Cooperative and Interactive Learning to estimate human behaviours for energy applications

Joana Nunes Nicolau Baptista da Silva

Thesis to obtain the Master of Science Degree in

Energy Engineering and Management

Supervisors: Prof. Carlos Augusto Santos Silva
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Abstract

To reduce the environmental impact of the residential sector, it is crucial to find ways to enhance sustainable energy behaviours. A new supervised learning approach is proposed to classify different instances related to human behaviour in a household context. It is based on a combination of Interactive Learning and Cooperative Learning relying only on timed data from a selected set of sensors and feedback from the occupants (labels) to collect the training data. The privacy of occupants is granted by avoiding the use of cameras and this approach can adapt not only to different household contexts but also, to distinct perspectives of the same reality (many profiles of users) and different types of data (numerical and non-numerical). A new method was introduced to assess and correct inconsistent labels, which assesses the errors and requests new information to the same context (*updates*). The methodology was tested for both occupancy and activity recognition, settling that using non-numerical labels leads to a more subjective environment but still reliable. Further, two different interaction criteria were analysed: *density* and *spread rate*; confirming that the optimal sensors/features selected depend not only on the household characteristics but also on the interaction criteria applied. The proposed methodology can be used to promote sustainable behavioural changes by sending suggestions to the occupants and also to study the impact of those suggestions in individual and energy community contexts (flexibility). It can be very useful in energy management systems improving energy efficiency and performing active demand-side management.

Keywords: Interactive Learning, Cooperative Learning, household characterization, machine learning, human behavior

Resumo

Dada a urgência em reduzir o impacto ambiental do setor residencial, é fundamental encontrar formas de potenciar um comportamento sustentável. Uma nova abordagem de aprendizagem supervisionada é proposta para caracterizar diferentes instâncias relacionadas com o comportamento humano num contexto doméstico. Baseada numa combinação de Aprendizagem Interativa e Aprendizagem Cooperativa, conta apenas com dados de sensores e feedback dos ocupantes (rótulos) para treinar o modelo. Nesta abordagem, destacam-se a garantia de privacidade dos ocupantes, evitando o uso de câmaras, e a adaptação não só a diferentes contextos domésticos, mas também, a diversas perspetivas da mesma realidade (variados perfis de usuários) e diferentes tipos de dados (numéricos e não numéricos). Foi introduzido um novo método para avaliar e corrigir rótulos inconsistentes, que avalia possíveis erros e solicita novas informações para o mesmo contexto (*updates*). A metodologia foi testada para o reconhecimento tando do nível de ocupação como das atividades realizadas pelos ocupantes, estabelecendo que o uso de rótulos não numéricos leva a um ambiente mais subjetivo, mas ainda confiável. Além disso, dois critérios de interação foram analisados: a densidade e a taxa de propagação; confirmando que os sensores/recursos selecionados dependem não apenas das características da residência, mas também dos critérios de interação utilizados. A abordagem proposta pode ser utilizada para promover comportamentos sustentáveis através do envio de sugestões aos ocupantes mas também para estudar o impacto dessas sugestões (flexibilidade). Pode no futuro vir a ser aplicada em sistemas de gestão de energia, contribuindo para a eficiência energética e gestão da procura.

Palavras-chave: Aprendizagem Interativa, Aprendizagem Cooperativa, caracterização em ambiente doméstico, aprendizagem de máquina, comportamento humano

Contents

List of Figures

List of Tables

Abbreviations

A	Number of asks
AS	Artificial System
CL	Cooperative Learning
CS	Number of confusion solvers
CW	Confusion word
D	Density criterion
DB	Acoustic pressure
EU	European Union
GA	Global accuracy
GHGs	Greenhouse gases
HA	Human actors
HO	Hour of the day
IHEMAS	Interactive Home Energy Management Aid System
IL	Interactive Learning
IR	Improvement ratio
KD	Knowledge database
PIS	Persuasive Interactive Systems
POW	Power consumption
RA	Resolution accomplishment
SR	Spread rate criterion
U	Number of updates

Chapter 1

Introduction

Since the mid-18th century, along with the industrial growth, the impact of human activities on the environment has dramatically increased yielding a great upcoming challenge for humankind: creating a more sustainable way of living. We are entering into a new era named Anthropocene, where humans must pay attention to the impact of their actions on the environment. Global warming is one of the most serious issues the world is facing today. It is a result of the increased emission of greenhouse gases (GHGs) mainly via the combustion of fossil fuels which production has risen by 260% since 1750 [1]. While energy consumption accounts for over 80% of the global GHGs, in Europe, residential buildings contributed more than 36% of all emissions in 2018 [2]. This leads to the necessity of reducing energy consumption in residential buildings. In an attempt to resolve these issues, the European Union (EU) has formulated targets to improve the energy performance of the European building stock by introducing measures and obligations for buildings – the *Energy Performance of Buildings Directive* (EPBD). According to the 2012 EPBD targets, by 2020, the GHGs emissions in the EU should be reduced by 20% compared to 1990 levels and 20% of primary energy consumption should be saved [3]. More recently, in 2018, the target for the reduction of emissions was set at 40% by 2030 and 80-95% by 2050 (compared to the 1990 levels) [2].

Better integration of awareness and flexibility of human behaviour in the design of energy systems has been highlighted as a requirement for energy efficiency solutions and associated regulations, e.g. in the *Réglementation Thermique RT2020* [4] in France and the *Decree Law no.101-D/2020* [5] in Portugal through the ADENE (the Portuguese national energy agency). Awareness and flexibility of human behaviour can be described, respectively and in this context, as the knowledge or perception of the impact of their actions on energy performance and the willingness to change or compromise specific behaviours. Indeed, numerous research works have been carried out to study the human behaviour influence on energy performance at the scale of housing, offices, urban blocks, etc. They deal with optimized energy management [6], modelling techniques/simulations of buildings and neighbourhoods/islet, the transformation of building system models [7], methods for guaranteeing performances [8] or performance verification methods [9]. It appears that when a building is low energy consumption, it becomes very sensitive to the occupant's activities [10]. Models to represent the diversity of human behaviours have been developed [10] and implemented, for instance, the dynamic energy simulation software *Pleiades* [11], with the AMAPOLA add-on (adds the statistical dimension to the simulation), developed by IZUBA Energies.

As pointed out by *Le Monde* [12], the major retrofitting effort carried out in Germany did not lead to any form of effective reduction in thermal consumption in private homes: in 2010, a household was consuming an average of 131kWh of primary energy (kWhpe) per square meter and, in 2018, it consumed 130 kWhpe/m^2/year. This happened due to the rebound effect, i.e. after the retrofitting the inhabitants tend to increase their comfort requirements and become less careful regarding consumption which is supposed to be lower. The scenario in Figure 1.1 designed by the NégaWatt association confirmed the technical possibility of France using 100% renewable energies in 2050 while achieving carbon neutrality [13]. NégaWatt's scenario covers all sectors (buildings, transport, industry, agriculture…) and it points out the importance of considering the awareness and flexibility of human behaviour to favour low energy services and lifestyle (energy sufficiency).

Although there is a slight difference in human influence between commercial and residential buildings, the solutions for helping people to become more aware are different: the former can be based on automation because the companies can support the often-large investments and the diversity of activities is often low, while the latter remains problematic. The INVOLVED project considered in [14] and [15] has provided responses by developing concepts for Persuasive Interactive Systems (PIS). It aims at supporting sustainable behaviours while involving the occupants of the Elithis tower in daily decisions that have an impact on consumption and comfort. This PIS focus on the perception, understanding and action capabilities of the inhabitants, thus avoiding the

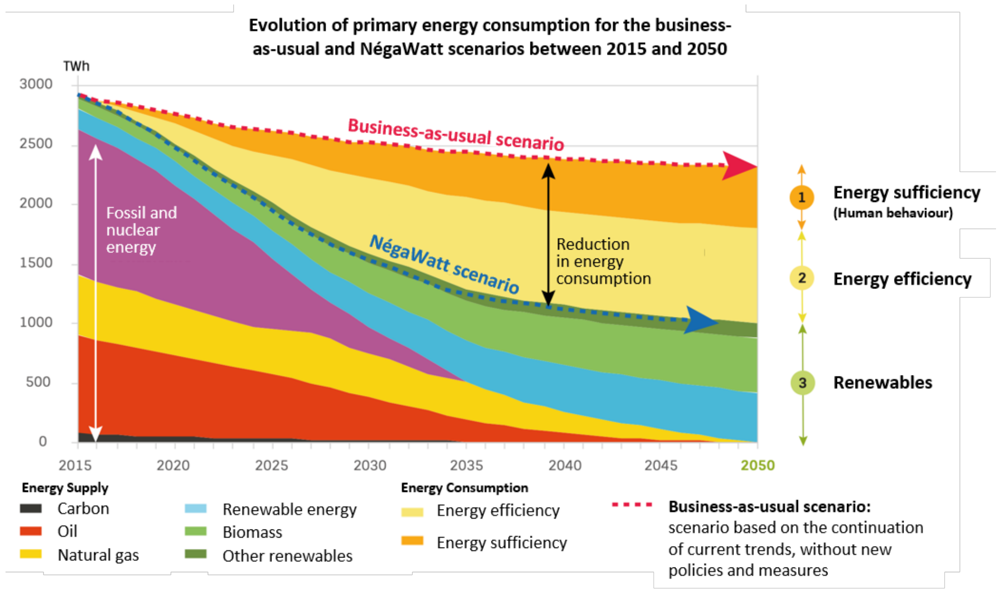


Figure 1.1: Evolution of primary energy consumption for the business-as-usual and NégaWatt scenarios between 2015 and 2050. It highlights the importance of both energy sufficiency (awareness and flexibility of the human behaviour) and energy efficiency [13].

pitfall of excessive automation. Beliefs, resistance to change, perception and misunderstanding were taken into account by the PIS in generating reports [6] and advice after the inhabitants specified their expectations [16]. There is no references to aware human practices insofar since the comfort requirements are specific to each household, but above all, the inhabitant's intentions remain inaccessible to the PIS. Mirroring, replay, explanation, focus and advising services have been developed and tested [17].

1.1 Motivation

Involving inhabitants from residential buildings is still a key challenge because each site is unique due to its architecture, equipment and sensors but also because of its inhabitants' different profiles. The site models, the sensor locations and human activities/preferences are mostly not available, however, these are required for mass deployment solutions.

In [18] an interactive approach based on direct interactions with the occupants was introduced. There an artificial system, called Interactive Home Energy Management Aid System (IHEMAS), models the household occupancy by collecting the relevant information directly from the human actors. An alternative approach can be designed considering that site knowledge results from a symmetrical confrontation between occupants' knowledge and the knowledge of an artificial system (IHEMAS). Each party is informing, explaining, asking, suggesting and learning from the other in a symmetrical way. In [19], a first application of a symmetrical co-definition of activities has been deployed. Here the occupants depict daily what they did during the day with their own meaningful labels and the IHEMAS analyses whether these labels can match its own perception based on sensor data and, if not, it suggests labelling errors.

In this thesis, we want to go further by designing an auto-adaptative learning solution, automatically adapting to a living area with its inhabitants and the available sensors – we want to make mass deployment possible. This research work focuses on the design of an Interactive/Cooperative Learning algorithm, which can be used to help the inhabitants getting a better understanding of their energy impact (increase their awareness and measure their flexibility). In the future, this approach can be applied to actively explore non-optimal occupant behaviours regarding costs/comforts compromises by supporting occupants in the analysis of their everyday behaviours.

1.2 Objectives

The objective of this thesis is to develop a new human-driven approach for the identification of different instances related to human behaviour in a household context. Meaningful data is collected from the human actors and, supported by a set of sensors, the algorithm models the reality. It can later be used to send sustainable behavioural suggestions to the residents and study the impact of those suggestions in individual and community contexts (flexibility). Moreover, in order to have a reliable solution and enable the mass deployment, the approach should comply with the following constraints:

- respect the privacy of occupants by avoiding the use of cameras;
- adapt to the diversity of environments (different households, sensors);
- adapt to different kinds of data (numerical and non-numerical);
- adapt to the different profiles of users (different perceptions);
- increase the user awareness of energy systems by including him (training data provided by the user).

1.3 Contributions

In this thesis, we addressed the following core challenges:

1. combining the best characteristics of Interactive and Cooperative Learning;
2. generalizing the model for both numerical (that can be grouped into ranges) and non-numerical data;
3. adjusting Interactive Learning triggering mechanism to accept an open set of labels free to human actors semantics;
4. implementing a new method to assess and correct defective training data (*update*).

Combining Interactive Learning with Cooperative Learning is the main contribution of this paper: it makes the collection of training data by the artificial learning system possible by inquiring human actors only when relevant. These approaches rely on direct interactions with the human actors and can be applied at the household level for identification of different time slots related to human behaviour.

We propose a new methodology that can be applied for occupancy, activity recognition or other relevant situation meaningful for the human actors. Besides, instead of a predefined set of labels used in the Interactive Learning approach, we consider an open and consistent set of labels that are entirely defined by the human actors, both in length and semantics.

Also, to assess and correct inconsistent labels given by the human actors, a new method is introduced. The artificial learning system will evaluate the mistrust data's context and look for the most up-to-date similar context in the past sensor's data. It will then request new information from the human actors in order to change the inconsistent label.

1.4 Outline of the thesis

The thesis proceeds as follow. In chapter 2 we perform a literature review of the current work regarding the latest developments in occupancy and activity recognition. In particular, we review the Interactive and Cooperative Learning approaches giving enough background for understanding their methodologies. The details of the proposed approach are described in chapter 3 and the case-study is presented in chapter 4. In chapter 5, we present and discuss the results. In chapter 6, the main conclusions of this thesis are summarized and future developments and applications suggested.

Chapter 2

Background on occupancy and activity recognition

In order to improve the performance of smart buildings, several approaches focused on human behaviour have been proposed. In this section, we overview the main approaches that have already been deployed for occupancy estimation and activity recognition in smart buildings. The existing methods generally involve probabilistic or statistical models trained via large training or a learning datasets. By learning and recognising patterns, these models manage to differentiate classes in the training data and apply this knowledge to predict/classify the test data. This allows the update of a solution without necessarily providing domain specific knowledge. Since their ground is pattern recognition such models are termed data-driven. [20] identifies such data-driven approaches and categorize them into generative modelling [21], discriminative modelling [22] and heuristic-based modelling [23]. It is noteworthy that other approaches that take advantage of both generative and discriminative learning simultaneously, called hybrid generative discriminative approaches, have been proposed recently in the literature [24], [25], [26], [27].

A large number of approaches are based on the use of video cameras and on the analysis of its content [28]. These methods are intrusive, which highly limits the implementation of the applications due to privacy issues [29]. Other approaches [30], [31], [32], [33] study activity recognition using mobile phone sensors or other wearable sensors. These methods are of interest because mobile phones provide/collect a lot of data from their sensors and have a great processing capacity. However, it is necessary for users to wear them at all times, which is not realistic in the context of a home. On the other hand, according to [29] [34] [35], people (mainly the elderly) have a good attitude towards smart home technologies and the associated low intrusive sensors.

The existing sensor-based methods depend on data sources. In [36], the occupancy estimation depends on proxy measurements such as CO_2 concentration, and indoor temperature. In [37] was investigated a solution for activity prediction using data from sensors (i.e. motion detectors and window contact sensors) by imitation learning, where the training data provided by an activity recognition algorithm serves as expert demonstrations. Sound processing has been widely used for activities recognition in smart houses. [38] uses Gaussian Mixtures Model (GMM) and Support Vector Machine to classify sound data sequences in order to be used in elderly people monitoring systems. In [39], an algorithm uses GMM and Hidden Markov Model for audio-based occupancy analysis. Moreover in [40], the authors proposed an approach for activity recognition with multimodal sensors based on Convolutional Neural Networks. In [41], a supervised learning approach is studied, where the authors, from a set of sensors (motion detection, power consumption, CO2 concentration sensors, microphone or door/window positions) determine those that shall be used to estimate and classify the approximate number of people. The selected data sources for occupancy estimation were: motion detection, power consumption and sound detection.

To avoid collecting data from scratch and disturbing the daily life of the users, some activity recognition approaches have been based on Transfer Learning. The main idea of Transfer Learning consists on reducing the data collection effort by transferring learned knowledge as much as possible from an existing environment, the so-called source domain, to a new target one where knowledge is applied. It is noteworthy that in Transfer Learning, feature sets, label sets as well as learning tasks, in both source and target domains datasets, can be different. In [42], for example, the authors proposed a feature-based approach to reuse previously learned knowledge to create a new environment. The approach was tested successfully to extract and transfer knowledge between two different smart-home environments, considering only single-resident scenarios. The problem was formulated as a classification task using Support Vector Machine by matching the different features of the source and target environments.

A compromise between supervised and unsupervised learning, called Semi-Supervised Learning, considers labelled data jointly with unlabelled data [43]. For example, in [44] a fraction of data labels has been collected as training data and used in a semi-supervised method for recognizing the user's activities. Label propagation has been used on a K-nearest neighbour graph to calculate the probability of the unlabelled data belonging in each class differentiated in the training phase. These probabilities have been used to train an Hidden Markov Model in a way that each of its hidden states corresponds to one class of activity. Other examples of Semi-Supervised Learning techniques are Active Learning and Interactive Learning which require an interaction with the user to get the desired outputs for new test data.

Active Learning is an important tool for many real-time applications. The main idea behind Active Learning is that a machine learning algorithm can achieve higher accuracy with fewer training labels if it is permitted to determine the data from which it learns, [45], [46]. For instance, different Active Learning strategies have been investigated in [47] for activity recognition.

Interactive Learning approaches have been explored for occupancy estimation using a set of sensors and self-labelling by occupants [48], [18]. One of the advantages of Interactive Learning is that useful feedback can be obtained from the end-user and increase their awareness of energy systems. The results lead to the conclusion that the interactive approach is more efficient for occupancy estimation than the other methods, taking the context into account. In [49], the concept of data quality is introduced to the interactive approach in order to evaluate and improve the quality of the database.

Cooperative Learning is a recent learning approach [19] proposed for activity recognition. This approach obtains a shared consistent representation, made of both recorded data and an open set of labels, between an artificial learning system perceiving an environment thanks to a set of sensors, and human actors using their own knowledge to label situations related to different time slots. Therefore, each label is identifying the activities of a person or a group during a time slot in a given place.

In the following, section 2.1 and section 2.2 describe the Interactive Learning and the Cooperative Learning, respectively. section 2.3 presents a comparison between the two previous approaches.

2.1 Interactive Learning

Interactive Learning (IL) is a supervised learning methodology that involves real-time interactions with human actors (HA) to request useful information related to a specific context. Interactive learning relies mainly on the assessment of a situation at a time slot t: how valuable is it to get a label depicting this situation considering what has already been collected?

The IL algorithm relies on machine learning and uses the contextual feedbacks (labels) provided by human actors as training data. The triggering of an interaction between both parties depends on whether the current situation has been met, or frequently met or not.

For instance, at the time interval t, the feedback given by the HA will be entitled label L_t. It could stand for an activity, a number of occupants or any kind of description of the situation during the time slot t. A *feature* $F_{i,t}$ is a data collected and possibly processed from one or several sensors, for instance, acoustic pressure from a microphone, motion detection, power consumption, etc.

To carry out a real-time interactive environment, the IL system might use an interaction mean like a graphical user interface where *asks* are displayed and human actors might return one of the predefined labels describing the situation. The closed list of labels is the main limitation of pure Interactive Learning: the combination with cooperative learning approach lifts this limit since any label can be used providing that it yields a consistent overall representation. Therefore, labels are the description of a current time slot related to an *ask* outcome as a question referring to a specified date and time (i.e. 'Question1, 05/05/2020 15:42:12 How many occupants in last 30 min?' $\Rightarrow$ discrete predefined feedback: (0, ..., 7)).

2.1.1 Concepts definition

Let's define an *ask* $\boldsymbol{A}_t$ related to a specific location at the same relevant time slot t as a vector of feature values from p sensors:

$$\boldsymbol{A}_t = (F_{1,t}, F_{2,t}, ..., F_{p,t}) \tag{2.1}$$

The feedbacks from the human actors are made of timed labels L_t belonging to a finite and discrete set of labels $\mathcal{L}$, in the case of pure Interactive Learning. Labels L_t represent a current context in a qualitative and meaningful manner for the human actors.

A *record* is defined as a recorded *ask* and label related to the same time slot: $(\boldsymbol{A}_t, L_t)$. For a time slot t', an *ask* $\boldsymbol{A}_{t'}$ for which there is no corresponding label $L_{t'}$ is called a *potential ask* when no label has yet been requested from human actors. Conversely, when a L_t exists, the *ask* $\boldsymbol{A}_t$ is called a *recorded ask*, or simply a *record*.

The database Δ is a collection of *recorded asks*. Generally speaking, $\Delta = ((F_{1,1}, F_{2,1}, ..., F_{p,1}), L_1), \ldots, ((F_{1,n}, F_{2,n}, ..., F_{p,n}), L_n)$ is denoted a database of *asks* with n p-dimensional tuples each associated with their complementary label (*recorded asks*).

Considering a set of *recorded asks* from a database Δ distributed in a non-normalized feature subspace $\mathcal{F} = [\check{F}_1, \hat{F}_1] \times ... \times [\check{F}_p, \hat{F}_p]$. The corresponding normalized database is given by Δ' with $\forall i \in \{1, \ldots, p\}, \forall k \in \{1, \ldots, n\}, (F_i')_k = \frac{(F_i)_k - \check{F}_i}{\hat{F}_i - \check{F}_i}$, distributed in a p-dimensional normalized space $S = [0, 1]^p$.

2.1.2 When to interact with the human actors?

Interactive Learning performance depends mainly on the interaction process that defines whether an *ask* is potentially useful or not, that is, to determine when it is the most valuable time slot to question human actors.

If we can improve the quality of the training database, a machine learning algorithm can perform higher accuracy with fewer training data [45], [50]. Considering this, some concepts to evaluate and/or determine the best time for interacting with human actors were introduced in [18] and [49]: the *density of the neighbourhood*, *classifier estimation error*, the *redundancy* (or *weight of each class*) and the *spread rate*.

These concepts are expected to allow the maximization of the information usefulness while limiting the number of interactions. They will work as triggering mechanism for *asks* by determining its utility function while taking into account the already available *records* and the data received from the sensors at the current time – *potential ask*.

2.1.3 Interaction mechanism

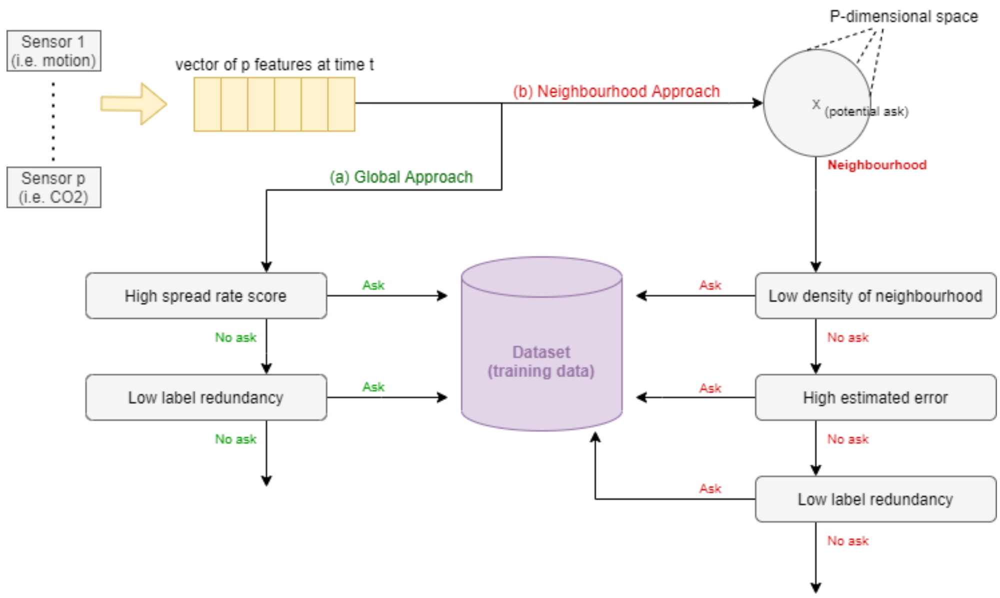


Figure 2.1: Interactive Learning process with global (a) and neighbourhood (b) approaches.

Determination of best times for interactions rely on more than one criteria. For instance, in the flowchart of Figure 2.1, two different situations are considered: a global approach (a) and a neighbourhood approach (b). In the first situation, two criteria have been checked for each new *potential ask*: the *spread rate score* of all *recorded asks* and *label redundancy*. Similarly, three criteria have been checked in (b): the *density of the neighbourhood* of the *potential ask*, estimated error in the neighbourhood of the *potential ask* and, likewise (a), the *label redundancy*. Depending on if these criteria are met, an *ask* is submitted or not by the artificial system to the human actors in order to possibly, if a label is returned, become an additional *record*.

The details of each criterion is described in detail in the following subsections.

2.1.3.1 Density of the neighbourhood

The *density of the neighbourhood*, or simply *density*, considers the number of *recorded asks* in the neighbourhood of a *potential ask*. In this way, if the *potential ask* does not have at least the established minimum number of neighbours, an *ask* is submitted to the human actors. The neighbourhood of a *record* can be modified according to a threshold $\epsilon \in [0,1]$ and a point is a neighbour if the distance between it and the *record* is lower than $\epsilon/2$.

Equation (2.2) gives the distance between a *potential ask* $\boldsymbol{A}_{t'} = (F_{1,t'}, F_{2,t'}, ..., F_{p,t'})$ at current time t' for p sensors and any *recorded ask* $\boldsymbol{A}_k \in \Delta_k = (\boldsymbol{A}_k, L_k) = ((F_{1,k}, F_{2,k}, ..., F_{p,k}), L_k)$, with $k \in \{1, \ldots, n\}$ being n the number of existing *records*, each corresponding to a specific time, and L_k its labels. $\hat{F}_i$ and $\check{F}_i$ stand respectively for the maximum and the minimum value of the recorded attributes F_i. The Tchebychev ∞ norm is used because it satisfies: $\forall \boldsymbol{A}_k \in [0,1]^p$, $\forall \boldsymbol{A}_{k'} \in [0,1]^p$, $\|\boldsymbol{A}_k - \boldsymbol{A}_{k'}\|_\infty \leq 1$.

$$\begin{gathered} d(\boldsymbol{A}_{t'}, \boldsymbol{A}_k) = \|\boldsymbol{A}_{t'} - \boldsymbol{A}_k\|_\infty = \\ = d((F_{1,t'}, F_{2,t'}, ..., F_{p,t'}), (F_{1,k}, F_{2,k}, ..., F_{p,k})) = \left\| (\tfrac{F_{1,t'} - F_{1,k}}{\hat{F}_1 - \check{F}_1}, \tfrac{F_{2,t'} - F_{2,k}}{\hat{F}_2 - \check{F}_2}, ...) \right\|_\infty \end{gathered} \tag{2.2}$$

The local density in the neighbourhood of $\boldsymbol{A}_{t'}$ is then given by the cardinality of the set of *records* that satisfy the expression:

$$\textit{Number of neighbours of}\, \mathbf{A}_{t'} = \left| \left\{ \begin{array}{c} ((F_{1,k}, F_{2,k}, ..., F_{p,k}), L_k) \in \\ \left\| (\tfrac{F_{1,t'} - F_{1,k}}{\hat{F}_1 - \check{F}_1}, \tfrac{F_{2,t'} - F_{2,k}}{\hat{F}_2 - \check{F}_2}, ...) \right\|_\infty < \tfrac{\epsilon}{2}, \\ \epsilon \in [0,1], \forall k \in \{1, ..., n\} \end{array} \right\} \right| \tag{2.3}$$

Based on the calculation of the number of neighbours for a *potential ask*, and considering an established minimum number of neighbours that an *ask* should have, a new *ask* $\boldsymbol{A}$ should be send to the human actors if:

$$\textit{Number of neighbours of}\, \mathbf{A}_{t'} \leq \textit{Minimum number of neighbours} \tag{2.4}$$

2.1.3.2 Classifier estimation error

This criterion checks the *classifier estimation error* for *records* in the neighbourhood of the *potential ask*, i.e. it checks the neighbourhood quality.

The *classifier estimation error* is used together with the *density of the neighbourhood* criterion acting as a second condition to calculate the number of neighbours of a *potential* *ask*. The quality of the neighbours is then going to be assessed. Taking the neighbours of a *potential ask* $\boldsymbol{A}_{t'}$, previously selected by the *density* criterion, if a *record* is precisely estimated by the classifier, it is considered a neighbour; otherwise it will be ignored. One drawback of this criterion is that it can only be used for numerical labels.

The error is calculated by $|L_{t,c} - L_t|$ where $L_{t,c}$ stands for the estimated label by the classifier (using sensor data for the time slot t), L_t is the actual recorded value collected thanks to an *ask*. Each neighbour of a *record* must satisfy the following condition:

$$|L_{t,c} - L_t| < E_r \zeta \tag{2.5}$$

$$\text{with,} \quad \zeta = \frac{1}{n} \times \sum_{k=0}^{n-1} |L_{t,c} - L_t| \tag{2.6}$$

where E_r is an error ratio that can be adjusted accordingly to the problem and ζ is the average estimation error of the n existing *records* [18].

If the *classifier estimation error* for a *record* does not meet the condition in (2.5), it means that the error is too high and that *record* will be ignored from the neighbourhood.

The number of neighbours of a *potential ask* will now be given by equation (2.7) considering the *classifier estimation error* with $L_{k,c}$ being the *estimated label* for the *record* k and L_k for its actual recorded label. A new *ask* should be send to the HA if it satisfies the condition in (2.4).

$$\textit{Number of neighbours of } \mathbf{A}_{t'} = \left| \left\{ \begin{array}{c} ((F_{1,k}, F_{2,k}, ..., F_{p,k}), L_k) \in \\ \left\| \left(\frac{F_{1,t'} - F_{1,k}}{\hat{F}_1 - \check{F}_1}, \frac{F_{2,t'} - F_{2,k}}{\hat{F}_2 - \check{F}_2}, ... \right) \right\|_\infty < \frac{\epsilon}{2} \cap |L_{k,c} - L_k| < E_r \zeta, \\ \epsilon \in [0,1], E_r \in [1,2], \forall k \in \{1, ..., n\} \end{array} \right\} \right| \tag{2.7}$$

2.1.3.3 Redundancy

This criterion is based on the minimum number of recorded data for each type of label in the set of all labels $\mathcal{L}$. This entails that each label in $\mathcal{L}$ must have at least the minimum acceptable number of *records* – *label redundancy* – and, if it does not, an *ask* must be sent to the HA until the *redundancy* criteria is met. The *label redundancy* can be adjusted according to the problem.

2.1.3.4 Spread rate

The *spread rate* is a global measurement of the quality of a database. It considers the whole database space (instead of a local neighbourhood) and evaluates how *records* are globally distributed. *Spread rate* can replace the *density of the neighbourhood*; instead of counting the records in a neighbourhood, it checks how *records* are globally distributed.

Figure 2.2 shows 5 cases of data distribution in 2-dimensional spaces: (a) and (b) representing perfectly spread cases; and (c), (d) and (e) poorly spread cases.

The patterns (a) and (b), represent two databases with regularly spread points all over the normalized feature subspace $S = [0,1]^p$. A perfect spreading database $P^*_{p,\lambda}$, where $\lambda \in \mathbb{N}$ stands for the number of points per dimension, in a p-dimensional space is met when:

1) the number of points $n^* = (1+\lambda)^p$, for a minimum of 2 points per dimension;

2) the infinite distance between each point and its closest neighbour is $\frac{1}{\lambda}$.

Perfectly spread databases have the best dispersion for recorded asks in our case. Conversely, the poorest quality for a database is met when all the points are at the same location, when the data presents patterns similar to (c), (d) and (e) in Figure 2.2.

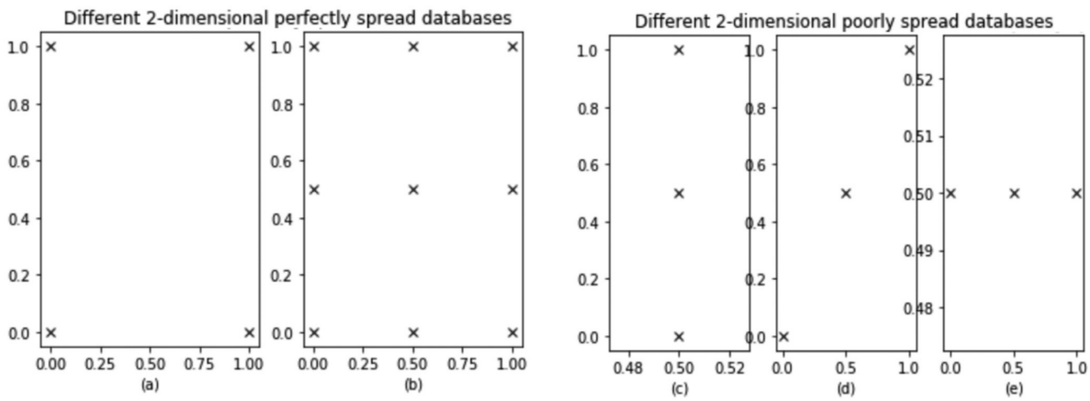


Figure 2.2: Different 2-dimensional spread databases [49].

But what if a database does not have its points regularly spread? When does it reach its highest quality? Generally speaking, the *spread rate* considers that the highest quality of a database is met when the spreading cannot be improved further (Figure 2.3).

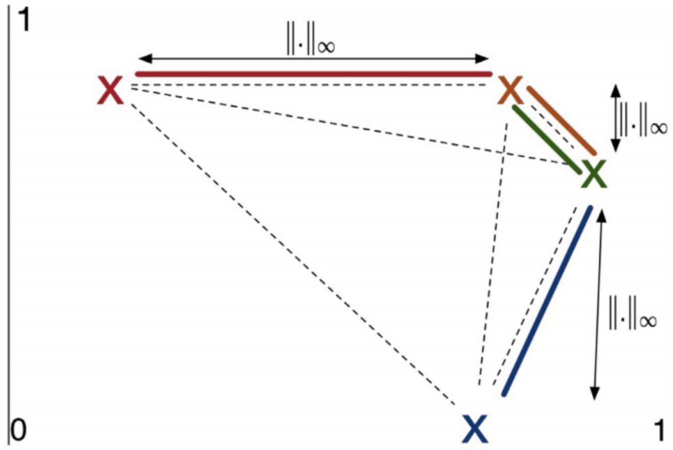


Figure 2.3: Spread rate definition [49].

Intuitive approach for the quality assessment of a database

To assess the quality of the database Δ, let's assume the *spread rate score* $Sscore(\Delta)$ that evaluates the distribution of the recorded points by assessing the quality of a $n \times p$ matrix of features values.

The *spread rate score* is given by the ratio of the average of minimum distances between each *recorded ask* and its closest neighbour (a), according to infinity norm to avoid exceeding the value 1, and the best theoretical distance between 2 points for a perfect distribution (a^*).

As seen before, a perfectly spread database is only known when $n^* = (1+\lambda)^p$ and the distance between 2 points in a perfect distribution is equal to $a^* = \frac{1}{\lambda}$. For a given $n \neq n^*$, the interpolated best theoretical distance between 2 points is given by $a^* = \frac{1}{n^{\frac{1}{p}}-1}$.

Based on the previous statements, $Sscore(\Delta_n')$ is given by equation (2.8) [49], in order to measure how much the points of a normalized database Δ_n' regularly cover the space $[0,1]^p$, $\forall p \in \mathbb{N}^*$ and $\forall n \in \mathbb{N}^* \backslash 1$.

$$Sscore(\Delta_n') = \frac{a}{a^*} = (n^{\frac{1}{p}} - 1) \times \frac{\sum_{i=1}^{n} (\min_{j \in \{1,\ldots,n\}} \|A_i - A_j\|_\infty)}{n} \tag{2.8}$$

Spread rate score alone does not take into account the density of points. Therefore, we need to introduce a new variable – the *resolution accomplishment* (RA) – that, for a p-dimensional database Δ'_n, considers the expected number of points p^f, being f the expected frequency of points per dimension. The *resolution accomplishment* is given by:

$$RA = 1 - e^{\frac{-3n}{p^f}} \tag{2.9}$$

where $RA \in [0,1]$. If $RA = 1$, the expected resolution is met, meaning that the number of *recorded asks* corresponds to the expected number of points; if $RA = 0$, the expected resolution is not met at all. 3 stands for an adjustment to reality [49].

Now considering the *resolution accomplishment*, it is possible to define $Qscore \in [0,1]$ as the product of *spread rate score* and *resolution accomplishment*, described in equation (2.10) for a normalized database Δ'_n.

$$Qscore(\Delta'_n, f) = Sscore(\Delta'_n) \times RA \tag{2.10}$$

Based on this approach, a *potential ask* should be considered as a new *ask* $\boldsymbol{A}$ if:

$$Qscore(\Delta'_n \cup \{\boldsymbol{A}\}) > [(1 + Improvement\ Ratio) \times Qscore(\Delta'_n)] \tag{2.11}$$

An *improvement ratio* constraint, typically in $[0, 0.1]$, is added in order to limit the number of *asks*. The best database quality is obtained for $Qscore = 1$, and the worst for $Qscore = 0$.

2.1.4 Complexity

The complexity of the interactive mechanism does not depend on the dimension p (number of sensors) but only on the number of points n (*recorded asks*) in order to build a good training database. In turn, the number of *asks* depends on the parameters used on the selected interaction method(s).

Starting by the *density of the neighbourhood* criterion, the number of *asks* vary accordingly to the value of $\epsilon \in [0,1]$, that defines the area of the neighbourhood. If we decrease the value of ϵ, the area of the neighbourhood around the point will be smaller, being in this way less probable to find any neighbours and thus the number of *asks* increases. If we also add the *classifier estimation error* criterion, the number of *asks* will also depend on the value of the error ratio $E_r \in [1, 2]$.

Using both criteria, or the *density of the neighbourhood* criterion alone, the variable *minimum number of neighbours* will dictate when to trigger an *ask* (equation (2.4)). If we increase its value, the number of *asks* will increase.

For the *redundancy* the number of *asks* increase if we increase the minimum *label redundancy* and, for the *spread rate*, the number of *asks* can be controlled by increasing the value of the *improvement ratio*.

2.2 Cooperative Learning

Cooperative Learning (CL) is a methodology based on the exchange of information between human actors and an artificial learning system, from now on referred simply by artificial system (AS), in order to build a common perception of the model thanks to a more advanced cooperation than Interactive Learning.

Similarly to IL, CL is a supervised learning methodology to identify named situations meaningful for the human actors, relying on sensors data and feedback collected from the occupants in the form of labels. However, instead of collecting the model's training data through real-time interactions, it uses a co-definition approach based on shared knowledge between an artificial system and human actors.

In this approach, each party own only a part of the knowledge. The HA know what actually happened within a past period, e.g. how many occupants are there or the more relevant activity at a particular time slot. On the other hand, the AS knows the quantitative data, from which it estimates its own guessed labels: timed data from a sensor set, the recorded past timed data, the labels validated by the human actors and the updated feature generator parameters. Each party is informing, explaining, asking, suggesting and learning from the other in a symmetrical way.

Human-system cooperation is then established through feedback on the AS's estimated labels to modify the perception of the system until a consistent representation is found. Here the occupants depict daily what they did during the day with their own meaningful labels and the AS analyses whether these labels can match its own perception based on sensor data and, if not, it suggests labelling errors.

Indeed, a shared consistent representation has to be compatible with both the perception of the environment by the artificial system, determined from available data coming from sensors, and the human actor perception, based on knowledge and memory. However, the frequency for interactions is predefined, generally once a day, with 2 drawbacks: (1) human actors have to remember what happened within the past time slots of a time period, and (2) human actors have to check all the labels proposed by the artificial system, no matter if the situations have been frequently met or not.

2.2.1 Problem statement and solving approach

Let $(\boldsymbol{A}_t, L_t) = ((F_{1,t}, F_{2,t}, \dots, F_{n,t}), L_t)$ be a *recorded ask* defined over a continuous invariant domain, $D = dom(F_{1,t}) \times dom(F_{2,t}) \times \cdots \times dom(F_{n,t})$, with $\forall i, dom(F_{i,t}) = [\check{F}_i, \hat{F}_i]$, corresponding to the feature space. An open set of labels can be associated with a partitioning of the feature space $\mathcal{D} = \{D_k(\Theta); \forall k\}$, where Θ is a set of parameters defining the partitioning. A classifier defined over the partitioning must assign a unique label to each partition $D_k(\Theta)$. A *confusion* is defined when the same partition $D_k(\Theta)$ leads to 2 distinct labels: the classifier will be said inconsistent.

Many partitioning can be considered but since it is about cooperation between HA and AS, the partitioning must be meaningful for HA in order to support them with the labels resembling. The most natural way to parameterized the feature space in a meaningful way is to decompose each interval feature domain $dom(F_{i,t})$ into a regular partitioning $\mathcal{F}_i(\theta_i)$ i.e. into a set of intervals parameterized by θ_i forming a partition of $dom(F_{i,t})$.

The cooperative learning problem is to find a consistent classifier to assig labels L_k provided by the HA to a partition corresponding to discretized features $F_1(\theta_{1,j1}) \times F_2(\theta_{2,j2}) \times \cdots \times F_n(\theta_{n,jn})$, where j is the level of discretization, belonging to the parameterized regular space $\mathcal{D} = \mathcal{F}_1(\theta_1) \times \mathcal{F}_2(\theta_2) \times \cdots \times \mathcal{F}_n(\theta_n)$. At time t, the discrete regular *ask* is denoted $(F_{1,t}(\theta_{1,j1}), F_{2,t}(\theta_{2,j2}), \dots, F_{n,t}(\theta_{n,jn}))$ is called a *word*.

The problem can be solved following these 4 steps:

1. for a new *ask* at time t, the existing parameter set Θ is used to generate a *word* $W_t(\Theta) = (F_{1,t}(\theta_{1,j1}), F_{2,t}(\theta_{2,j2}), \ldots, F_{n,t}(\theta_{n,jn}))$ i.e. a tuple of values of the discretized feature space;

2. using the existing database $\{(\boldsymbol{A}_i, L_i)\}$, the AS suggests to the HA the most likely label L_t for each $W_t(\Theta)$ using a classifier;

3. considering the *word* $W_t(\Theta)$, the user can validate or change the label L_t to any value, existing or not in the database;

4. the AS determine whether there are *confusions* and if so, it adjusts the parameter set Θ to remove as much *confusions* as possible. In case of remaining *confusions*, the related *recorded asks* are selected to be presented to the HA for potential correction.

2.2.2 Confusion – A more intuitive definition

Confusion is the difference in perception between the AS and the human actors, that is, when the system perceives data characterized by a particular label while, in reality, the HA indicate that it is not correct.

For better visualization, we can define the features as a set of human recognizable representations – which are called *words* – that are generated from the raw sensor data transformation by a parameterized feature generator. The feature generator proceeds as follows:

1. it takes the input time series sensor data and the set of defined feature generator parameters Θ (initially with equal weights or with predefined weights if it is not the first process iteration);

2. the data from the sensors is discretized in accordance with the feature parameters;

3. generates the *words*.

For instance, in order to generate a *word*, the raw data coming from a sensor i can be discretised according to five levels: Very Low (VL or $F_i(\theta_{i,1})$), Low (L or $F_i(\theta_{i,2})$), Medium (M or $F_i(\theta_{i,3})$), High (H or $F_i(\theta_{i,4})$) and Very High (VH or $F_i(\theta_{i,5})$); where θ_i is a vector of the feature generator parameters for sensor i representing the weight of each one of the levels of discretization. That is, the parameters of θ_i establish the data range for each of the levels VL, L, M, H and VH, within the minimum and maximum values reached by sensor i. For example, taking the power consumption range to be between 130W and 580W: VL represents data between 130W and 220W, L between 220W and 310W, M between 310W and 400 W, H between 400W and 490W and VH between 490W and 580W.

Suppose that, we have a set of three sensors: power consumption (POW), acoustic pressure (DB) and motion (MOT). Taking their continuous raw data the system can discretize the data of each sensor into VL, L, M, H or VH. In this way, for a particular time slot, the AS will generate a combination of the discretized raw data of each sensor that describes the set of sensors for the time slot – a *word*. For instance and in accordance with Figure 2.4, assuming for a specific time slot the discretization of the raw data of a set of 3 sensors: POW, DB and MOT; into L, VL and H respectively, the system would generate the *word*: *LVLH* (i.e. $W_t(\Theta) = (F_{POW,t}(\theta_{POW,2}), F_{DB,t}(\theta_{DB,1}), F_{MOT,t}(\theta_{MOT,4})))$.

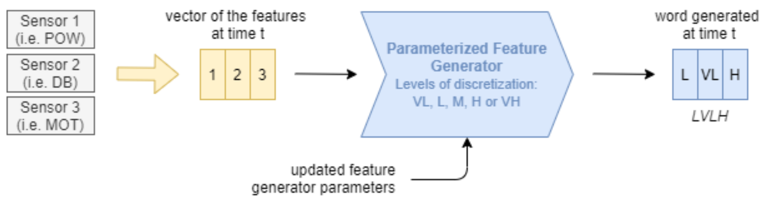


Figure 2.4: Word generation process for a 3-sensors set-up.

We can now say that a *confusion* arises when one *word* is associated with two or more different labels. In other words, a *confusion* occurs when the HA associate one *word* to two or more different situations while the system perceives those situations as one – the AS needs to adjust its perception.

In Figure 2.5, the *word LHM* represents a *confusion* – the *word LHM* is associated with two activities: Working and Break. Note that more than one *word* can be used to describe the same label, it constitutes different views to describe the same activity.

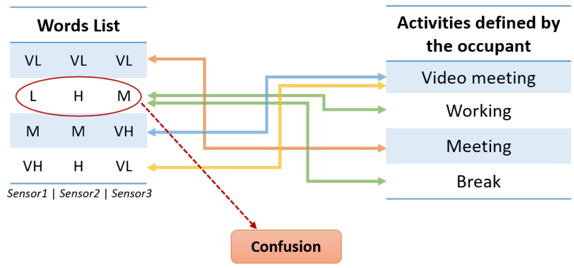


Figure 2.5: Confusion definition.

2.2.3 How do the learning system and the HA cooperate?

At first, the system has no record of any predefined labels. The *words* will be generated from the raw sensor data using a parameterized feature generator – processed with predefined initial feature generator parameters – to create the AS' initial perception.

Based on this first definition, the system can make a first interaction with the human actors.

The AS-HA interactions happen typically at the end of the day, when the AS presents the occupants *temporal daily forms* – a breakdown of the day into time intervals: it can be a constant time period e.g. 30 minutes, or a time varying period. Each of those intervals have the corresponding features processed from raw sensor data and a label estimated by the system. Then the HA are expected to validate, correct or set to unknown the estimated labels, based on his memories of the day.

The first *temporal daily form* will be presented without suggested labels (at the moment the system had not learnt any). A label is used to depict situations within a past time slot, i.e. what has been done within the past day for each time slot. These labels are in the first instance created by the human actors, who describe the situations on his own semantics thanks to labels.

The system can now name a set of perceived data and use this new knowledge to suggest labels for other times of the day.

From here, the co-definition loop is going to be set up over the days (Figure 2.6), adjusting the system's perception. The system uses the corrections and new labels provided by the HA to adapt the feature generator parameters and this way improve the classification, allowing more accurate suggestions.

As proposed, the CL methodology is based on a cycle of suggestions by the AS and correction and addition of information by the HA. Those corrections correspond to errors in the recognition of the information by the AS (wrong classification of the *words*), which we call *confusion*.

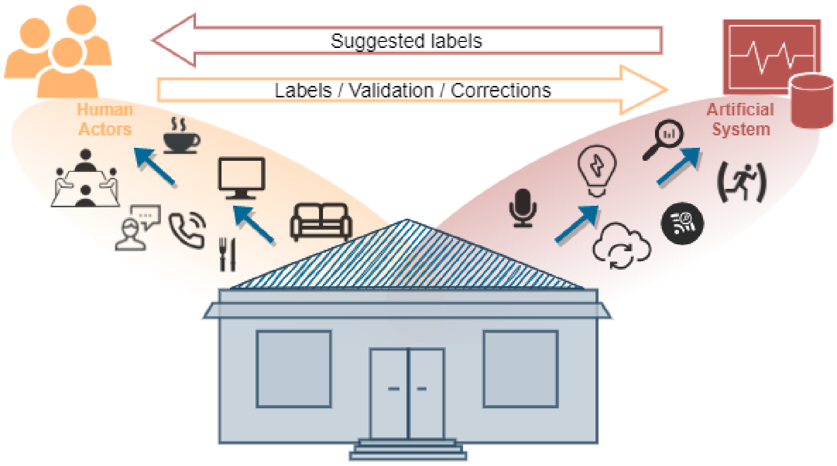


Figure 2.6: Cooperative structure.

2.2.4 Confusion processing

There are two approaches that can be used to solve *confusions*:

- the labels under *confusion* can be verified by the HA;
- the discretized feature generator parameters can be improved by an adjustment algorithm.

In the first instance, the system should consider possible lapses of memory and mistakes made by the HA – it may be difficult to remember every past event correctly. Also the labels specified may be too specific and the system does not have enough sensors to discriminate them: a more generic term should be used to replace the labels associated to the *confusion* (replacing for instance reading a book/newspaper by resting). Thus, the artificial system will report the existing *confusions* and ask the HA to recheck the labels.

If the HA correct some labels, there's a chance to solve a *confusion*. Otherwise, the system will use a confusion solver that, using an optimization algorithm (evolutionary algorithms), adjusts the parameterization of the feature generator.

The parameterization provides additional degrees of freedom to better recognize different labels with very similar raw sensor records. Thus, by adjusting the parameters, the feature generator can generate different weights for the levels of discretization that can better define the HA perspective.

Considering Figure 2.7, on the first run, the five levels' weights are all set to be equal, each one of them representing one-fifth of the original data range. After the confusion solver, the levels' weights will change in order to adapt the parameters to fit the HA's labelling while removing all the *confusions*.

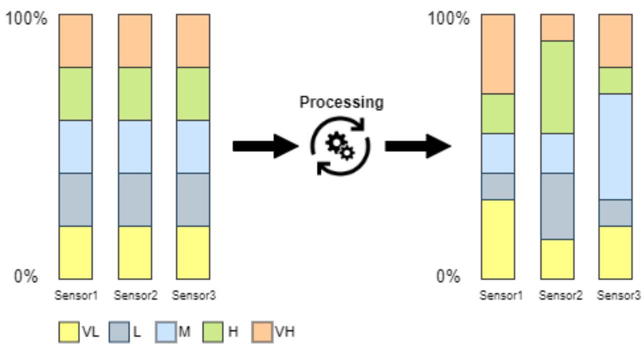


Figure 2.7: Update of the feature generator parameters in order to solve confusions.

2.2.5 System overview

The CL system (Figure 2.8) is divided into three main parts: a feature generator, a classifier and a confusion processor.

The feature generator discretizes the input time series data from the sensors for the past day, using a set of parameters Θ and generates *words*. The classifier relies on a *word-label* database with past timed data and assigns the *words* generated in the feature generator to labels.

Those relations *word-label* are used to fill the *temporal daily form* that will be sent to the HA for feedback.

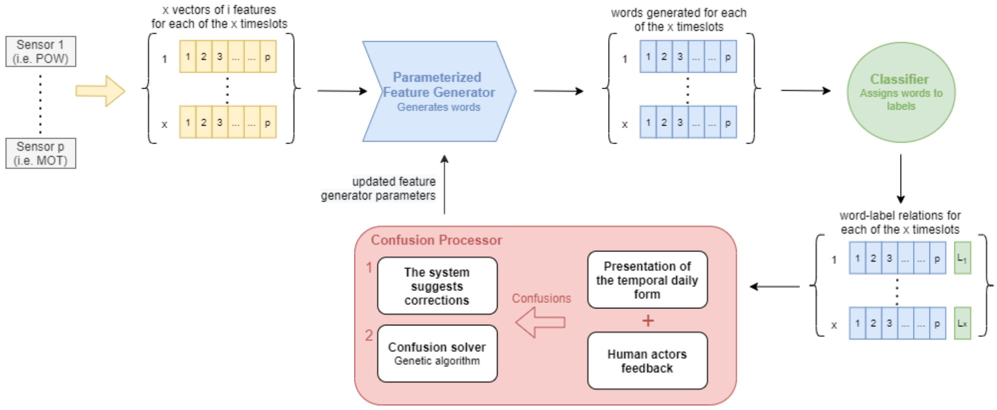


Figure 2.8: Overview of the cooperative learning system.

The confusion processor solves the *confusions* and generates new parametrization parameters. It executes in three steps: identifies the existing *confusions*, requests the HA for corrections and operates a confusion solver that runs a genetic algorithm in order to modify the weights of the feature generator parameters.

In detail, the system proceeds as follow:

1. At some specific moment, the AS is going to suggest labels to the HA, using the feature generator and the classifier;
2. The human actors validate, correct or set to unknown the suggested labels;
3. The AS is going to analyse the consistency of the resulting *word-label* database and will detect *confusions* i.e. same *word* leading to different labels;
4. If there is *confusion*, the AS notifies the HA and advises the most likely causes for each *confusion* (most likely labelling error);
5. If the *confusion* persists, the AS uses an optimization algorithm to adjust the parametrization parameters in order to solve the *confusion*;
6. Using the updated parametrization parameters, new *words* are generated for each time slot, and the classifier is retrained to take into account these modifications for future suggestions.

2.3 Interactive Learning vs Cooperative Learning

Interactive Learning and Cooperative Learning are two different approaches to solve the same goal: to describe situations related to human behaviour in a specific location at each time slot. In this section, we analyse the limitations and strengths of both approaches.

In terms of limitations, one of the main disadvantages of CL is the time that the HA spend correcting the suggested labels at the end of the day (for 30min slots, it corresponds to 48 labels a day), which may end up in not filling all the labels or making mistakes. On the other hand, the IL tries to limit the number of *asks* but uses predefined labels, which means that the model will not be completely adjusted to the HA experience.

Also, both IL and CL do not always take into account that the HA may unconsciously commit mistakes while labelling the events (even after the corrections) – the *asks*/validated labels are appended to the training database and are not susceptible to later correction. Only when using the *classifier estimation error* criterion, the IL can ignore some *records* that are considered as possible mistakes, however this criterion can only be used for a neighbourhood approach like *density* (not with *spread rate*). Also, it can only be used for numerical labels.

Regarding the strengths of the models, IL collects unitary and real-time labels using a limited number of *asks*, promoting valuable participation of the HA and fewer mistakes. Those limited number of *asks*, selected by the chosen criteria, will grant the maximization of useful information. For CL, its main strength is that it can differentiate additional features (*words*) for very similar raw sensor records, by adjusting the discretization of the raw data. In doing so, the model will easily endorse a better classification *word-label*. Also, the CL approach does not use a set of predefined labels; labels are indeed defined by the human actors accordingly to their own semantic.

Chapter 3

Proposed Methodology

A new approach is proposed in this thesis with the objective of estimating household specific situations based on data from non-intrusive sensors plus occupants' feedback.

The previously presented weaknesses of IL and CL methodologies indicates that there are opportunities for further improvement. Thus, the new approach incorporates the best characteristics of both IL and CL, avoiding the limitations of each method.

The model adopts the Interactive Learning triggering mechanism ensuring fewer *asks* and a quality ground truth database. However, unlike in IL, this mechanism will not use predefined labels, instead, the HA can choose their own labels according to their semantics. From CL, it uses the parameterized feature generator and the confusion solver in order to generate *words* from the raw data and run the optimization algorithm to adjust the parameters – the classifier's input will be *words* to assign to labels.

The new methodology incorporates searches for *confusions* the IL data stored in the *knowledge database*. Besides, keeping the cooperation with the HA, specific updates to the ground truth data can be requested whenever necessary.

3.1 Knowledge Database

After each interaction with the human actors, the label will be stored in the *knowledge database* (KD), together with the raw data from the sensors at the time of the interaction (*raw data-label* relations).

The quality of the KD data is ensured by the IL triggering mechanism which determines the best time for interacting and it is considered as the ground truth. Thus, the model will be built and optimized based on the KD *raw data-label* relations. That is, the KD will be the source of the *confusions* which will be used to optimize the model.

In case the confusion solver is not able to solve the *confusion* it is necessary to consider some inconsistencies in the KD data. Thus, a new method is introduced, the *updates*.

3.2 Updates

An *update* question will be sent in order to correct the wrong labels in the ground truth database taking into consideration that the HA may have committed some mistakes on the feedback previously given.

This way, if the system cannot solve one or more *confusions* it will assume that some faulty information may exist in the KD. It will then assess the context of the *word* causing each *confusion* – *confusion word*: *word* with more than one label associated – and will look for an up-to-date similar situation in the past time raw sensor data. Having this information, the system will request the label at that specific past time which must be as up-to-date as possible in order to be more likely for the HA to remember the corresponding label.

The returned *updated label* will generate a new *raw data-label record* in the KD that will be now considered as the ground truth label related to the *confusion word* context. Then, accessing all the *word-label records* in the ground truth: if *word=confusion word* and its corresponding label is not the *updated label*, the *record* must be removed from the KD.

After the *update*, the confusion solver will run again, and new feature generator parameters will be defined and new *words* generated. If the *confusion* persists, a new *update* will be requested. However, it is expected that the *confusion* is solved by now since the *updated label* was selected for being the source of the *confusion*.

The value of the *update* method stands in the capability of guarantying that all the confusions are solved, which may lead to a better interpretation of human reality.

3.3 Classifier

The classifier's inputs are *words* which will be assigned to labels. Thus, before proceeding with any estimation, there is the need to convert the raw sensors data into *words* in the parameterized feature generator. The training data will be the data stored in the KD converted into *word-label*.

Unlike in both Cooperative and Interactive Learning approaches, the classifier doesn't play an important role in the model optimization. Besides the role in the triggering mechanism, it is only used to estimate the relations *word-labels* after the optimization of the parameters by the KD and the confusion solver.

Nevertheless, the classifier has a role in the triggering mechanism since its estimated label for the *potential ask* is a central element for the *redundancy* criterion. Besides, it also uses that estimated label, when an *ask* is sent to the HA in order to suggest a label. This suggestion has the sole purpose of facilitating the interaction for the HA, who can simply validate the suggestion as correct (saving user time). If the estimation is not correct, then the HA must substitute it for the correct label.

3.4 Implementation

Figure 3.1 describes the implementation process of the proposed approach and identifies the interactive and cooperative parts.

Using an IL triggering mechanism the system will interact with the HA in real time while ensuring the quality of the data. This mechanism processes the raw data from the sensors together with the data previously recorded in order to determine the best interaction time. If the conditions are met, an *ask* requesting a label for a specific context is sent to the HA. The triggering mechanism also uses a classifier to predict the label for the current time in order to perform the *redundancy* criterion. After the feedback, the *raw data-label* relation will be stored in the KD and it will be considered as the ground truth data.

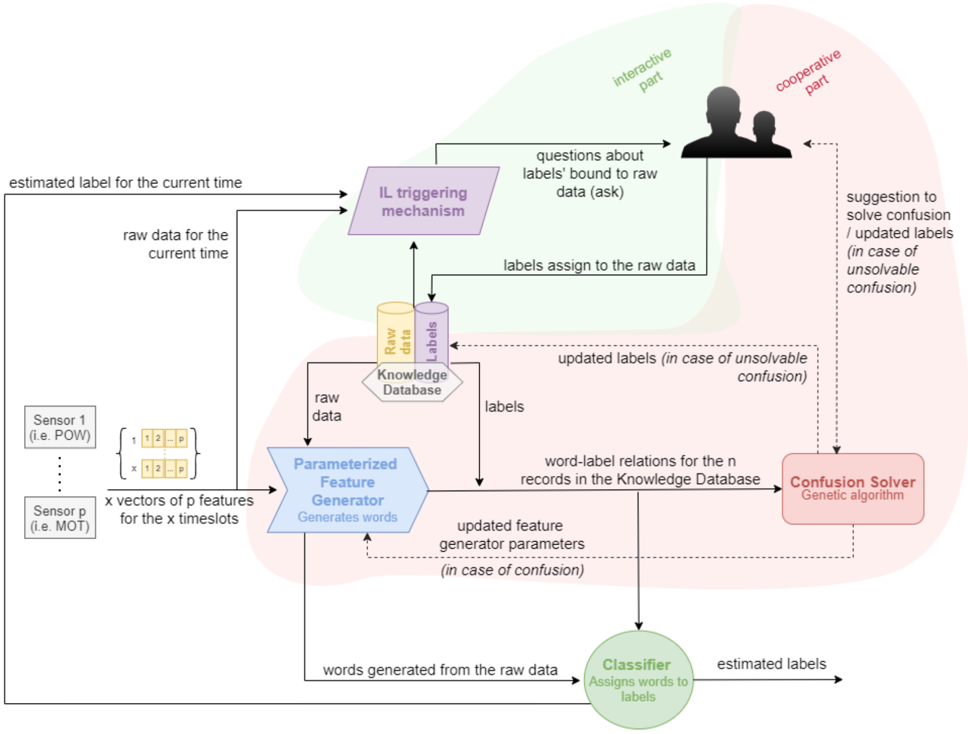


Figure 3.1: Proposed methodology.

The parameterized feature generator and the confusion solver work accordingly with the described on the CL: the first is used to convert raw sensor data into *words* and the second to optimize the parameters to execute that conversion.

To perform the optimization of the feature generator parameters, it is necessary to adjust the system perspective to the ground truth data provided by the HA. Thus, the confusion solver must search for *confusions* (which occurs when one *word* corresponds to more than one label) on the data from the KD. To do so, the parameterized feature generator will generate *words* from the raw sensor data stored in the KD, resulting in a *raw data-label* converted into *word-label* ground truth database, ready to be checked with the confusion solver.

When a *confusion* is detected, the confusion solver will run a genetic algorithm in order to adjust the feature generator parameters and solve the *confusion*. By adjusting the parameters the feature discretization will be different, so it is possible to distinguish different *words* every time the parameters are updated hence, the raw data stored in the KD will generate different *word-label* databases.

In case the confusion solver's optimization algorithm does not succeed in solving the *confusion*, the issue must be reported to the HA. A new *update* will be sent to the HA requesting for specific information to solve the *confusion*, this time, completely independent from the IL triggering mechanism.

Chapter 4

Case Study

To demonstrate the application of the proposed methodology, we used data from an office in the Grenoble Institute of Technology, which accommodates a professor and 3 PhD students. By the time the data was collected, the office frequently housed visitors with a lot of meetings and presentations throughout the week. For the experience, the room is equipped with an ambiance sensing network, which measures luminance, temperature, relative humidity, motions, CO_2 concentration, power consumption, door and window positions and acoustic pressure from a microphone.

From the large set of available sensors, some may not be useful to achieve our target of classification. After removing the less important features according to the information gain formulation in [41], the following three main features were considered: power consumption, acoustic pressure from a microphone and motion.

At this step, the interaction with HA in the office was simulated, hence all the answers to the *asks* are coming from the data obtained from video cameras. These cameras are installed only for the purpose of assembling the simulation and its data is use with the propose of collecting the training database (requests to the *asks*) and, also the complete database is used to calculate the model's estimation accuracy.

In this work two different situations were considered: the first uses occupancy labels to estimate the number of occupants per time slot T_s in a period of 15 days; and the second one works with activity labels in order to estimate what are the occupants doing at each T_s during a 3 days dataset. All the results presented in this work are for periods of time $T_s = 30$ min and the available dataset from the office (sensors and labels) was collected in May 2015.

In our proposed model, the set of labels $\mathcal{L}$ is freely chosen by the HA, in this way, we can have a very different number of labels and/or semantics. In this paper, we used the sets of labels describe in Table 4.1.

Table 4.1: Context of the two situations under study.

	Number of occupants	**Activities performed by the occupants**
Labels	[0], [1-2], [>3]	[absence], [working], [meeting], [visio]
Testing period	15 days – 4-20 of May 2015 (815 timeslots of 30min)	3 days – 5-7 of May 2015 (144 timeslots of 30min)

The main reason we analyse two different contexts (number of occupants and activities) is the different types of labels: numerical and non-numerical. In the first case, the labels represent how many people were in the room. These numerical labels are exact and do not depend on the HA interpretation of the reality. On the other hand, when working with non-numerical labels, in the case of activity labels, the labels will be entirely dependent on the HA perception and semantics. In fact, on the available dataset of the present work, the HA labelled the following activities: *absence*, *working*, *visio* and *meeting*. Some other HA would probably perceive the same reality with a completely different set of labels or, for a different environment, labels like *working* would have a completely different representation for the system (very different sensor data).

Other difference between the two datasets is their size. For occupancy we have a dataset with 815 time slots T_s of 30min and, for activities, we have only 144 time slots T_s. This will also influences the results (global accuracy and total number of *asks*), for this reason the the two situations can't be directly compared. The global accuracy stands for the fraction of predictions our model got right when compared with our simulated ground true datasets obtained from video cameras.

For the IL triggering mechanism of the proposed model, both *density* and *spread rate* criteria were tested and compared. Also, for a more robust validation, different scenarios have been investigated by changing the number of labels and the criteria's parameters: the value of ϵ and the *number of neighbours* for the *density* criterion and the *improvement ratio* for the *spread rate* (see Table 4.1). The variations on the *label redundancy* parameter weren't considered relevant when compared with the others so it was used a *label redundancy* equal to 3 for all the tests.

Since the model was constructed to work both with numerical and non-numerical labels, the *classifier error estimation* criterion wasn't considered (only for numerical labels). Besides it wouldn't be relevant since the proposed model has an integrated way to eliminate/correct the wrong labels (*updates*).

After testing both Random Forest and Support Vector Machine, the first was considered the most suitable classifier thus, all the presented tests in this thesis are deployed using Random Forest. Also, besides the selected features from the sensors (power consumption, acoustic pressure from a microphone and motion), in this work, we tested the use of an additional feature: the hour of the day. This feature creates a correlation with the daily routine.

4.1 Testing parameters

Different scenarios have been tested by changing some parameters of the global and neighbourhood IL approaches (Table 4.2) and using two different set of features:

1. Power consumption, acoustic pressure and motion (POW, DB, MOT);
2. Power consumption, acoustic pressure, motion and hour of the day (POW, DB, MOT, HO).

Table 4.2: Test parameters for density and spread rate criteria.

Criterion	Variable	Parameters
Density	ϵ	0.1, 0.2, 0.3
	Minimum number of neighbours	1, 2, 3, 4
Spread rate	Improvement ratio	0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08

By plotting the results in graphs correlating the number of *asks* with the global accuracy of the proposed methodology, the parameters values were optimize through a grid search and the best ones were selected. The set of optimal parameters represent the state at which any variable is optimized in a way that one dimension cannot improve without a second worsening. All optimal solutions are considered equally good if no additional preference is added. However, we want the minimum possible number of *asks* while keeping a good global accuracy, thus only the points that best fit the required should be selected.

It is also important to take into consideration the number of confusion solvers invocation related to each situation. Each confusion solver used to solve emerging *confusions*, implies the adjustment of the parameterized feature generator parameters using a genetic algorithm. Many confusion solvers means a lot of *confusions* and an increased simulation time, which we want to avoid.

No more values besides the ones in Table 4.2 were selected since, for more than 4 neighbours in the *density* criterion, the number of *asks* and the number of confusion solver increase a lot while the global accuracy decreases or remains the same. For both an $\epsilon > 0.3$ in the *density* or an $IR > 0.08$ in the *spread rate*, the number of *asks* are lower but the global accuracy decreases a lot. The value of the redundancy was kept constant for all the scenarios, with a value equal to 3.

Chapter 5

Results

In this chapter, we present and discuss the performance results of the model for the different parameters of Table 4.2 (*density* and *spread rate*) and two different sets of features ([POW, DB, MOT] and [POW, DB, MOT, HO]), while considering both occupancy and activities labels. Since the two label-datasets for occupancy and activities have different sizes, we couldn't compare them directly.

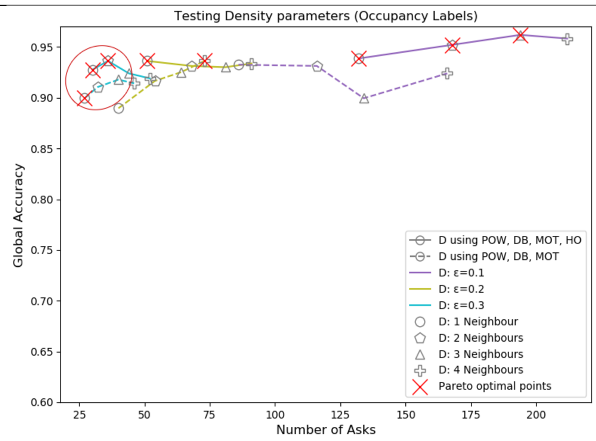
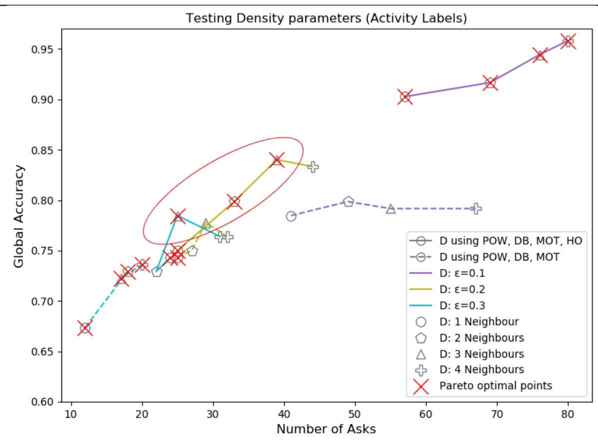
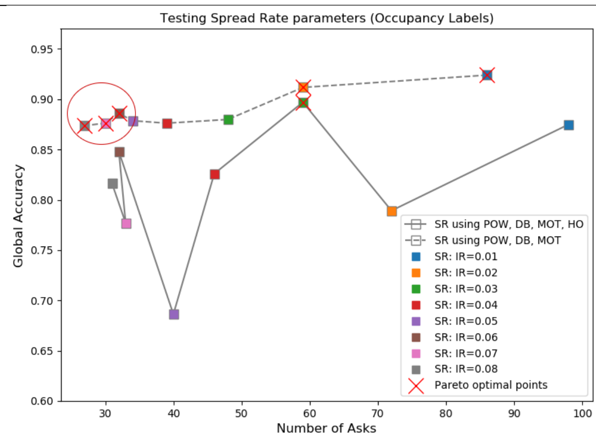
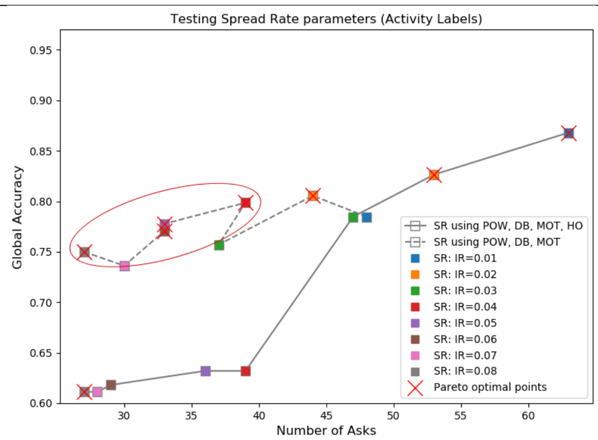
In section 5.1, we tested, for occupancy and activity recognition, both sets of features and each of the parameters of Table 4.2 in order to select the optimal parameter values for each scenario. The following sections 5.2 and 5.3 highlight the performance of the new methodology when using a different type of labels (occupancy or activities) and IL criteria (*density* or *spread rate*), respectively. In section 5.4, we analyze the influence of the number of labels on the global performance of the model. Lastly, a comparison between the proposed methodology and the original Interactive Learning and Cooperative Learning was performed in section 5.5.

5.1 Optimal parameters values

The new methodology was tested for occupancy and activity recognition considering the different parameters of Table 4.2 (*density* and *spread rate*) and two different sets of features ([POW, DB, MOT] and [POW, DB, MOT, HO]). The results are presented in Table 5.1 by correlating the number of *asks* and the global accuracy of the model for each scenario.

The optimal parameters were selected based on the conditions described before, from which we selected those that satisfy both the maximization of the global accuracy and the minimization of the number of *asks*.

Table 5.1: Optimal points (parameter values) for occupancy and activity labels with both density (D) and spread rate (SR) criteria. ϵ=0.1, 0.2, 0.3 and number of neighbours=1, 2, 3, 4 for D criterion. Improvement ratio (IR)= 0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08 for SR criterion. The results correspond to two different set of features: power consumption (POW), acoustic pressure (DB) from a microphone, motion (MOT), and hour of the day (HO). [POW, DB, MOT, HO] in solid line and [POW, DB, MOT] in dashed line

	Occupancy Labels	Activity Labels
Density Criterion	 (a)	 (b)
Spread Rate Criterion	 (c)	 (d)

For the neighbourhood approach represented by graphs (a) and (b) in the Table 5.1, the best parameters for occupancy labels are: $\epsilon = 0.3$ with 1 and 2 neighbours; and for activity labels: $\epsilon = 0.3$ with 3 neighbours and $\epsilon = 0.2$ with 2 or 3 neighbours.

On the other hand, for the global IL approach, the best IR values were determined from graphs (c) and (d). For occupancy labels $IR = 0.06$, 0.07 and 0.08; while for activity labels: $IR = 0.04$, 0.05, 0.06 and 0.08.

Considering now the number of confusion solvers and updates for each of the optimal points (tables A.1 and A.2), we selected the ones that present the lower number of *confusions*, limiting the optimal points to the ones in the Table 5.2.

Table 5.2: Optimal parameter values for occupancy and activity labels with both density (D) and spread rate (SR) criteria. Description of the number of asks (A), global accuracy (GA), number of confusion solvers (CS) and number of updates (U) for each situation.

		Parameters	A	GA	CS	U
Occupancy Labels	Density	$\epsilon = 0.3$ 1 neighbour	30	0.93	0	0
	Spread Rate	$IR = 0.08$	28	0.87	0	0
Activity Labels	Density	$\epsilon = 0.2$ 2 neighbours	33	0.80	4	0
	Spread Rate	$IR = 0.08$	27	0.75	5	1

5.2 Occupancy vs Activity labels

In order to compare the two datasets, we did an analysis to the daily *asks* frequency. From Table 5.3, Table 5.4, Table 5.5 and Table 5.6 we can conclude that the activity labels present more *asks* in a 3-day dataset than the all 15-day dataset of occupancy labels. This happens because the activity labels assigned by the human actors are more subjective and according to their perception.

The greater number of *asks* is directly related to the increased number of *confusions* and *updates* when using non-numerical labels. This fact can also be perceived in Table 5.2.

Table 5.3: Number of asks per day for occupancy labels. Density criterion: $\epsilon = 0.3$, 1 neighbour.

Day	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	
Number of Asks	17	3	4	0	0	0	0	0	4	1	0	0	0	0	1	= 30

Table 5.4: Number of asks per day for occupancy labels. Spread rate criterion: $IR = 0.08$.

Day	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	
Number of Asks	16	3	2	1	0	0	0	0	3	2	0	0	0	0	1	= 28

Table 5.5: Number of asks per day for activity labels. Density criterion: $\epsilon = 0.2$, 2 neighbours.

Day	1	2	3	
Number of Asks	21	9	3	= 33

Table 5.6: Number of asks per day for activity labels. Spread rate criterion: $IR = 0.08$.

Day	1	2	3	
Number of Asks	17	8	2	= 27

5.3 Density vs spread rate criteria

From the graphs of the Table 5.1, we can straightaway conclude that both neighbourhood and global IL approaches behave very differently for the different sets of features, while *density* performs with better accuracy when using the *hour of the day* feature, *spread rate* substantially worsens its performance. Thus, a different set of features must be selected accordingly to the IL triggering criteria used. Important to notice that despite not meeting our established goals (maximization of the global accuracy and the minimization of the number of *asks*), for larger datasets (long-term testing periods) by adding the feature hour in the day HO, the accuracy increases always for a higher number of *asks*, independent on the IL criteria used.

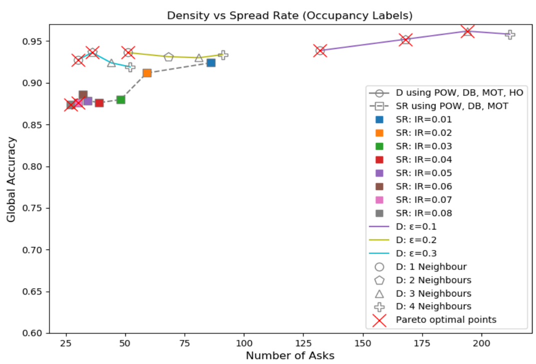


Figure 5.1: Comparing the results for density and spread rate criteria using occupancy labels.

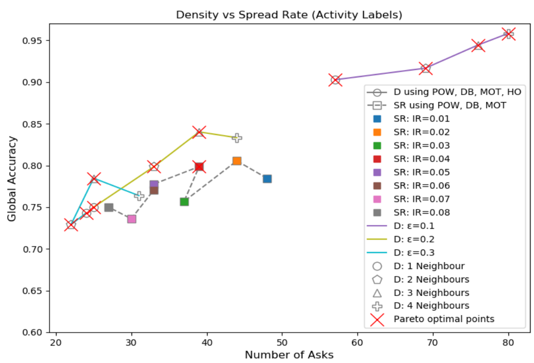


Figure 5.2: Comparing the results for density and spread rate criteria using activity labels.

Considering only the scenarios that use the optimal feature sets ([POW, DB, MOT, HO] for *density* criterion and [POW, DB, MOT] for *spread rate* criterion), from Figure 5.1 and Figure 5.2 we can conclude that *density* performs always better than *spread rate*, representing almost the total of the optimal points.

5.4 Influence of the number of labels

To assess the influence of the number of labels provided by the user (in the set of labels $\mathcal{L}$), we analysed an extra dataset for the level of occupation in the same site described in the case study. We compared the previous 3-labels dataset {[0], [1-2], [≥3]} with a 5-labels dataset {[0], [1], [2], [3], [≥4]}. The results are presented below for both *density* and *spread rate* criteria.

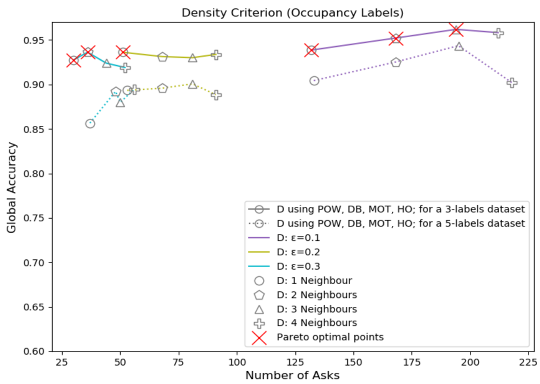


Figure 5.3: Comparing the results for density criterion using different sets of occupancy labels. 3-labels dataset: {[0], [1-2], [>3]}; 5-labels dataset: {[0], [1], [2], [3], [>4]}

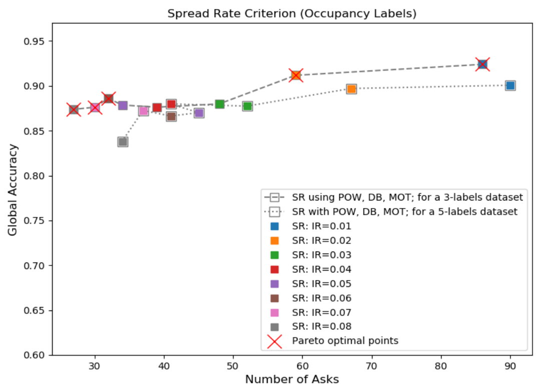
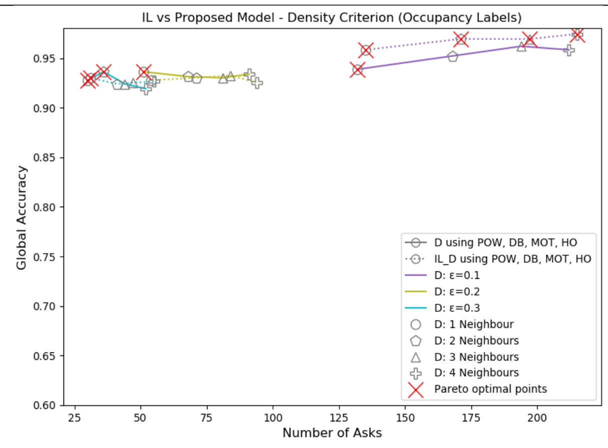


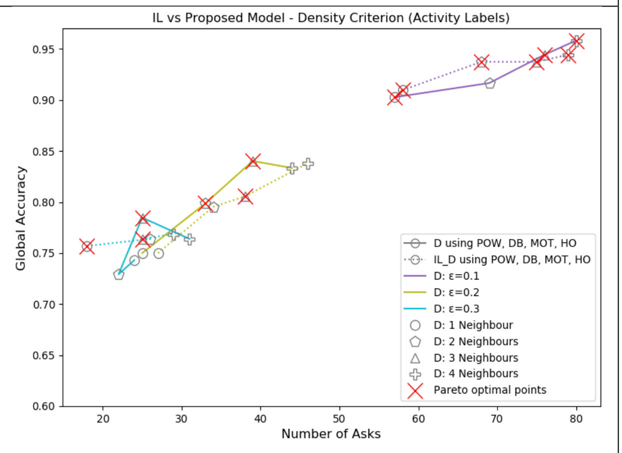
Figure 5.4: Comparing the results for spread rate criterion using different sets of occupancy labels. 3-labels dataset: {[0], [1-2], [>3]}; 5-labels dataset: {[0], [1], [2], [3], [>4]}

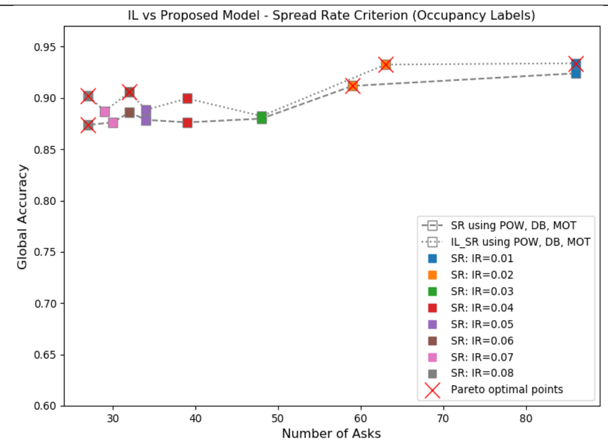
We can conclude that by increasing the number of available labels, it leads to an increase in the number of *confusion solvers* and *updates* while decreasing the global accuracy of the model. From the two cases in Figure 5.3 and Figure 5.4, we can also remark that the *density* criterion is more sensible to the number of labels.

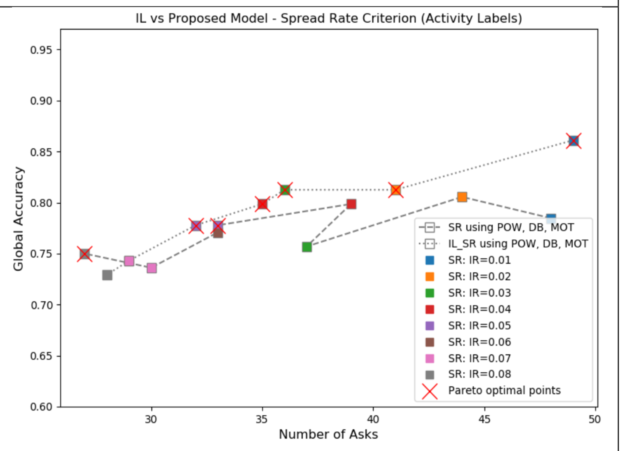
5.5 Comparison between the proposed methodology and the originals Interactive Learning and Cooperative Learning

Table 5.7: Comparison of the proposed methodology with the Interactive Learning (IL) methodology (dotted line) for occupancy and activity labels with both density (D) and spread rate (SR) criteria. The optimal set of features (power consumption (POW), acoustic pressure (DB) from a microphone, motion (MOT), and hour of the day (HO)) were selected for each scenario according to the IL criterion used.

<table>
<tr><td></td><td>Occupancy Labels</td><td>Activity Labels</td></tr>
<tr><td>Density Criterion</td><td>

(a)</td><td>

(b)</td></tr>
<tr><td>Spread Rate Criterion</td><td>

(c)</td><td>

(d)</td></tr>
</table>

From the graphs from Table 5.7 we can conclude that, when using the *density* criterion, the proposed methodology is slightly better than the original Interactive Learning approach, however for the *spread rate* criterion the proposed model has always a slightly lower global accuracy.

The proposed methodology does not show great improvements when compared with the IL, yet, this is related to the fact that IL uses predefined labels.

Related with the Cooperative Learning, we tested the accuracy using the 2 datasets: [POW, DB, MOT, HO] and [POW, DB, MOT]. Since CL methodology is based on *temporal daily forms* instead of single *asks*, the global accuracy of the model dependents only on the number of days.

Table 5.8: Cooperative Learning results for occupancy and activity labels. Description of the global accuracy (GA), number of confusion solvers (CS) and number of remaining confusions by the end of the testing period, for each situation and using different sets of features: power consumption (POW), acoustic pressure (DB) from a microphone, motion (MOT), and hour of the day (HO).

	Features	GA	CS	Remaining confusions
Occupancy Labels (15 *temporal daily forms*)	[POW, DB, MOT]	0.76	15	5
	[POW, DB, MOT, HO]	0.48	15	3
Activity Labels (3 *temporal daily forms*)	[POW, DB, MOT]	0.55	3	2
	[POW, DB, MOT, HO]	0.63	3	3

Comparing with the results obtained for the proposed methodology, we can conclude that the CL approach not only results in a lower global accuracy but also always terminates the process with *remaining confusions* that it cannot resolve. Note that the proposed methodology always ends the process with zero *confusions* due to the update mechanism that requests the human actors to correct the specific labels that are causing the *confusion*.

Chapter 6

Conclusions

In this thesis, we propose a new supervised human-driven learning approach for the classification of different instances related to human behaviour in a household context. Our approach can also be described as a non-invasive practice annotation system. The annotations or labels are collected directly from the end-users and describe their reality, allowing us to build a model that aligns the human actors' perception.

This methodology was designed based on Interactive Learning and Cooperative Learning taking the best characteristics of each. Relying only on feedback from human actors and timed data from a selected set of sensors, the approach grants the privacy of occupants while increasing their awareness of the energy systems. It can be applied to any household context, by selecting the relevant sets of sensors, and to any type of relevant data collected from the occupants, numerical or non-numerical. This makes our approach very flexible for numerous applications.

The artificial learning system is prepared to accept an indefinite number of different labels that are entirely defined according to the human actors' semantics. Moreover, a new method was introduced to assess and correct inconsistent labels given by the human actors, the *updates*. When the artificial learning system is not able to solve one *confusion*, it will evaluate the context in which the *confusion* happens and look for the most up-to-date similar context in the past sensor data. It will then request the human actors to provide a new label in order to correct the mistake.

We applied the proposed methodology for both occupancy and activity recognition in an office in Grenoble, France, using a set of three sensors: motion, acoustic pressure and power consumption. We stated that when the *asks*' triggering mechanism uses the *density* criterion, the efficiency of the model would improve when using an extra feature, the hour of the day; however, for the *spread rate* criterion, it would result in a considerable decrease of the global accuracy of the model. Thus, we concluded that the sensors/features used depend not only on the household characteristics but also on the interaction methodology used.

While comparing the model for numerical and non-numerical labels – occupancy and activity recognition respectively –, we settled that non-numerical labels lead to a more subjective environment making it harder for the system to distinguish the different labels. This results in more *confusion solvers* and *updates* but still reliable global accuracy. Furthermore, another matter that influences the performance of the model is the length of the labels dataset defined by the human actors. When the labels dataset is large, it can lead to a considerable increase in the number of *confusion solvers* and *updates* while decreasing the global accuracy of the model.

For our case study, we also tested different parameters for the interaction methodology namely the value of *epsilon* and the *number of neighbours* for the *density* criterion and the *improvement ratio* for the *spread rate* criterion, with two different sets of features ([POW, DB, MOT] and [POW, DB, MOT, HO]). The optimal points selected in Table 5.2 satisfy both the maximization of the global accuracy and the minimization of the number of *asks* and also present a low number of *confusion solvers* and *updates*.

Being our approach based on Interactive and Cooperative Learning, we compared the results of the three models. We concluded that Cooperative Learning alone presents a lower global accuracy than any of the other methods as well as *remaining confusions*, holding the least reliable approach. Comparing the Interactive Learning and the proposed methodology, we stated that both performances are very similar, however, we must take into consideration that the Interactive Learning approach uses predefined labels, thus its adaptation capability to another context is much smaller.

6.1 Limitations

The greatest limitation of the proposed methodology is related to the number of labels. The proposed methodology allows an open set of labels since it gives the human actors total freedom to add new labels according to their perception. This can lead to a high number of labels which results in an abrupt decrease in the global accuracy of the model.

Other limitation is the fact that we need to analyse the relevance of the sensors/features every time we apply the methodology for a new environment and/or use a different interaction methodology.

Finally, with the available 3-day dataset wasn't possible to properly compare how the global accuracy varies for non-numerical labels. We can conclude that for the first 3 days, the model behaves poorly when using activities labels, however, it is not possible to demonstrate if this behaviour is due to the greater number of labels (4) or if it improves for a bigger dataset. Also, the results of the *update* method couldn't be properly explored.

6.2 Future work

There are some interesting potential future work to improve the proposed approach. For instance, to correct the main limitations of the model, we will explore how to control the number of labels. If these labels are numbers, the artificial learning system can group them by ranges, however, if they are non-numerical labels, the system must find a way to aggregate similar labels. Our proposal passes by suggesting to the human actors to introduce an encompassing activity representing the set of activities presenting a *confusion* (in the case of having *dinner* and *lunch*, it can be replaced by the *eating* activity). This could be deployed as an additional *update* method that, instead of simply request a new label to solve the *confusion*, could also advise the possibility of providing an encompassing activity.

Other potential improvements to the approach could be dedicated to integrating streaming feature selection in case new sensors are introduced and/or the system is implemented in a different environment. The overall goal would be to propose a unified approach that takes into account simultaneously the quality of the data and the relevance of the features.

6.3 Applications

Empowered by the co-decision between the system and the human actors our approach offers in-depth knowledge of the end-users consumption patterns. This can be used to provide the inhabitants with contextualized advice (to correct bad habits favouring more aware and sustainable behaviours), co-exploration of possibilities and explanations/justifications for the suggestions. For instance, these new behaviour suggestions can include information from nudges (red/green period), economic signals, commitments, practice analysis reports, etc.

Based on labels displayed by the human actors, the system can also evaluate their flexibility to new and more sustainable changes in their daily lives. If after the system's suggestions the behaviour of the occupants doesn't change it means that they are not susceptible to change. Having this information about inhabitants can be useful when developing multi-agent stochastic models of practice impacts at individual, collective and societal scales.

Capable of not only recommending more sustainable habits but also quantifying the flexibility of the inhabitants, our approach can be successfully applied as part of an Interactive Home Energy Management Aid System. In this way, the IHEMAS can change smart houses systems' controls based on the daily behaviours of the occupants and their preferences or intentions (Figure 6.1). Thus, the proposed approach can be used to improve energy efficiency and perform active demand-side management. This has the potential to reduce household energy costs as well as providing support to the broader energy grid.

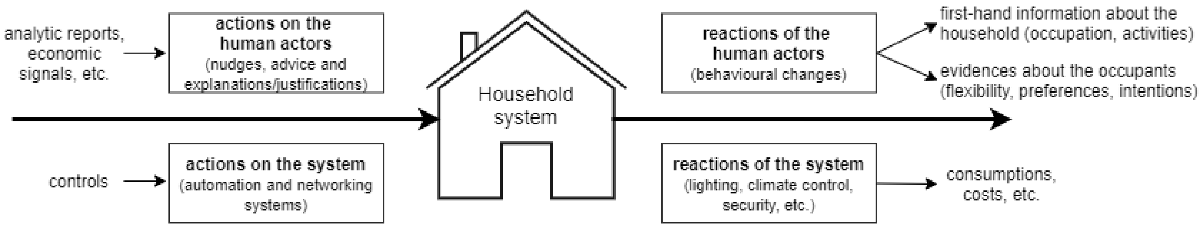


Figure 6.1: Interactive Home Energy Management Aid System using the proposed methodology.

Researchers started realizing that we cannot rely only on the machine, therefore interaction is essential. This leads to considering that interactive and cooperative principles are the first step to build a general interactive annotation system. Thus, we can go further than household solutions to other possible interesting applications from machine translation to medical diagnosis to transportation to robotic automation and game playing.

With this in mind, we should considered the impact of involving the occupants in daily decisions. The question arises: will it work appropriately once deployed in the real world with an Interactive annotation system in which humans feature so prominently?

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Appendix A

Results for different testing parameters

A.1 Spread rate criterion

Table A.1: Analyses of spread rate criterion results for occupancy and activity labels with different values for the improvement ratio (IR). Description of the number of asks (A), global accuracy (GA), number of confusion solvers (CS) and number of updates (U) for each situation and using different sets of features: power consumption (POW), acoustic pressure (DB) from a microphone, motion (MOT), and hour of the day (HO). Highlighted in green we have the selected optimal points, being the darker green considered the best ones.

	Features: POW, DB, MOT								Features: POW, DB, MOT, HO							
	Occupancy				Activities				Occupancy				Activities			
	A	GA	CS	U	A	GA	CS	U	A	GA	CS	U	A	GA	CS	U
IR=0.01	86	0.92	19	6	48	0.78	21	10	98	0.88	3	0	63	0.87	4	0
IR=0.02	59	0.91	15	4	44	0.81	20	10	72	0.80	2	0	53	0.83	0	0
IR=0.03	48	0.88	0	0	37	0.76	13	5	59	0.90	0	0	47	0.78	0	0
IR=0.04	39	0.88	1	0	39	0.80	13	3	46	0.83	1	0	39	0.63	0	0
IR=0.05	34	0.88	0	0	33	0.78	12	3	40	0.69	0	0	36	0.63	0	0
IR=0.06	32	0.89	2	0	33	0.77	4	2	32	0.85	0	0	29	0.62	0	0
IR=0.07	30	0.88	1	0	30	0.74	6	1	33	0.78	0	0	28	0.61	0	0
IR=0.08	28	0.87	0	0	27	0.75	5	1	31	0.82	0	0	27	0.61	0	0

A.2 Density criterion

Table A.2: Analyses of density criterion results for occupancy and activity labels with different values for ϵ and minimum number of neighbours. Description of the number of asks (A), global accuracy (GA), number of confusion solvers (CS) and number of updates (U) for each situation and using different sets of features: power consumption (POW), acoustic pressure (DB) from a microphone, motion (MOT), and hour of the day (HO). Highlighted in green we have the selected optimal points, being the darker green considered the best ones.

				1 Neighbour				2 Neighbours				3 Neighbours				4 Neighbours			
				A	**GA**	**CS**	**U**	**A**	**GA**	**CS**	**U**	**A**	**GA**	**CS**	**U**	**A**	**GA**	**CS**	**U**
Features:	POW, DB, MOT	Occupancy	ϵ=0.1	86	0.93	33	13	116	0.93	51	32	134	0.90	50	36	166	0.92	94	60
			ϵ=0.2	40	0.89	0	0	54	0.92	0	0	64	0.93	5	1	73	0.94	12	3
			ϵ=0.3	27	0.90	0	0	32	0.91	0	0	40	0.92	0	0	46	0.91	3	0
		Activities	ϵ=0.1	41	0.78	16	4	49	0.8	27	14	55	0.79	39	18	67	0.79	57	34
			ϵ=0.2	25	0.74	7	0	27	0.75	8	1	29	0.78	5	1	32	0.76	8	2
			ϵ=0.3	12	0.67	0	0	18	0.73	2	0	17	0.72	0	0	20	0.74	0	0
Features:	POW, DB, MOT, HO	Occupancy	ϵ=0.1	132	0.94	8	1	168	0.95	7	1	194	0.96	9	2	212	0.96	22	6
			ϵ=0.2	51	0.94	0	0	68	0.93	0	0	81	0.93	4	0	91	0.94	3	0
			ϵ=0.3	30	0.93	0	0	36	0.94	0	0	44	0.92	0	0	52	0.92	0	0
		Activities	ϵ=0.1	57	0.90	0	0	69	0.92	10	2	76	0.94	6	1	80	0.96	14	2
			ϵ=0.2	25	0.75	0	0	33	0.80	4	0	39	0.84	3	0	44	0.83	6	1
			ϵ=0.3	24	0.74	1	0	22	0.73	0	0	25	0.78	1	0	31	0.76	0	0