Cooperative and Interactive Learning to estimate human behaviours for energy applications

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Abstract

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 methodology 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 (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

1. Introduction

Global warming is one of the most serious issues the world is facing as a result of the increased emission of greenhouse gases (GHGs). While energy consumption accounts for over 80% of the global GHGs, in Europe, residential buildings contribute more than 36% of all emissions in 2018 [1]. It leads to the necessity of reducing energy consumption in residential buildings.

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 [2] [3]. Indeed, numerous research works have been carried out to study the human behaviour influence on energy performance dealing with optimized energy management [4], modelling simulations of buildings and neighbourhoods, the transformation of building system models [5], methods for guaranteeing performances [6] or performance verification methods [7]. It appears that when a building is low energy consumption, it becomes very sensitive to the occupant activities [8].

As pointed out by *Le Monde* [9], the major retrofitting effort carried out in Germany did not lead to any form of effective reduction in thermal consumption in private homes. The cause is the rebound effect, i.e. after the retrofitting the inhabitants tend to increase their comfort requirements and become less careful about consumption which is supposed to be lower. The awareness and flexibility of human behaviour in order to favour low energy services and lifestyle must be taken into account.

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 [10] an interactive approach models the household occupancy by collecting the relevant information directly from the human actors (Interactive Learning). An alternative approach was studied in [11] for a first application of a symmetrical co-definition of activities between the occupants and an artificial learning system (Cooperative Learning).

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. 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. Moreover, in order to have a reliable solution and enable the mass deployment, the approach should comply with the constraints: (1) respect the privacy of occupants by avoiding the use of cameras; (2) adapt to the diversity of environments (different households, sensors); (3) adapt to different kinds of data (numerical and non-numerical); (4) adapt to the different profiles of users (different perceptions); (5) increase the user awareness of energy systems (training data provided by the user).

1.3. Contributions

Combining Cooperative Learning with Interactive 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.

We propose a new methodology that can be applied for occupancy, activity recognition or other relevant situation meaningful for the human actors. Besides, 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 in order to correct mistrust data.

1.4. Outline of the thesis

In section 2 we perform a literature review of the current work regarding the latest developments in occupancy and activity recognition. The details of the proposed approach are described in section 3 and the case-study is presented in section 4. In section 5, we present and discuss the results. In section 6, the main conclusions of this thesis are summarized and future developments and applications suggested.

2. Background on occupancy and activity recognition

A large number of approaches are based on the use of video cameras and on the analysis of its content [12]. These methods are intrusive, which highly limits the implementation of the applications because of privacy issues [13]. Other approaches [14], [15] study activity recognition using mobile phone sensors or other wearable sensors. These methods are interesting 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.

The existing sensor-based methods depend on the data sources. In [16], the occupancy estimation depends on proxy measurements such as CO_2 concentration, and indoor temperature. In [17] was investigated a solution for activity prediction using data from sensors (i.e. motion detectors and window contact sensors) by imitation learning. Sound processing has been widely used for activities recognition in smart houses [18] or [19]. In [20], a supervised learning approach is studied, to determine, from a set of sensors, 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.

Interactive Learning approaches has been explored for occupancy estimation using a set of sensors and self-labelling by occupants [21], [10]. The results lead to the conclusion that the interactive approach is more efficient for occupancy estimation than the other methods taking into account the context.

Cooperative Learning is a recent learning approach proposed for activity recognition [11]. This approach obtains a shared consistent representation between an artificial learning system perceiving an environment thanks to a set of sensors, and human actors using their own knowledge to label situations.

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 current situation has been met, or frequently met or not.

2.1.1 Concepts definition

Let's define an *ask* $\mathbf{A}_t = (F_{1,t}, F_{2,t}, ..., F_{p,t})$ at the time slot *t* as a vector of feature values from *p* sensors. 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: $(\mathbf{A}_t, L_t)$. For a time slot t', an *ask* $\mathbf{A}_{t'}$ 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* $\mathbf{A}_t$ is called a *recorded ask*, or simply a *record*. The database Δ is a collection of *recorded asks*. Generally speaking, $\Delta = ((F_{1,1}, F_{2,1}, ..., F_{p,1}), L_1), ..., ((F_{1,n}, F_{2,n}, ..., F_{p,n}), L_n)$ 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 $\forall i \in \{1, \dots, p\}, \forall k \in \{1, \dots, n\}, (F'_i)_k = \frac{(F_i)_k - \check{F}_i}{\hat{F}_i - \check{F}_i}$, distributed in a *p*-dimensional normalized space $S = [0, 1]^p$.

2.1.2 Interaction mechanism

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.

Some concepts to evaluate and/or determine the best time for interacting with human actors were introduced in [10] and [22]: the *density of the neighbourhood*, *classifier estimation error*, the *redundancy* and the *spread rate*. These concepts are expected to allow the maximization of the information usefulness while limiting the number of interactions.

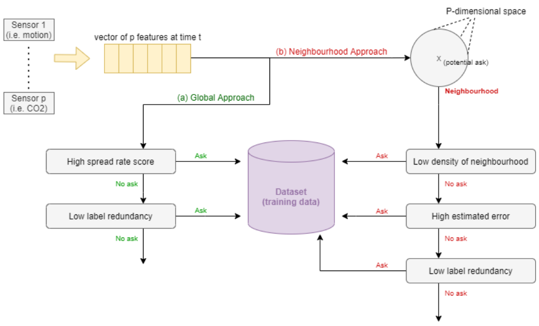


Figure 1: Interactive Learning process with global (a) and neighbourhood (b) approaches.

Determination of best times for interactions rely on more than one criteria. For instance, the flowchart of Figure 1, presents the different criteria considered for both a global approach (a) and a neighbourhood approach (b). 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.

i. Density of the neighbourhood

The *density of the neighbourhood* 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 (1) gives the distance between a *potential ask* $\mathbf{A}_{t'}$ and any *recorded ask* $\mathbf{A}_k \in \Delta_k = (\mathbf{A}_k, L_k)$, with $k \in \{1, \dots, n\}$ being n the number of existing *records* 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.

$$\|\mathbf{A}_{t'} - \mathbf{A}_k\|_\infty = \left\| \left(\frac{F_{1,t'} - F_{1,k}}{\hat{F}_1 - \check{F}_1}, \frac{F_{2,t'} - F_{2,k}}{\hat{F}_2 - \check{F}_2}, \dots \right) \right\|_\infty \quad (1)$$

The local density in the neighbourhood of $\mathbf{A}_{t'}$ is given by:

$$\textit{Number of neighbours of } \mathbf{A}_{t'} =$$

$$= \left| \left\{ \begin{array}{c} ((F_{1,k}, F_{2,k}, ..., F_{p,k}), L_k) \in \\ \left\| \left(\frac{F_{1,t'} - F_{1,k}}{\hat{F}_1 - \check{F}_1}, \frac{F_{2,t'} - F_{2,k}}{\hat{F}_2 - \check{F}_2}, \dots \right) \right\|_\infty < \frac{\epsilon}{2}, \\ \epsilon \in [0, 1], \forall k \in \{1, ..., n\} \end{array} \right\} \right| \quad (2)$$

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* $\mathbf{A}$ should be send to the human actors if:

$$\begin{array}{c} \textit{Number of} \\ \textit{neighbours of } \mathbf{A}_{t'} \end{array} \leq \begin{array}{c} \textit{Minimum} \\ \textit{number of neighbours} \end{array} \quad (3)$$

ii. Classifier estimation error

The *classifier estimation error* is used together with the *density of the neighbourhood* criterion to add a second condition to calculate the number of neighbours of a *potential ask*. The quality of the neighbours is then going to be assessed. 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:

$$|L_{t,c} - L_t| < E_r \zeta \quad (4)$$

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* [10].

If the *classifier estimation error* for a *record* does not meet the condition in (4), 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 (5) considering the *classifier estimation error*'s condition (4). A new *ask* should be send to the HA if it satisfies the condition in (3).

$$\textit{Number of neighbours of}\, \mathbf{A}_{t'} =$$

$$= \left| \left\{ \begin{array}{c} ((F_{1,k}, F_{2,k}, ..., F_{p,k}), L_k) \in \\ \left\| \left(\frac{F_{1,t'} - F_{1,k}}{\hat{F}_1 - \check{F}_1}, \frac{F_{2,t'} - F_{2,k}}{\hat{F}_2 - \check{F}_2}, ... \right) \right\|_\infty < \frac{\epsilon}{2} \\ \cap |L_{k,c} - L_k| < E_r \zeta, \\ \epsilon \in [0,1], \forall k \in \{1, ..., n\} \end{array} \right\} \right| \qquad (5)$$

iii. 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.

iv. 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 neighbourhood*; instead of counting the records in a neighbourhood, it checks how *records* are globally distributed.

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. *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.

Now it is possible to define $Qscore \in [0, 1]$ for a normalized database Δ'_n as:

$$Qscore(\Delta'_n, f) = Sscore(\Delta'_n) \times RA \qquad (6)$$

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

$$Qscore(\Delta'_n \cup \{\mathbf{A}\}) > \left[\begin{array}{c} (1 + \textit{Improvement Ratio}) \\ \times Qscore(\Delta'_n) \end{array} \right] \qquad (7)$$

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 $Qscore = 0$.

2.1.3 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 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 (3)). 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

Similarly to IL, Cooperative Learning (CL) is a supervised learning methodology relies on sensors data and feedback collected from the occupants. However, it uses a co-definition approach based on shared knowledge between an artificial system (AS) and human actors in order to build a common perception of the model.

Human-system cooperation is then established through feedback on the AS's estimated labels to modify the perception of the system. 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. 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 actors perception, based on knowledge and memory.

2.2.1 Confusion 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 using a parameterized feature generator. For instance, the raw data from a sensor *i*, the feature F_i, can be discretised in: 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. Θ is a set of parameters θ_i, $\forall i \in [1, ..., p]$, for a setup of p sensors.

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 and Θ, a parameterized feature generator will generate a combination of the discretized raw data of each sensor – a *word*. In accordance with Figure 2, assuming for a particular time slot the discretization of the raw data of POW, DB and MOT; into L, VL and H respectively, it generates the *word*: *LVLH*.

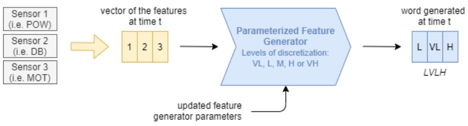


Figure 2: Word generation process for a 3-sensors set-up.

We can now say that 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 other words, a *confusion* arises when one *word* is associated with two or more different labels.

2.2.2 Confusion processing

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.

Otherwise, the system will use a confusion solver that, using an optimization algorithm (evolutionary algorithms), adjusts the parameterization of the feature generator Θ. By adjusting the parameters, the feature generator can generate different weights for the levels of discretization that can better define the HA perspective and solve all the *confusions*.

2.2.3 System overview

The CL system (Figure 3) is divided into three main parts: a feature generator, a classifier and a confusion processor.

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;

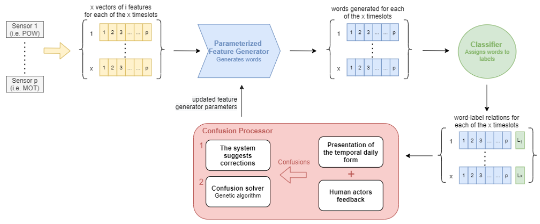


Figure 3: Overview of the cooperative learning system.

3. The AS is going to analyse the consistency of the resulting *word-label* database and will detect *confusions* i.e.one *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 Θ 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

One of the main disadvantages of CL is the time that the HA spend correcting the suggested labels at the end of the day, which may end up in they 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.

Both IL and CL do not always take into account that the HA may unconsciously commit mistakes while labelling the events. Only when using the *classifier estimation error* criterion, the IL can ignore some *records* that are considered as mistakes (only for IL neighbourhood approaches and only 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. For CL, its main strength is that it can easily endorse a better classification *word-label* by adjusting the discretization of the raw data. 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.

3. Proposed Methodology

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 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 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 inconsistent data in the KD. It will assess the context of the *word* causing each *confusion* — *confusion word*: *word* with more than one label associated – and will look for a 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*.

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.

3.4. Implementation

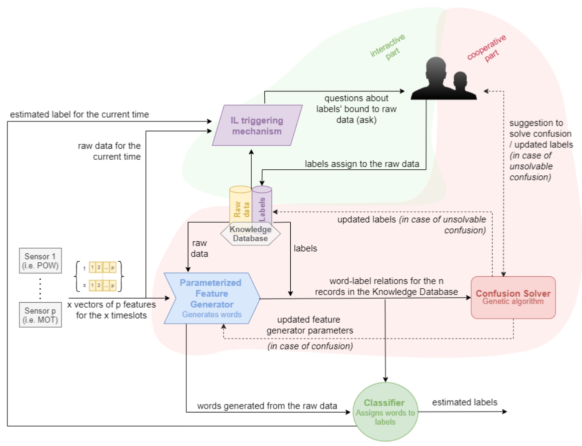


Figure 4: Proposed methodology.

Figure 4 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. If the conditions are met, an *ask* is sent to the HA. After the feedback, the *raw data-label* relation will be stored in the KD and it will be considered as the ground truth data.

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.

The confusion solver must search for *confusions* 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* database, ready to be checked with the confusion solver.

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.

4. Case Study

To demonstrate the application of the proposed methodology, we used data from an office in the Grenoble Institute of Technology, equipped with an ambiance sensing network. 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 [20], the following three sensors 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.

In this work two different situations were considered: the number of occupants per time slot T_s in a period of 15 days; and activity per time slot T_s. 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 1.

Table 1: Context of the two situations under study.

	Number of occupants	**Activities performed by the occupants**
Labels	[0], [1-2], [$\geq$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 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.

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 number of *asks*). For this reason the the two situations can't be directly compared.

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 (see Table 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).

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 2) and using two different set of features: power consumption, acoustic pressure and motion (POW, DB, MOT) and power consumption, acoustic pressure, motion and hour of the day (POW, DB, MOT, HO).

Table 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. 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. Many confusion solvers means a lot of *confusions* and an increased simulation time, which we want to avoid.

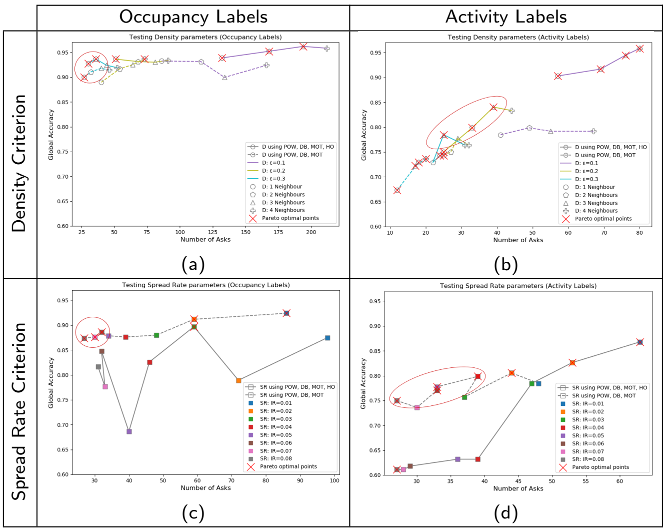
5. Results & discussion

In this chapter, we present and discuss the performance results of the model for the different parameters of Table 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 label-datasets. The results are presented by correlating the number of *asks* and the global accuracy of the model for each scenario.

5.1. Optimal parameters values

The optimal parameters presented in Table 3 satisfy both the maximization of the global accuracy and the minimization of the number of *asks*.

Table 3: Optimal points 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



Considering now the number of confusion solvers and updates for each of the optimal points, we selected the ones that present the lower number of confusions, limiting the optimal points to the ones in the Table 4.

Table 4: 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. Further analyses

5.2.1 Occupancy vs Activity labels

In order to compare the two datasets, we analysed the daily *asks* frequency. We stated that a 3-day dataset of activity labels result in a higher number of *asks* 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.

5.2.2 Density vs spread rate criteria

From the graphs of the Table 3, 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.

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), we can conclude that *density* performs always better than *spread rate*, representing almost the total of the optimal points.

5.2.3 Influence of the number of labels

By increasing the number of available labels from a 3-labels to a 5-labels dataset, the global accuracy will always decrease. We can also remark that the *density* criterion is more sensible to the number of labels.

5.2.4 Proposed methodology vs the originals Interactive and Cooperative Learning

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

Comparing now with the results obtained for the Cooperative Learning, 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.

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, based on Interactive Learning and Cooperative Learning. Relying only on feedback from human actors and timed data from a selected set of sensors, it 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 the system is prepared to accept an indefinite number of different labels that are entirely defined according to the human actors' semantics, numerical or non-numerical. This makes our approach very flexible for numerous applications.

A new method was introduced to assess and correct inconsistent data, the *updates*. It evaluates the context in which the *confusions* happen request specific information to correct the mistrust data.

We applied the proposed methodology for both occupancy and activity recognition in an office in Grenoble, France, using a set of 3 sensors: motion, acoustic pressure and power consumption. We concluded that the sensors/features used depend not only on the household characteristics but also on the interaction methodology used. Besides, we settled that non-numerical labels lead to a more subjective environment but still with reliable global accuracy. Further, we depicted that for larger label datasets the global accuracy of the model is lower. We also tested different parameters for the methodology. The optimal points selected in Table 4 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*.

By comparing our approach with Interactive and Cooperative Learning, we stated that CL alone presents the lowest global accuracy as well as *remaining confusions*, holding the least reliable approach. Comparing with Interactive Learning, we stated the 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 proposed approach allows an open set of labels since it gives the human actors total freedom to add new labels according to their perception. However, this can lead to a high number of labels resulting 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 and the results of the *update* method couldn't be properly explored.

6.2. Future work

In order 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 (encompassing label).

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, co-exploration of possibilities and explanations/justifications for the suggestions.

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. Having this information about inhabitants can be useful when developing multi-agent stochastic models of practice impacts at individual, collective and societal scales.

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. Thus, it 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.

Interactive and cooperative principles can be 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.

References

[1] Directive 2010/31/eu on the energy performance of buildings and directive 2012/27/eu on energy efficiency. `https://eur-lex.europa.eu/legal-content/EN/TXT/?toc=OJ:L:2018:156:TOC&uri=uriserv:OJ.L_.2018.156.01.0075.01.ENG`, 2018.

[2] Réglementation thermique 2020. `http://www.rt-2020.com/`, 2020.

[3] Decreto-lei 101-d/2020. `https://dre.pt/web/guest/home/-/dre/150570704/details/maximized`, url=https://dre.pt/web/guest/home/-/dre/150570704/details/maximized, 2020.

[4] Monalisa Pal, Amr Alzouhri Alyafi, Stéphane Ploix, Patrick Reignier, and Sanghamitra Bandyopadhyay. Unmasking the causal relationships latent in the interplay between occupant's actions and indoor ambience: A building energy management outlook. *Applied Energy*, 238:1452–1470, 2019.

[5] Yanis Hadj Said. *Prise en compte de la complexité de modélisation dans la gestion énergétique des bâtiments*. PhD thesis, Grenoble Alpes, 2016.

[6] Simon Ligier, Maxime Robillart, Patrick Schalbart, and Bruno Peuportier. Energy performance contracting methodology based upon simulation and measurement. In *Building Simulation 2017*, 2017.

[7] Rozenn Josse. *Méthode et outils pour l'identification de défauts des bâtiments connectés performants*. PhD thesis, Grenoble Alpes, 2017.

[8] Éric Vorger. *Étude de l'influence du comportement des habitants sur la performance énergétique du bâtiment*. PhD thesis, Paris, ENMP, 2014.

[9] Cécile Boutelet. En allemagne, les rénovations énergétiques des bâtiments n'ont pas fait baisser la consommation. https://www.lemonde.fr/economie/article/2020/10/04/en-allemagne-les-renovations-energetiques-des-batiments-n-ont-pas-fait-baisser-la-consommation_6054715_3234.html, Oct 2020.

[10] Manar Amayri, Stéphane Ploix, Patrick Reignier, and Sanghamitra Bandyopadhyay. Towards interactive learning for occupancy estimation. In *ICAI'16-International Conference on Artificial Intelligence (as part of WORLDCOMP'16-World Congress in Computer Science, Computer Engineering and Applied Computing)*, 2016.

[11] Amine Awada, Patrick Reignier, Stéphane Ploix, Mireille Jacomino, and Elabed Elsafadi. Identification collaborative d'activités dans une zone habitée. In *IBPSA*, 2020.

[12] Michalis Vrigkas, Christophoros Nikou, and Ioannis A Kakadiaris. A review of human activity recognition methods. *Frontiers in Robotics and AI*, 2:28, 2015.

[13] Deepika Singh, Ismini Psychoula, Johannes Kropf, Sten Hanke, and Andreas Holzinger. Users' perceptions and attitudes towards smart home technologies. In *International Conference on Smart Homes and Health Telematics*, pages 203–214. Springer, 2018.

[14] Xizhe Yin, Weiming Shen, Jagath Samarabandu, and Xianbin Wang. Human activity detection based on multiple smart phone sensors and machine learning algorithms. In *2015 IEEE 19th international conference on computer supported cooperative work in design (CSCWD)*, pages 582–587. IEEE, 2015.

[15] Tanzeem Choudhury, Gaetano Borriello, Sunny Consolvo, Dirk Haehnel, Beverly Harrison, Bruce Hemingway, Jeffrey Hightower, Predrag Pedja, Karl Koscher, Anthony LaMarca, et al. The mobile sensing platform: An embedded activity recognition system. *IEEE Pervasive Computing*, 7(2):32–41, 2008.

[16] Ming Jin, Nikolaos Bekiaris-Liberis, Kevin Weekly, Costas J Spanos, and Alexandre M Bayen. Occupancy detection via environmental sensing. *IEEE Transactions on Automation Science and Engineering*, 15(2):443–455, 2016.

[17] Bryan David Minor, Janardhan Rao Doppa, and Diane J Cook. Learning activity predictors from sensor data: Algorithms, evaluation, and applications. *IEEE transactions on knowledge and data engineering*, 29(12):2744–2757, 2017.

[18] Rafael Valle. Abroa: audio-based room-occupancy analysis using gaussian mixtures and hidden markov models. In *2016 Future Technologies Conference (FTC)*, pages 1270–1273. IEEE, 2016.

[19] Francisco Javier Ordóñez and Daniel Roggen. Deep convolutional and lstm recurrent neural networks for multimodal wearable activity recognition. *Sensors*, 16(1):115, 2016.

[20] Manar Amayri, Abhay Arora, Stephane Ploix, Sanghamitra Bandhyopadyay, Quoc-Dung Ngo, and Venkata Ramana Badarla. Estimating occupancy in heterogeneous sensor environment. *Energy and Buildings*, 129:46–58, 2016.

[21] Manar Amayri, Stephane Ploix, Nizar Bouguila, and Frederic Wurtz. Estimating occupancy using interactive learning with a sensor environment: Real-time experiments. *IEEE Access*, 7:53932–53944, 2019.

[22] Manar Amayri, Stephane Ploix, Nizar Bouguila, and Frederic Wurtz. Database quality assessment for interactive learning: application to occupancy estimation. *Energy and Buildings*, 209:109578, 2020.