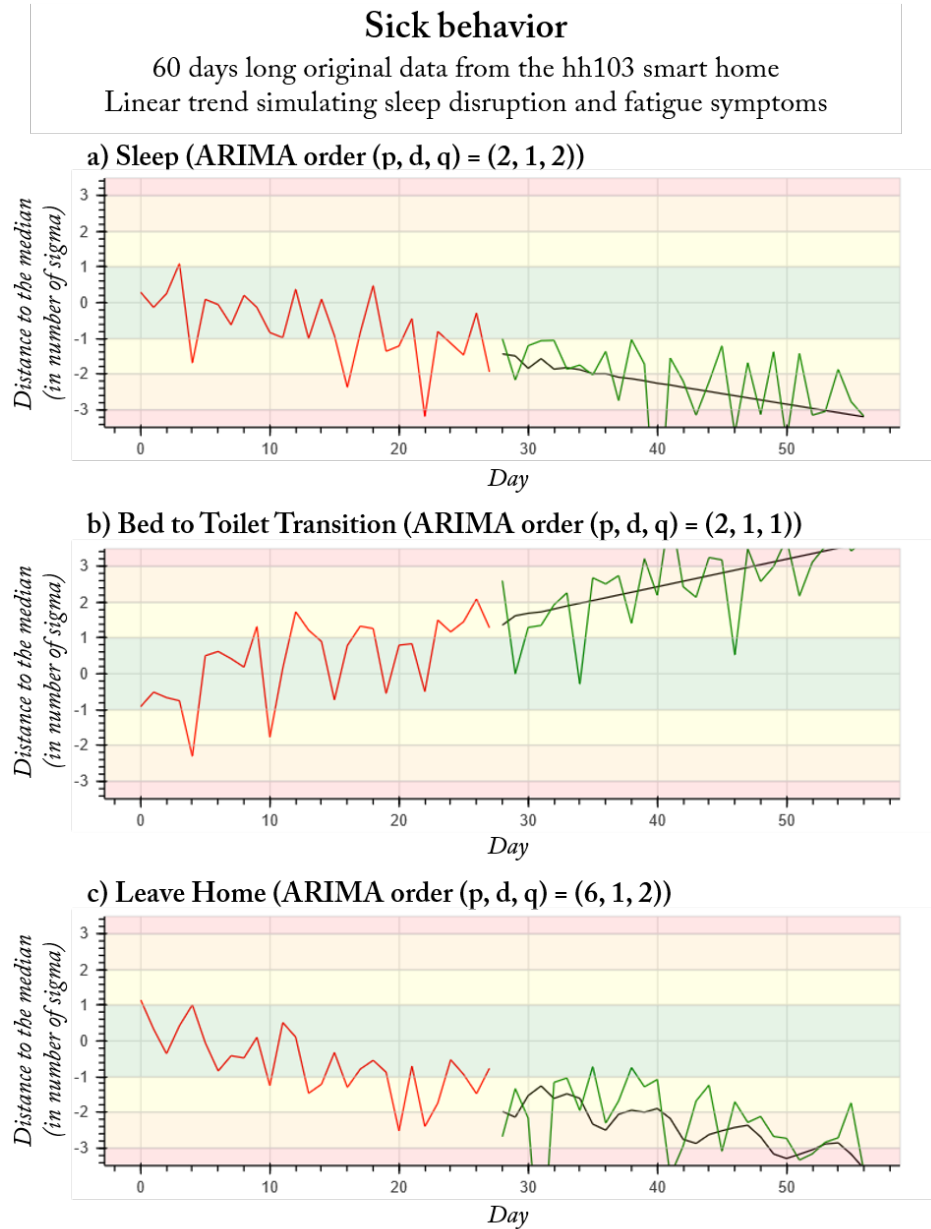


Figure 5.12: Prediction for activities Sleep, Bed to Toilet transition and Leave home for original data (a, b, c). The first 30 days are training data in red, last 30 days are validation data in green and ARIMA forecasting is in black.

## 5.4 Conclusion

Most of diseases induce a brutal change in the behavior of an individual. However, some specific declines which typically affect the elderly trigger a slow decline in their behavior. These slow declines are detected tardily by anomaly detection techniques, which is critical as an early treatment is often the best option for remedy.

Consequently, a methodology is presented to earliest possible an anomaly in the inhabitant behavior.

Concerning activity ordering, it is mainly affected by episodes of confusion which are a all-or-none event. Either the behavior is usual, or it is shortly irrational due to confusion. The earliest detection possible consequently consists in detecting the first anomaly occurrence. On the other hand, activity ordering evaluation produces a score assessing the regularity of the observed activity. An anomaly is detected when the score exceeds a given threshold. However, the score value can be exploited before the occurrence of an anomaly to estimate if the inhabitant's behavior is stable or tends to evolve into a concerning threshold. Consequently, this chapter only focus on the activity ordering feature.

Considering the type of data and the objective, forecasting is a promising method, exploited in some works about predictive maintenance. A short review of the most used techniques and a short case study on a real database highlighted the efficiency of the ARIMA forecasting technique, relying on the autocorrelation within the data to produce successful results.

This method has been applied on case study, consisting in artificial data simulating the worst case scenario for the ARIMA technique as the generated test data were likely not to possess autocorrelations. Nevertheless, it produces convincing results as the methodology allow to detect the occurrence of anomalies and critical situations several weeks before their occurrence, offering medical staff a precious time for extensive examination and treatment.



# Conclusion

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*"Encore du travail ?"*  
- Paysan humain, *Warcraft III: Reign of Chaos* -

## Summary

The objective of this thesis is to develop a framework to detect changes in the life routine of a single smart home inhabitant in order to help medical diagnosis and prognosis at home. It focus on binary information to enable privacy saving solutions and to be independent of a specific technology as any sensor can be used.

Three types of information have been identified as relevant for medical staff:

- **The life habits of the inhabitant**, as it can offer a clear overview of his health status.
- **Behavioral anomalies**, as the behavior of an individual is likely to be modified when he is suffering from a disease. Depending on the type of anomaly, medical staff can refine their prognosis.
- **Long-term deviation**, as numerous diseases affecting the elderly are degenerative and are challenging to detect early, such as Alzheimer's disease or physical decline.

Human behavior is incredibly rich and diverse. A literature review has been conducted in order to identify behavior features which are relevant for health diagnosis and prognosis. Five features were identified: activity ordering, activity execution, activity duration, activity time, and the number of activities. A closer inspection of diseases of interest and associated symptoms motivated the choice to focus on activity ordering and duration as they cover most symptoms.

## A methodology to model life habits of a smart home inhabitant

To extract the usual routine of a smart home inhabitant, a life habits model generated after a training phase is proposed. Stochastic Timed Automaton (STA) is proposed as it eases communication with medical staff, is able to model several different life habits, and handle potential anomalies during the training phase. The activity ordering feature is expressed through the probabilities associated with transitions, while activity duration is expressed through probabilistic distribution. The required duration for efficient training is also explored using perplexity and entropy computation.

Methodology is applied on several case studies. They highlighted the efficiency of log-normal distribution for activity duration modeling, and validated the choice for personal model as each inhabitant offered widely different models as they possess distinct life habits.

### **An approach for behavioral anomaly detection**

When an individual gets sick, his behavior is likely to be impacted and modified. Detecting these changes can help medical for their prognosis and diagnosis. It consists in the computation of two distances: the normalized likelihood which is related to the activity ordering feature and the time distance which is the distance between the observed activity duration and the expected distribution from the model.

Proposed approach is applied on real and artificial case studies to test various scenarios, and to assess the quality of the anomaly detection and the interest for medical staff.

### **A methodology for long-term deviation detection**

The elderly population is susceptible to suffer from degenerative diseases, i.e. diseases which slowly evolve on long time period. As early detection is critical for their treatment, long-term deviation detection is proposed. It focus on activity duration and rely on data forecasting to detect future behavioral anomalies by observing trends within the inhabitant behavior. ARIMA forecasting methodology is explored after a review of features within real smart home databases.

A case study applied to different smart home highlighted the efficiency of the proposed approach, able to detect future behavioral anomalies weeks before their occurrence.

### **An assessment of potential ethical impacts**

Due to massive improvements in data collection, storage, and processors, new applications and technologies can have significant impact to our life and society. These impacts might be unintended, invisible, and/or negative.

The works presented in this thesis make no exception. As critical and private information are manipulated, multiple negative impacts may occur, such as privacy threat, work conditions, etc. In appendix A, a framework for ethical impact assessment is proposed. As stakeholders have to be involved, the evaluation is not complete but proposes a discussion about the potential negative impact, how to evaluate them, and how to mitigate them if they appear to be significant.

## **Outlooks**

### **Application on sick inhabitant**

The proposed methodology was applied on real smart home databases in order to assess of its relevancy. The health problems and associated symptoms were artificially

generated in order to test various and critical situations. The case studies highlighted the efficiency of the proposed approach to detect various health problems, and to offer relevant information to identify a limited list of responsible diseases.

The natural next step of this work is to apply the methodology on real individuals in real time. The experimentation has to be conducted in collaboration with medical staff in order to know which activities are of interest depending on the medical records of the inhabitant.

In a first step, the detected behavioral deviations can be compared to the health diagnosis of medical staff to confirm the links between behavioral features and symptoms and diseases.

In a second step, the behavioral deviation detection is used to help medical staff in their prognosis and to validate the relevancy of the proposed tools.

Implication of users, medical staff, and smart home equipment providers also enable first assessment of ethical impacts by conducting internal analysis and data collection. If negative impacts are already identified, countermeasures could be applied, or dashboard can be refined to better assess which feature is at fault.

It should be noted that this experimentation phase is particularly difficult, as it engages numerous stakeholders. Moreover, as the test subject is a human, it also brings multiple administrative constraints regarding the ethical aspects. Finally, it also requires to observe the experimenter on a sufficient time duration, for instance several years, in order to be able to test various scenarios where he is sick.

## **Extend the work to multi-inhabitant scenarios**

This thesis work focus on inhabitants living alone as they are more likely to suffer from degenerative diseases [Wilson et al., 2007] and being alone makes emergency call harder in case of critical accident. However, this assumption can be relaxed in order to consider multi-inhabitant homes.

Several solutions can be explored. On the one hand, inhabitant can be distinguished thanks to specific sensors, such as RFID (radio frequency identification) sensors or smartphones. In that case, the activity database enlists each carried out activity with its duration and the inhabitant performing it. It is consequently possible to split this database into one for each inhabitant, and to generate a distinct model for each of them.

This solution is straightforward and requires few adjustments, but it requires the inhabitants to always wear sensors which is invasive and not easily accepted. The inhabitant might also forget to wear them. Another possible approach is to use previous knowledge about the personal life habits of each inhabitant, obtained for instance thanks to a questionnaire, in order to pre-generate life habits models. This way, during the training phase, when an activity is carried out, the inhabitant performing it is identified depending on the life habits model the activity fit the best. The model is updated and the training phase may continue. A particular attention should, however, be given to activities the inhabitants perform together, such as meal activities.

### Other behavioral features

A literature review identified five different behavioral features to observe in order to assess the health status of an individual. This work focus on activity ordering and duration only as they cover most symptoms. In order to refine prognosis of medical staff, the other features could be considered to deliver more diverse information to medical staff.

For the activity execution feature, models developed for activity recognition such as the Probabilistic Finite Automaton introduced in [Viard, 2018] can be exploited, while requirement models such as the requirement flower presented in [Saives et al., 2015] could be considered. The requirement flower depicts the life habits considered as healthy by the medical team. If the objective is to detect a change in the life pattern of an individual, this model has to be generated after a training phase instead to reflect his personal habits. Finally, numerous existing works proposed to model activity time through normal distribution [Azefack et al., 2019]. As activity duration, the relevancy of this distribution should be investigated in more details. A distinction should also be made between activities expected to occur at a specific time, such as meal activities, and activities which can occur at any moment, such as going to the toilet.

Similarly to the activity ordering feature, activity execution is mainly affected by period of confusion or sundowning syndrome which are episodic symptoms. Anomaly detection consequently already offers the earliest possible trouble detection. Considering the activity number and time features, long-term deviation detection can be considered by using the same ARIMA technique if these features are subject to autocorrelation. Otherwise, exponential smoothing should be explored.

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# APPENDIX A

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## Ethical Impact Assessment

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### Introduction

For a few decades, growth of scientific applications and knowledge has been significant. Large improvements in data collection and storage, associated to development of processors able to handle extreme number of operations, enabled impressive progress in multiple domains: health, finance, transportation, etc. These improvements have transformed our relation to science in a so massive way that many experts call it the fourth Industrial Revolution [Colombo et al., 2017].

These new applications and technologies, and the ones to come, have and will significantly impact our life and our societies. Obviously, as these applications are developed in order to answer a need, these impacts are most of the time positive. However, they can have unintended or invisible negative impacts. These negative impacts can be of multiple nature, for instance threat of privacy, inequality, misinformation, etc.

The works presented in this thesis make no exception. Potential unintended negative impacts may appear as private data is manipulated, as it concerns the health status of an individual which is a critical information, and as it influences the work conditions of health-care providers. Other invisible negative impacts may also exist.

Moreover, as the main purpose of our work is precisely to positively affect the quality of life and health of individual, existence of harmful impacts could negate our contribution and makes it invalid.

Consequently, assessment of these impacts is necessary. This appendix proposes a framework to assess the impact of our work on the well-being of individuals and society in general. An evaluation of this sort requires to involve the different stakeholders of the application, such as the users, the medical staff, the smart home equipment providers, etc. Moreover, it requires the application to be test on real scale for months or even years to assess some potential impacts. As this thesis proposes a proof of concept, this assessment is not bring to its conclusion. Nevertheless, this appendix proposes reflection elements about the possible negative impacts, how it would be possible to assess them, and possibly negate or mitigate them.

## A.1 Framework to assess well-being implications of AI

### A.1.1 Required definitions

Ethics is a large and sometimes vague concept. In order to make the concept clearer and to present the proposed framework, a few definitions are required and introduced below.

**Definition A.1 (Ethics for intelligent systems)** *Ethics is a large concept, which has been extensively explored and debated by many philosophers. It is generally considered as a code of both personal and universal values most people consider as desirable which aims at providing a safe, healthy and comfortable world to anyone [Adamson et al., 2019]*

*Due to the rapid acceleration of intelligent systems, these codes have to be transcribed to clear laws these systems have to imperatively obey. Basic ethical principles for intelligent systems include, among others, transparency, accountability, lack of negative bias, non-manipulation, privacy, trustworthiness, society and individual well-being, etc. [Adamson et al., 2019], [Schiff et al., 2020].*

Ethics encompass numerous different domains. Well-being concepts is explored in more details and defined below.

**Definition A.2 (Well-being [IEEE, 2020])** *Well-being is the continuous and sustainable physical, mental and social flourishing of individuals, communities and populations where their needs are cared for within a thriving environment. Well-being includes but is not limited to 12 identified domains: affect, community, culture, education, economy, environment, human settlements, health, government, psychological and mental well-being, satisfaction with life, and work.*

As the works presented in this paper both aim at providing better life conditions to individuals, and to reduce the burden imposed to our societies, this appendix will focus on the well-being concept for ethics impact assessment. Moreover, well-being is a large concept which encompasses many different scientific fields and different scale, as it considers well-being of individuals, groups, and societies as a whole. Consequently, the other ethical domains, such as privacy or transparency, are also partly included in this concept.

### A.1.2 Proposed framework

Since a few years, there is a growing and critical needs for ethical assessment principles and frameworks. Ethical and well-being assessment is a complex, multidimensional and sometimes contested subject [Schiff et al., 2020]. It encompasses multiple domains such as education, economy, environment, health, government, well-being, etc.

To answer this need, non-governmental organizations (NGOs) or governments proposed some guidelines or policy. The European General Data Protection Regulation

(GDPR) is an example of regulation applied on European Union (EU) members. It is also used as a reference by many other nations for data privacy.

However, these guidelines are relatively new, focus on specific ethical features and propose no global overview, and do not offer measurements or metrics, except metrics focusing on economic growth or financially driven efficiency assessment.

Consequently, to answer this need, the IEEE Standard 7010-2020 Recommended Practice for Assessing the Impact of Autonomous and Intelligent Systems on Human Well-being (called IEEE 7010 Standard for the rest of this appendix) introduces a framework for well-being implications of new applications [IEEE, 2020]. IEEE standards are developed by groups of volunteers from many different countries and from various scientific fields. IEEE 7010 is part of the IEEE P70xx series of standard considering different ethical aspects and implication of intelligent systems. The IEEE P70xx series of standard include considerations about ethics in design (IEEE P7000), transparency (IEEE P7001), data privacy (IEEE P7002), algorithmic bias (IEEE P7003), child and student data (IEEE P7004), employer data governance (IEEE P7005), data agents (IEEE P7006), ontologies for ethics (IEEE P7007), nudging (IEEE P7008), fail-safe design (IEEE P7009), trustworthiness of news (IEEE P7011), machine-readable privacy (IEEE P7012), facial recognition (IEEE P7013), and empathy (IEEE P7014). Contrary to what its name suggests, the IEEE P70xx series of standard is rather a series of recommended practices. Recommended practice is less restrictive than a standard (stating how adherents must comply) but stronger than a guidance document (stating how adherents can apply).

Considering the field, objective and type of manipulated data in this work, the IEEE 7010 standard is the most adapted to our case.

### A.1.3 IEEE 7010 Well-being Impact Assessment

IEEE 7010 proposes a holistic and impact-based approach to identify the intended and unintended influences of intelligent systems. This means it does not only focus on the technical solutions which can be brought by engineers and scientists, but also consider social, governmental and corporations responsibility to assess the various impacts of systems on human and societal well-being.

Its objective is to propose a framework to identify and measure both intended and unintended, visible and invisible impacts of a given application through the 12 domains introduced in the definition of well-being A.2: affect, community, culture, education, economy, environment, human settlements, health, government, psychological and mental well-being, satisfaction with life, and work.

This framework is introduced in figure A.1. It is an iterative process of five activities which involves application users, stakeholders and society in general.

First activity is an internal analysis and user and stakeholder engagement. It consists in engaging the designers, users and stakeholders, i.e. any individual or groups which is affected by the application, in order to think and brainstorm about the possible impacts of the application. It implies defining who might be influenced by the system and how. Reflection has to be as large as possible, meaning it should imply the most possible stakeholders and should be creative in the possible impacts they might suffer. To help for reflection, IEEE 7010 possess propositions of domains -the twelve domains

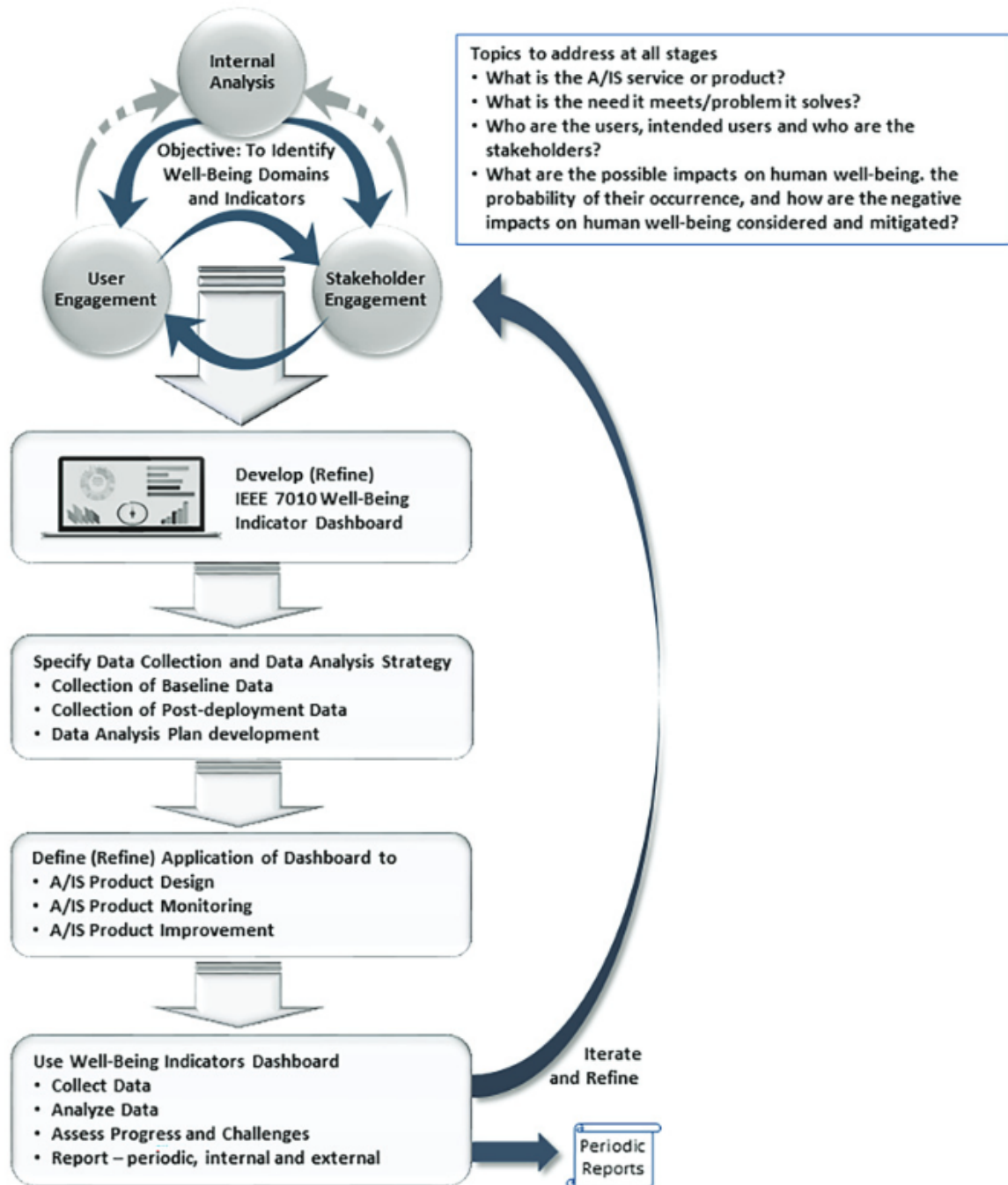


Figure A.1: Illustration of proposed framework by IEEE 7010. Extracted from [IEEE, 2020]

defined earlier- and subdomains, but possible impacts are not limited to them. These domains and subdomains are defined in [IEEE, 2020] and illustrated in table A.1.

Activity 2 focus on the refinement of proposed impacts, and development of a well-being indicators dashboard. It consists in defining indicator and measurement method for each possible impact identified in activity 1, and to produce a dashboard classifying identified impacts and their indicator within corresponding domain or subdomain. Figure A.2 is an example of a dashboard for well-being impacts of autonomous vehicles [Schiff et al., 2019].



Figure A.2: Well-being indicators dashboard for autonomous vehicles [Schiff et al., 2019]

Activity 3 is about data planning and collection. It consists in involving the stakeholders identified during activity 1 and to collect data conforming to the chosen indicators and measures in the dashboard of activity 2.

Last activity proposes to analyze the collected data to draw conclusions about the actual impacts of the application. It allows to objectively filter domains where the impact of the application is moderate or nonexistent. On the other hand, if negative

## A.1. Framework to assess well-being implications of AI

Domains	Sub domain	Description
<b>Satisfaction with life</b>	-	An overall assessment of feelings and attitudes about one's life at a particular point in time
<b>Affect</b>	-	Can also be called "feelings", "mood", or "emotions", define how a perso is feeling in the moment or on a lasting emotional experience. Positive affect include for instance feelings such as feeling happy, calm, peaceful, etc. and negative affects might include feeling sad, depressed, anxious, etc.
<b>Psychological well-being</b>	-	"The experience of feeling good and fonctionning effectively" [Huppert, 2009]. Feeling that the things one does are worthwhile and meaningful
<b>Community</b>	Sense of belonging	Feeling that people matter to one another and to the group, and that their needs will be met through their commitment to be together [McMillan and Chavis, 1986]
	Participation	Activism, volunteerism, and/or donations
	Social support	The assistance that people give and receive from each other
	Community Safety	Feeling safe in every-day life, feeling that people can be trusted
	Discrimination	Any distinction or restriction which limit the recognition of human rights and fundamental freedom in the fileds of politics, economic, social, etc. (UNESCO)
<b>Culture</b>	-	Culture
<b>Education</b>	Formal Education	Training typically provided by an eduction or training institution, leading to certification (UNESCO)
	Lifelong learning	People aged 25 or older in education and training
<b>Economy</b>	Standard	Level of comfort and wealth
	Equity/equality	Ressources and goods distribution is considered fair
	Jobs	Jobs
	Natural resources, consumption, production	Consumption is considered to be sustainable. Sustainable consupcion is minimizing the use of material resources, toxic materiels, emissions of waste and pollutants in order to not jeopardize needs of future generations
	Entrepreneurship	Capacity and willingness to develop business with any of its risks to make a profit
<b>Environment</b>	Not displayed	Encompasses environment in general, climate change, and air, water, and soil quality, and biodiversity
<b>Government</b>	Human rights	Includes Civil and political rights, Economic, social and cultural rights, and Collective rights (UN Human Rights Office)
	Institutions	Complex of positions, roles, norms and values in particular social structures
	Civic Engagement	"Working to make a difference in the civic life of our communities and developing the combination of knowledge, skills, values and motivation to make that difference" [Ehrlich, 2000]
	Trust	Citizens believing the system and political to be responsive, honest, and competent
<b>Health</b>	Physical health	Physical health
	Mental health	State of well-being in which the individual realizes his own abilities, able to contribute to his community (WHO)
<b>Human settlements</b>	Settlement	Global satisfaction with ones living area
	Housing	Satisfaction and quality of its housing
	Food	Access, satisfaction and quality of food for an active and healthy life
	Transportation	Safe, affordable, efficient and resilient transport services. Also include environmental impacts
	ICT	Access to technologies used to share, distribute, inform and communicate (UN)
<b>Work</b>	Governance	Quality of the control and direction
	Environment	Physical work condition and equipment
	Work-life balance	Balance between work and personal life

Table A.1: List of well-being domains, subdomains, and description. Adapted from [IEEE, 2020]

impact is attested by the data, improvement has to be done to explore more in depth these impacts if necessary and to negate or at least reduce these negative impacts.

All these activities are part of an iterative process. Once last activity is carried out, the whole analysis has to be repeated throughout the product lifecycle. Stakeholders implication, internal analysis, dashboard, and data collection is refined as the understanding grows at each iteration.

#### A.1.4 Application to our work: Limitations and adjustments

To assess its potential invisible or unintended negative impacts, it is proposed to apply this framework to this work. However, this thesis proposes a proof of concept. It implies limitations concerning stakeholders engagement and data collection, as they are not accessible for now.

Consequently, adjustments are proposed and are listed below:

- For the first activity, only internal analysis can be carried out. User and stakeholder engagement is not possible. Stakeholder identification and study of potential impacts can still be made, but we cannot contact them to engage them in the reflection process for now.
- The dashboard from activity 2 is produced as expected.
- In activity 3, data collection plan is partially described by proposing metrics to assess the existence and the amplitude of identified potential impacts. It, however, does not propose data collection as stakeholders are not accessible yet.
- As data is not collected, next activities -Data analysis, applications improvements, iteration- is not accessible. However, adjustment is proposed to enrich the study. For each identified potential negative impact, improvement measures are proposed to counter or lower it.

Additionally, it should be noted that this appendix proposes a procedure for well-being assessment and ethical impacts study, but cannot apply it as proposed work is only a proof of concept for now.

This appendix will consequently not offer conclusion. Instead, a discussion is proposed to discuss about the procedure, details the obtained dashboard and the potential negative impacts.

## A.2 Results

From the internal analysis (activity 1), 5 different stakeholders were identified: The user, i.e. is a frail individual whose home is equipped with binary sensors to monitor his every-day life, health care providers, smart home equipment providers and installers, user family members and other relatives, and society as a whole.

For each identified stakeholder, potential impacts are listed (activity 1) and classified with its associated domain and subdomain (activity 2). Indicators to assess the

amplitude of these impacts are also proposed (activity 2). They can be straightforward, for instance the number of new entrepreneurs in smart home equipment fields, or require surveys to be addressed to the stakeholders, for instance satisfaction with his job. When a survey is proposed, a source stating the relevancy of the question is associated. They are listed in tables A.7 and A.8. Finally, if the impact is potentially negative, mitigation is proposed to cancel it, or at least reduce its magnitude.

These results are depicted in dashboards tables A.2, A.3, A.4, A.5 and A.6.

## APPENDIX A. Ethical Impact Assessment

Domain	Sub domain	In which way is the domain impacted	Indicators	If the impact is negative, how to mitigate it?
Satisfaction with life	-	Having the possibility to stay at home rather than going to a specialized institutions improve user satisfaction	Satisfaction with life as a whole	-
Affect	-	User might feel anxious or depressed to know his life habits are observed	European Social Survey's Europeans' Personal and Social well-being	<ul style="list-style-type: none"> <li>- Extensive survey to know which aspect of life is impacted by monitoring</li> <li>- Use of less invasive technologies</li> <li>- Communication with the user about the protocols used for data privacy</li> <li>- Psychological support for user feeling depressed alone at home</li> </ul>
Psychological well-being	-	User at home can carry out his life as he desires contrary to specialized institutions	Sense that one leads a purposeful and meaningful life	-
Community	Sense of belonging	User still can have contact with his neighborhood / friends as desired	Sense of belonging to a neighborhood	-
	Social support	<ul style="list-style-type: none"> <li>- User know medical staff can intervene in case of medical trouble</li> <li>- As user is monitored by the app, relatives might consider the user safe and may be less willing to aid, visits, or call for news</li> </ul>	<ul style="list-style-type: none"> <li>- Sense that if one were in trouble, they would have relatives or friends they can count on</li> <li>- Satisfaction with relationships</li> </ul>	Include tools for communication with relatives (computer, specific applications, internet connection, etc.)
Culture	-	User can more easily participate in arts and cultural activity rather than in specialized institution	Participation in arts or cultural activity	-
Economy	Standard	Application offer cheaper solution for elderly compared to institutions	Solutions cost comparison	-
	Equity / equality	Insurance cost might be influenced if insurance company know user's home is equipped or if user's health status is known	Comparison of insurance cost for people of same age	Insurance company might know about the use of application, but information about user's health status should stay private
	Natural resources, consumption, production	As the user stay in an individual home, resources consumption and pollution generation may rise up	Material consumption and compared to consumption in institutions	<ul style="list-style-type: none"> <li>- Raising awareness about resource consumption, buying habits, recycling, energy saving, climate change, pollution in general, etc.</li> <li>- Funding for better equipment (heat insulation, energy saving equipment)</li> </ul>
Environment	Not displayed	See above	-	-
Health	Physical health	Application has positive impact on the physical health of the user	<ul style="list-style-type: none"> <li>- Healthy life expectancy</li> <li>- Satisfaction with quality of health care</li> </ul>	<ul style="list-style-type: none"> <li>- Extended survey to know which diseases are well-treated thanks to the application, and which are not</li> <li>- Discussion with medical staff to get information on how to improve the application for the badly treated diseases: which activities to monitor, which behavioral indicators to observe, when and how alert medical staff when anomalies are found.</li> <li>- Users who might suffer from the diseases which are not well-treated by the application might be sent to specialized institutions instead</li> </ul>
	Mental health	Application has positive impact on the mental health of the user	(same)	(same)
Human settlements	Housing	User is satisfied to stay at home	Satisfaction with quality of housing	-

Table A.2: Well-being impact assessment - User dashboard

## A.2. Results

Domain	Sub domain	In which way is the domain impacted	Indicators	If the impact is bad, how to mitigate it?
Economy	Equity/equality	-	-	-
	Jobs	Impact on the number of required doctor (might be more or less)	Numbers of jobs in health care	-
Work	Environment	Having information about daily life patterns of user allow for better diagnostic	Sense that the conditions of one's job allows one to be about as productive as one could be	-
	Work-life balance	Might give additional work and tasks to medical staff	<ul style="list-style-type: none"> <li>- Satisfaction with the balance between the time spent on the job and the time spent on other aspects of life</li> <li>- Proportion of employed people working 50 hours or more a week</li> </ul>	<ul style="list-style-type: none"> <li>- Pay attention to the workload of medical staff. If workload exceed limits, public authorities should consider an increase in the number of doctors</li> <li>- Interpretation of results from the application could be delegated to dedicated services (public or private)</li> </ul>

Table A.3: Well-being impact assessment - Health care provider dashboard

Domain	Sub domain	In which way is the domain impacted	Indicators	If the impact is bad, how to mitigate it?
Psychological well-being	-	Providers and installers work to increase well-being of the elderly, giving meaning to there work	<ul style="list-style-type: none"> <li>- Sense that one leads a purposeful and meaningful life</li> <li>- Feeling that the things one does are worthwhile</li> </ul>	-
Economy	Jobs	New jobs creation	Numbers of created jobs	-
	Natural resources, consumption, production	Sensors used for the application may use battery or other polluting and hardly recyclable materials	Recycling rates of devices (waste + re-use)	<ul style="list-style-type: none"> <li>- Limiting to the minimum the number of sensors used in user home</li> <li>- Evaluating the impact on the environment of the material and process used to build the sensors, and use solutions more respectful of the environment: Recycled plastics, less polluting batteries, etc.</li> <li>- Re-use of the sensors in other homes when a user does not use the application anymore</li> <li>- Collection of the no more useable sensors to bring them to specific and adapted recycling centers</li> </ul>
	Entrepreneurship	Application offer new opportunities for businesses	Number of new entrepreneurs in this field	-
Environment	Not displayed	See "Natural resources, consumption, production" in Economy domain	-	-
Work	Environment	Working for elderly well-being increase satisfaction towards one's job	<ul style="list-style-type: none"> <li>- Satisfaction with job</li> <li>- Sense that current work life is interesting</li> </ul>	-

Table A.4: Well-being impact assessment - Smart home equipment providers and installers dashboard

Domain	Sub domain	In which way is the domain impacted	Indicators	If the impact is bad, how to mitigate it?
Satisfaction with life	-	Relatives know the user is in good health and independent	Satisfaction with life as a whole	-
Affect	-	Relatives are reassured	European Social Survey's Europeans' Personal and Social well-being	-
Government	Institutions	Relatives are satisfied with the experience and engagement of public services	- Satisfaction with one's last experience of public services - Sense there is respect for individual human rights at present in one's country	-

Table A.5: Well-being impact assessment - User's family members and relative dashboard

Domain	Sub domain	In which way is the domain impacted	Indicators	If the impact is bad, how to mitigate it?
Community	Community Safety	If ill-intentioned people get access to daily life habits information, it may ease robbery	Crime number evolution	<ul style="list-style-type: none"> <li>- It is crucial for the user's life habits information to be private, only medical staff should have access to this information</li> <li>- Data privacy must be respected at any cost. It means installer and smart home technology provider should not have access to the data generated by the sensor</li> <li>- Except for very specific medical reasons (for an appointment, an emergency call, etc.) user identity information (name, address, etc.) should not be available for application stakeholders, even medical staff. Only information useful for diagnosis should be accessible (for instance age, sex, etc.)</li> </ul>
	Discrimination	Every user should have the same opportunities offered by the application, no matter their sex, skin color, etc.	Application results comparison between groups of different sex, ethnicity, etc.	<ul style="list-style-type: none"> <li>- Discussion with medical staff / other stakeholders to understand the reasons of these differences</li> <li>- Some of them might be health related (male tends to live less longer than female, obesity rate is more important in a specific group of population, etc.)</li> <li>- Some other might be due to the approach or material being unadopted to specific population. In that case, research works must be done to understand why and how to adapt the application</li> </ul>
Economy	Equity/equality	Application might be too onerous for poor people	User's wealth compared to same age population	Consider public funds to help poor populations
	Jobs	Increase of jobs in healthcare and smart home equipment providers	-	-
Government	Institutions	Specialized institutions are less occupied and can offer better service to resident	Satisfaction with one's last experience of public services	-
Human settlements	Housing	As more elderly stay in their home, housing market increases	<ul style="list-style-type: none"> <li>- Proportion of population living in households with access to basic services</li> <li>- Satisfaction with availability of good affordable housing</li> </ul>	-

Table A.6: Well-being impact assessment - Society dashboard

## APPENDIX A. Ethical Impact Assessment

Domain or subdomain	Chosen associated indicator	Indicator source	Indicator description
<b>Satisfaction with life</b>	Satisfaction with life as a whole	World Values Survey. WVS Wave 6 (2010–2014).	258 questions survey about quality of life in general
<b>Affect</b>	European Social Survey's Europeans' Personal and Social well-being	European Social Survey. Personal and Social Well-Being (ESS3 2006, ESS6 2012)	Around 100 questions surveys (depending on the user country)
<b>Psychological well-being</b>	<ul style="list-style-type: none"> <li>* Sense that one leads a purposeful and meaningful life</li> <li>* Feeling that the things one does are worthwhile</li> </ul>	<ul style="list-style-type: none"> <li>* Organisation for Economic Co-Operation and Development (OECD). "Better Life Index."</li> <li>* United Kingdom Office for National Statistics. "Measures of National Well-being Dashboard."</li> </ul>	<ul style="list-style-type: none"> <li>* Grading from 0 to 10 ones satisfaction with different aspects of life (housing, work, life satisfaction, etc.) + their importance to the user. Results displayed per countries</li> <li>* Satisfaction with jog, leisure time, and volunteering</li> </ul>
<b>Sense of belongings</b>	Sense of belonging to a neighborhood	United Kingdom Office for National Statistics. "Measures of National Well-being Dashboard"	Around 10 questions specific to living area + involvement of neighbors in personal life
<b>Social support</b>	<ul style="list-style-type: none"> <li>* Sense that if one were in trouble, they would have relatives or friends they can count on to help them</li> <li>* Satisfaction with relationships</li> </ul>	<ul style="list-style-type: none"> <li>* Organisation for Economic Co-Operation and Development (OECD). "Better Life Index."</li> <li>* United Kingdom Office for National Statistics. "Measures of National Well-being Dashboard"</li> </ul>	<ul style="list-style-type: none"> <li>* Grading from 0 to 10 ones satisfaction with different aspects of life (housing, work, life satisfaction, etc.) Results displayed per countries</li> <li>* 3 question about relationships (happy-unhappy, feelings of loneliness and frequency, has someone to rely one)</li> </ul>
<b>Community safety</b>	Crime rate	United Kingdom Office for National Statistics. "Measures of National Well-being Dashboard."	Crime against the person (per 1000 adults)
<b>Discrimination</b>	Application results comparison between groups of different sex, ethnicity,	No source	Prefered to "Sense of discrimination in one's community" proposed in the standard
<b>Culture</b>	Engagement with/participation in arts or cultural activity	No associated source	-
<b>Standard of living</b>	Cost comparison between home monitoring and institution placement	No source	-
<b>Economic equity and equality</b>	<ul style="list-style-type: none"> <li>* Comparaision of insurance cost for people of same age</li> <li>* User's wealth compared to same age population</li> </ul>	<ul style="list-style-type: none"> <li>* No source</li> <li>* Adapted from Gini index, Central Intelligence Agency, "Country Comparison: Distribution of Family Income—Gini Index" from The World Fact Book</li> </ul>	<ul style="list-style-type: none"> <li>* -</li> <li>* Gini index score from 0 to 100 degree of inequality in the distribution of family income in a country (the lower the better). Adapted to application user and same age population</li> </ul>
<b>Jobs</b>	<ul style="list-style-type: none"> <li>* Number of jobs in health care domains</li> <li>* Number of jobs created in smart home technologies manufacturers, providers, installer, maintainers, etc.</li> </ul>	No source	<ul style="list-style-type: none"> <li>* Have to include potentially created jobs in healthcare (for this application or in health in general) + job impact in retirement residence and equivalent</li> <li>* -</li> </ul>
<b>Natural rressources, consumption, and production</b>	<ul style="list-style-type: none"> <li>* Material consumption and compared to consumption in institutions</li> <li>* Recycling rates of devices (waste + re-use)</li> </ul>	<ul style="list-style-type: none"> <li>* No source</li> <li>* United Nations. "Sustainable Development Goals Indicators."</li> </ul>	<ul style="list-style-type: none"> <li>* Have to include energy, waste, generated pollution, etc. to evaluate impact on environment</li> <li>* Recycling rate, tons of products recycled</li> </ul>
<b>Business and entrepreneurs hip</b>	* Number of new entrepreneurs in this field	No source	More practical than proposed indicator "Sense that the area where one lives is a good place to live for entrepreneurs forming a new business"

Table A.7: Source and description for each indicator associated to well-being domains and subdomain

## A.2. Results

Domain or subdomain	Chosen associated indicator	Indicator source	Indicator description
<b>Institutions</b>	Satisfaction with one's last experience of public services	United Nations. "Sustainable Development Goals Indicators"	Various indicators: Public services density and distribution, total net official development assistance, capacity, affordability, parity, discrimination, research funds, access, corruption, user satisfaction
<b>Physical health</b>	* Healthy life expectancy * Satisfaction with quality of health care	* United Kingdom Office for National Statistics. "Measures of National Well-being Dashboard." * World Values Survey. WVS Wave 6 (2010–2014).	* Average number of years that a person can expect to live in "full health" by taking into account years lived in less than full health due to disease and/or injury (WHO) * 258 questions survey about quality of life in general
<b>Housing</b>	* Satisfaction with quality of housing * Proportion of population living in households with access to basic services * Satisfaction with availability of good affordable housing	* World Values Survey. WVS Wave 6 (2010–2014). * United Nations. "Sustainable Development Goals Indicators." * same	* 258 questions survey about quality of life in general * - * Proportion of population with large household expenditures on health as a share of total household expenditure or income
<b>Workplace environment</b>	* Sense that the conditions of one's job allows one to be about as productive as one could be * Satisfaction with job * Sense that current work life is interesting	* Department of Health and Human Services, Centers for Disease Control and Prevention & National Institute for Occupational Health and Safety. "Fundamentals of Total Worker Health Approaches." * Smith, T., P. Marsden, M. Hout, and J. Kim, General social surveys, 1972–2012 [cumulative file] Ann Arbor, MI: Inter-University Consortium for Political and Social Research, 2013.129 * same	* Method for brainstorming teams about their current work conditions and what / how they can be improved * 41 survey questions with pre-sentenced answer to choose the more fitting one
<b>Work life balance</b>	* Satisfaction with the balance between the time spent on the job and the time spent on other aspects of life * Proportion of employed people working 50 hours or more a week	* European Social Survey Round 5 Work Family Well-being Module * Organisation for Economic Co-operation and Development (OECD). "Better Life Index."	* Length of working hours, the prevalence of asocial working hours, the intensity of work, and the level of job security. Worker gender influences impact of these conditions on work life balance satisfaction * Grading from 0 to 10 ones satisfaction with different aspects of life (housing, work, life satisfaction, etc.) + their importance to the user. Results displayed per countries

Table A.8: Source and description for each indicator associated to well-being domains and subdomain

### A.3 Discussion and further works

The potential negative impacts are manifold. It was expected, as the works proposed in this thesis handle private and critical data. Moreover, the review of potential negative impacts is as wide as possible to compensate for the absence of users and stakeholders engagement. This dashboard does not claim to cover every potential negative impact. It is part of the process to iterate and refine the dashboard by removing impacts detected as negligible and improve data collection for those detected as predominant.

Even if potential impacts are numerous, it was still possible to propose an adapted indicator for each of them. It ensures that potential negative impacts can be detected, which is the very first step for its resolve.

The last steps of the procedure could not be achieved as the works presented in this thesis is a proof of concept and is not currently used in real smart homes. Data collection, and consequently its analysis, is not possible at the stage of development.

The analysis of these potential impacts thanks to proposed metrics allows to determine which ones are significant and which ones are irrelevant. If a negative impact is confirmed, development and management of the system have to be improved to negate or at least reduce assessed impact. In our case, proposed solutions for each negative impact is documented in the dashboard. This is reassuring, as it means a negative impact is not a fatality and can be mitigated.

A periodic reports have to be filled, enlisting the data collection and analysis strategy and a summary of the different impacts evaluated. The objective of such reports is to be able to detect potential trends in the next iterations, as the ethical consideration and the public might change over time. This is particularly worthwhile as it enables metric refinement to set preemptive actions and modifications before a potential negative impact becomes too concerning.

Finally, the process is iterated. The dashboard evolves depending on and the results from the analysis phase. If a potential impact has been proven to be marginal or non-existent, it is removed from the dashboard. For other assessed impacts, data collection and analysis is refined in order to help application developers to reduce the well-being impacts. Users and stakeholders are also implicated again in order both to explore solutions for identified negative impacts and refined the dashboard.

The frequency of such iteration is widely dependent on the nature of the system and the stakeholders. In our case, as the objective is to monitor the health status of individuals which evolve on the scale of months or even years, the iteration frequency should be of the same order of magnitude.



# APPENDIX B

## Proof

### B.1 Probability computation with deterministic PFA structure

This section over a proof of Theorem 1. The theorem is reminded below:

Baum-Welch EM algorithm and Viterbi re-estimation algorithm produce the same, unique solution after only one iteration when the structure of the PFA is deterministic (definition 3.4). This solution corresponds to a global maximum and thus is the most satisfying solution.

In order to prove this theorem, several notations have to be introduced.

In the following, we consider the STA structure  $A = \langle Q, q_0, \Sigma, \delta \rangle$  and the PFA  $PFA = \langle A, P \rangle$  such as defined in definitions 3.1 and 3.2. We also introduce the event sequence  $w = [w_1, \dots, w_{|w|}]$  with  $|w|$  length of  $w$ .

#### Prerequisites

Prefix probability  $\alpha_w(i, q), \forall q \in Q$  and  $0 \leq i \leq |w|$  is the probability to generate the prefix  $w_1, \dots, w_i$  and reaching state  $q$ . It has primarily defined for HMM [Knill and Young, 1997] and adapted for PFA [Vidal et al., 2005a]. Here is proposed a slightly modified version for the PFA introduced in definition 3.2:

$$\alpha_w(i, q) = \sum_{(s_0, \dots, s_i) \in \Theta_A(w_1, \dots, w_i)} \prod_{j=1}^i P(s_{j-1}, w_j, s_j) \cdot 1(q, s_i) \quad (\text{B.1})$$

with  $\Theta_A(w_1, \dots, w_i)$  denoting the set of sub-paths states reachable by sequence  $(w_1, \dots, w_i)$  (definition 3.7) and  $1(q, s_i) = \begin{cases} 1 & \text{if } q = s_i \\ 0 & \text{else} \end{cases}$

The same way, suffix probability  $\beta_w(i, q)$  is presented, referencing to the probability of generating the suffix  $w_{i+1}, \dots, w_{|w|}$  from the state  $q$ :

$$\beta_w(i, q) = \sum_{(s_i, \dots, s_{|w|}) \in \Theta_A(w_{i+1}, \dots, w_{|w|})} 1(q, s_i) \cdot \left[ \prod_{j=i+1}^{|w|} P(s_{j-1}, w_j, s_j) \right] \quad (\text{B.2})$$

To use the Baum-Welch algorithm [Baum, 1972], two additional definitions are required. These definitions were initially defined for HMM. A slightly modified version fitting with PFA model is proposed below:

Let  $\gamma(q_i, t)$  be the probability of being at state  $q_i$  at time  $t$ , i.e. state  $q_i$  is reached after firing an event sequence of length  $t$ , given a training sample  $T$  and the PFA  $\langle A, P \rangle$ :

$$\gamma(q_i, t) = P(q(t) = q_i | T, \langle A, P \rangle) \quad (\text{B.3})$$

$$= \frac{P(q(t) = q_i, T | \langle A, P \rangle)}{P(T | \langle A, P \rangle)} \quad (\text{Bayes Theorem}) \quad (\text{B.4})$$

$$= \frac{\alpha_T(t, q_i) \cdot \beta_T(t, q_i)}{P(T | \langle A, P \rangle)} \quad (\text{B.5})$$

with  $q(t)$  the state reached after firing a sequence of length  $t$ . Denominator  $P(T | \langle A, P \rangle)$  is not developed.

The probability  $\xi_{ijk}(t)$  of being at state  $q_i$  at time  $t$  and  $q_j$  at time  $t + 1$  after firing a transition labeled with event  $\sigma_k$ , given  $T$  and  $\langle A, P \rangle$  is also defined here:

$$\xi_{ijk}(t) = P(q(t) = q_i, (q_i, \sigma_k, q_j) | T, \langle A, P \rangle) \quad (\text{B.6})$$

$$= \frac{P(q(t) = q_i, (q_i, \sigma_k, q_j), T | \langle A, P \rangle)}{P(T | \langle A, P \rangle)} \quad (\text{Bayes Theorem}) \quad (\text{B.7})$$

$$= \frac{\alpha_T(t, q_i) \cdot P(q_i, \sigma_k, q_j) \cdot \beta_T(t + 1, q_j)}{P(T | \langle A, P \rangle)} \quad (\text{B.8})$$

### Baum-Welch algorithm

With these temporary variables, Baum-Welch algorithm can be applied.

It consists in an iterative process where each probabilities are refined at each iteration. The theorem introduced in [Baum and Sell, 1968] ensures to always obtain a better result at each iteration, and to converge to a local maximum. The algorithm is straight forward and is presented by a pseudo-code in algorithm 3.

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#### Algorithm 3 Baum-Welch Expectation Maximization algorithm

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**Require:** Initial probability function  $P$  and PFA  $\langle A, P \rangle$

**Require:** Training sample  $T$

**Ensure:** Refined probability function  $P^*$

- 1: **while** Non convergence **do**
  - 2:   Compute  $P^*$  using  $P$
  - 3:    $P \leftarrow P^*$
  - 4: **end while**
- 

For each transition  $(q_i, \sigma_k, q_j)$  in  $\delta$ , the refined probability  $P^*(q_i, \sigma_k, q_j)$  is computed by dividing the expected number of transitions from state  $q_i$  to state  $q_j$  by occurrence of event  $\sigma_k$  by the expected total number of transitions from state  $q_i$ :

$$P^*(q_i, \sigma_k, q_j) = \frac{\sum_{t=1}^{T-1} \xi_{ijk}(t)}{\sum_{t=1}^{T-1} \gamma_i(t)} \quad (\text{B.9})$$

which leads to:

$$P^*(q_i, \sigma_k, q_j) = \frac{\sum_{t=1}^{T-1} \alpha_T(t, q_i) \cdot P(q_i, \sigma_k, q_j) \cdot \beta_T(t+1, q_j)}{\sum_{t=1}^{T-1} \alpha_T(t, q_i) \cdot \beta_T(t, q_i)} \quad (\text{B.10})$$

### Use of deterministic STA structure consequences

Working with a deterministic STA structure leads to significant simplifications.

First, as at most one path can be fired from a given sequence, the prefix and suffix probabilities can be simplified:

$$\alpha_w(i, q) = \sum_{(s_0, \dots, s_i) \in \Theta_A(w_1, \dots, w_i)} \prod_{j=1}^i P(s_{j-1}, w_j, s_j) \cdot 1(q, s_i) \quad (\text{B.11})$$

$$= \prod_{\substack{(s_0, \dots, s_i) \in \Theta_A(w_1, \dots, w_i) \\ j=1}}^i P(s_{j-1}, w_j, s_j) \cdot 1(q, s_i) \quad (\text{as } |\Theta_A(w_1, \dots, w_i)| \leq 1) \quad (\text{B.12})$$

with the convention  $\prod_{(s_0, \dots, s_i) \in \Theta_A(w_1, \dots, w_i)} P(s_{j-1}, w_j, s_j) = 0$  if  $\Theta_A(w_1, \dots, w_i) = \emptyset$ .

The same way:

$$\beta_w(i, q) = \sum_{(s_i, \dots, s_{|w|}) \in \Theta_A(w_{i+1}, \dots, w_{|w|})} 1(q, s_i) \cdot \left[ \prod_{j=i+1}^{|w|} P(s_{j-1}, w_j, s_j) \right] \quad (\text{B.13})$$

$$= \prod_{\substack{(s_i, \dots, s_{|w|}) \in \Theta_A(w_{i+1}, \dots, w_{|w|}) \\ j=i+1}}^{|w|} 1(q, s_i) \cdot P(s_j, w_{j+1}, s_{j+1}) \quad (\text{B.14})$$

In that case,  $P^*(q_i, \sigma_k, q_j)$  can be simplified.

On the one hand:

$$\sum_{t=1}^{T-1} \alpha_T(t, q_i) \cdot \beta_T(t, q_i) = \sum_{t=1}^{T-1} \left[ \prod_{\substack{(s_0, \dots, s_t) = \Theta_A(T_1, \dots, T_t) \\ j=1}}^t P(s_{j-1}, T_j, s_j) \cdot 1(s_t, q_i) \times \right. \quad (\text{B.15})$$

$$\left. \prod_{\substack{(s_t, \dots, s_{|T|}) = \Theta_A(T_{t+1}, \dots, T_{|T|}) \\ j=t+1}}^{|T|} 1(s_t, q_i) \cdot P(s_j, T_{j+1}, s_{j+1}) \right] \quad (\text{B.16})$$

$$= \sum_{t=1}^{T-1} P(T | \langle A, P \rangle) \cdot 1(s_t, q_i) \quad (\text{B.17})$$

$$= P(T | \langle A, P \rangle) \sum_{t=1}^{T-1} 1(s_t, q_i) \quad (\text{B.18})$$

$$= P(T | \langle A, P \rangle) \times N(q_i, T) \quad (\text{B.19})$$

with  $N(q_i, T) = \sum_{t=1}^{T-1} 1(s_t, q_i)$  number of occurrences of  $q_i$  in the path fired by  $T$ , except for the last state.

On the other hand:

$$\sum_{t=1}^{T-1} \alpha_T(t, q_i) \cdot P(q_i, \sigma_k, q_j) \cdot \beta_T(t+1, q_j) = \sum_{t=1}^{T-1} \left[ \prod_{\substack{(s_0, \dots, s_t) = \Theta_A(T_1, \dots, T_t) \\ j=1}}^t P(s_{j-1}, T_j, s_j) \cdot 1(s_t, q_i) \times \right. \quad (\text{B.20})$$

$$P(q_i, \sigma_k, q_j) \times \quad (\text{B.21})$$

$$\left. \prod_{\substack{(s_{t+1}, \dots, s_{|T|}) = \Theta_A(T_{t+2}, \dots, T_{|T|}) \\ j=t+2}}^{|T|} 1(s_{t+1}, q_j) \cdot P(s_j, T_{j+1}, s_{j+1}) \right] \quad (\text{B.22})$$

$$= \sum_{t=1}^{T-1} P(T | \langle A, P \rangle) \cdot 1(s_t, q_i) \cdot 1(s_{t+1}, q_j) \quad (\text{B.23})$$

$$= P(T | \langle A, P \rangle) \sum_{t=1}^{T-1} 1(s_t, q_i) \cdot 1(s_{t+1}, q_j) \quad (\text{B.24})$$

$$= P(T | \langle A, P \rangle) \times N(q_i \rightarrow q_j, T) \quad (\text{B.25})$$

with  $N(q_i \rightarrow q_j, T) = \sum_{t=1}^{T-1} 1(s_t, q_i) \cdot 1(s_{t+1}, q_j)$  number of time state  $s_i$  is followed by state  $s_j$  in the path fired by  $T$ .

Thus, we have:

$$P^*(q_i, \sigma_k, q_j) = \frac{\sum_{t=1}^{T-1} \alpha_T(t, q_i) \cdot P(q_i, \sigma_k, q_j) \cdot \beta_T(t+1, q_j)}{\sum_{t=1}^{T-1} \alpha_T(t, q_i) \cdot \beta_T(t, q_i)} \quad (\text{B.26})$$

$$= \frac{N(q_i \rightarrow q_j, T)}{N(q_i, T)} \quad (\text{B.27})$$

Consequently, the following properties are deduced:

- In a deterministic model, the computation of  $P^*$  does not depends on the initial probabilities  $P$  (equation B.27). Consequently, according to pseudo code in algorithm 3, the Baum-Welch algorithm converges after only one iteration;
- The solution is unique (global maximum);
- This solution can be computed using counters (equation B.27);

These properties also hold for Viterbi re-estimation algorithm. Viterbi algorithm is often used with EM methods to reduce the computational complexity by considering the optimal path approximation rather than the true likelihood. In a PFA with a deterministic structure, as only one path at most can be fired for a given sequence of events, the likelihood is exactly the optimal path, leading to the same result.

**Titre:** Détection des évolutions d'habitudes de vie de personnes fragiles dans un habitat intelligent

**Mots clés:** Système à événements discrets, Ambient Assisted Living, Smart home, Détection d'anomalies

**Résumé:** Face à l'augmentation du nombre de personnes fragiles dû au vieillissement mondial de la population, des solutions innovantes sont explorées afin d'assurer un accès de soin efficace aux personnes restant à leur domicile. Le domaine scientifique de l'Ambient Assisted Living (AAL) exploite les technologies des habitats intelligents afin de faciliter le vieillissement à domicile et d'offrir un niveau de sécurité satisfaisant. En particulier, de nombreux travaux existants exploitent des capteurs embarqués sur la personne afin de surveiller leurs constantes vitales : température, rythme cardiaque, etc. Ces capteurs offrent des informations pertinentes au corps médical, mais certains troubles tels que le déclin physique, ou les troubles cognitifs, entraînent en premier lieu un changement du comportement de l'habitant, ce qui entraîne alors dans un second temps des altérations dans ses constantes vitales. Cette situation est particulièrement complexe pour le corps médical, puisque l'observation seule des signes vitaux entraîne une détection tardive et difficile du trouble responsable. Ainsi, cette thèse propose une démarche pour la surveillance de comportement, c'est-à-dire la manière dont l'habitant conduit ses activités quotidiennes, afin de détecter des déviations de comportement et d'en renseigner le corps médical afin d'assister sa prise de décision. Cette approche est rendue possible grâce aux travaux récents concernant la reconnaissance des activités qui permettent d'identifier l'activité menée par l'habitant en fonction des événements capteurs générés à son domicile.

Une revue de la littérature médicale et concernant l'AAL a été menée afin d'identifier les troubles médicaux et symptômes associés d'intérêt pour le corps médical, et les caractéristiques du comportement qu'ils affectent. Deux caractéristiques ont été identifiées comme particulièrement pertinentes du fait de leur couverture : l'ordonnancement et la durée des activités menés par l'habitant. De plus, deux

types de déviation de comportement ont également été identifiés comme pertinent à détecter : les anomalies de comportement, c'est-à-dire les changements brusques de comportement qui peuvent être dues à un accident ou une maladie se déclarant du jour au lendemain, et les déviations de long terme qui résultent de changements lents et progressifs du comportement dus à des troubles dégénératifs.

Les travaux présentés dans cette thèse visent à détecter ces deux types de déviations de comportement concernant les caractéristiques de comportement identifiées comme pertinentes chez un habitant vivant seul au sein d'un habitat instrumenté. Seules les informations binaires sont considérées, permettant d'utiliser tout type de capteur et proposant ainsi les solutions les plus versatiles, et rendant possibles des approches plus respectueuses de la vie privée de l'habitant.

Les travaux de cette thèse se décomposent en trois parties. Afin de détecter des changements de comportement, une approche basée modèle est proposée. La première contribution de cette thèse est un modèle d'automate à temporisation stochastique (STA) représentant les habitudes de vie de l'habitant et sa génération durant une phase d'entraînement. Dans un second temps, le modèle est employé pour détecter des anomalies au sein du comportement de l'habitant durant une phase d'observation. La troisième contribution de cette thèse vise à employer le modèle afin de détecter des déviations de long terme, signe de l'apparition de troubles dégénératifs. À chaque contribution, deux études de cas sont proposées, l'un permettant de soumettre les contributions à des scénarios artificiels exigeants, le second permettant d'apprécier la méthodologie sur un cas réel. Enfin, puisque les données manipulées dans cette thèse sont particulièrement sensibles, une réflexion concernant les potentiels impacts éthiques et les méthodes pour les évaluer et réduire leur portée est proposée en annexe.

**Title:** Detection of life habits evolution of frail people in a smart dwelling

**Keywords:** Discrete event systems, Ambient Assisted Living, Smart home, Anomaly detection

**Abstract:** To face the increase of the number of frail people due to global population ageing, innovative solutions are explored to ensure to people staying at home a satisfying quality of health. Ambient Assisted Living (AAL) scientific field aims at exploiting smart home technologies to ease ageing at home and to offer satisfying health and living conditions. In particular, numerous existing works exploit wearable sensors in order to monitor their vital signs: temperature, heart rate, blood pressure, etc. These sensors offer relevant information to medical staff to assess the health status of an individual. However, some health troubles such as physical decline or cognitive impairments trigger first behavior changes, which trigger in a second step alterations of vital signs. This situation is complex for medical staff as observing vital signs only consequently leads to late and difficult diagnostic of the original disease. As these diseases typically impair the elderly, this problem is particularly critical.

Therefore, this thesis proposes an approach for smart home inhabitant behavior monitoring. Behavior refers to the way the inhabitant carries his everyday tasks. The objective is to detect behavioral deviations and to inform the medical staff in order to help them in their prognosis and diagnosis. This methodology is enabled thanks to recent existing works in activity recognition, allowing to know which activity the inhabitant is carrying according to the sensors he triggers.

Human behavior is extremely rich. An extensive literature review is proposed, concerning both the medical and AAL scientific field, in order to identify the health trouble and symptoms of interest for medical staff, and the way they impact patient behavior. Two behavioral features were identified as relevant due to their

wide coverage: activity ordering, and activity duration. Moreover, the behavior of an individual might be impacted in two different manners: behavioral anomalies which correspond to brutal behavioral changes due to accidents or sudden diseases, and long-term deviations which are slow and progressive changes of behavior mainly due to degenerative troubles.

The work presented in this thesis aims at detecting these two types of behavioral deviations regarding the two identified features. It focuses on a single smart home inhabitant, and considers binary information only. This way, any sensor type can be used, including the most respectful of life privacy.

The contributions of this thesis can be decomposed into three parts. In order to detect behavior deviations, model-based approach is proposed. Therefore, the first contribution is a Stochastic Timed Automaton (STA) model which represents the usual life habits of the inhabitant after a training phase. In a second step, this model is exploited in order to detect anomalies within inhabitant's behavior during a monitoring phase. Lastly, the model is used to detect long-term deviations through data forecasting in order to detect potential degenerative troubles. For each of these contributions, two case studies are proposed. The first one is based on artificial data generated from a real smart home in order to test challenging scenarios, while the second scenario is proposed to assess the relevancy of the proposed approach on a real scenario.

Finally, as the handled data is particularly sensitive, a reflection about the potential negative ethical impacts and a method to evaluate their seriousness is proposed in an appendix, along with consideration to decrease their severity.

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