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Towards Context-aware Power Forecasting in Smart-homes

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Abstract

Forecasting future power consumption in residential buildings is important to optimize the power grid, to assist inhabitants in everyday activities, and to save energy. Several machine learning methods have been proposed to predict future electricity consumption in smart homes based on the history of past consumption data acquired from smart meters. However, the increasing availability of smart home sensors can provide insights about the routines and activities of inhabitants, that may be exploited to provide more accurate predictions. In this paper, we propose a machine learning approach to forecast future energy consumption considering not only past consumption data, but also context data such as inhabitants' actions and activities, use of household appliances, interaction with furniture and doors, and environmental data. We performed an experimental evaluation with real-world data acquired in an instrumented environment from a large set of users. The results of a comparison with two baseline methods show that our approach is promising.

Keywords: Power forecasting; Smart homes; Artificial intelligence;

1. Introduction

In recent years, there has been increasing interest in forecasting electricity consumption in residential buildings [1, 5, 10]. Indeed, homes are a major source of energy consumption, especially in urban areas. Forecasting energy consumption in buildings may thus help improving the smart grid, reducing costs and emissions. Energy forecasting is also useful to support human activities in ambient intelligence systems [12].

Several machine learning models have been proposed in the literature to forecast electricity consumption in smart homes. A review of the main artificial intelligence techniques applied to the problem of electrical forecasting in buildings is proposed in [1]. Ahmad et al. describe in detail the performance of Artificial Neural Network and Support Vector Machines, comparing them with classical models such as ARIMA. Similar work has been done by Camara et al. [5], who use two approaches to forecast residential energy consumption. Specifically, they compare predictive performances of Seasonal ARIMA model with Artificial Neural Network, based on historical energy consumption. Mo-

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canu et al. [16] compare three machine learning techniques for time series prediction of energy consumption. Namely, they compare the Conditional Restricted Boltzman Machine (CRBM) with both Artificial Neural Networks and Hidden Markov Models. Their work focuses on CRBM for energy forecasting, using load profiles on measured data. Other researchers applied deep learning techniques to forecast energy consumption. In their work, Dey et al. [10] provide a comparison between classical time-series forecasting algorithms and a Group Method Data Handling (GMDH) neural network. In that work, the objective was twofold: forecasting energy consumption, and gaining insights about the behaviour and lifestyles of users. Bhatt et al. [3] trained a Convolutional Recurrent Neural Network to find an energy consumption prediction model under different climatic conditions.

Most existing energy forecasting methods rely only on the history of power consumption data, sometimes extended with external data such as temporal information and weather forecasts [9]. A few studies investigated the use of heterogeneous sensor data to improve energy forecasting in smart buildings [21]. Ziekov et al. use wireless sensors, called ZeeBee, to record the electricity consumption in each socket in the smart home. They then apply the collected data to their forecasting methods. One example is the work of Barbato et al. [2], in which a system for predicting the usage states of household appliances is proposed. Dobbe et al. [11] used Bayesian estimation for identifying the optimal number of sensors for the energy forecasting task. Namely, they provide simulation results considering two types of sensors: magnitude sensors and PMUs. Their employment leads to the collection of the voltage magnitude and angle values. In [19], Truong et al. proposed an algorithm to predict users daily habits and the interdependency of used devices employing the Gibbs sampling procedure. For example, the probability of using a single household appliance during an entire day is used to predict future consumption.

The limitations of the sensors described so far may be related to the fact that they all involve previous electricity consumption. In our work, the sensors used are independent of any energy consumption.

We believe that the increasing availability of sensors in smart homes could provide a valuable data source for improving the forecast of power consumption. In particular, energy consumption is strongly influenced by human activities and other contextual conditions. Hence, heterogeneous context data, including the observation and forecast of human activities, may increase the precision of future energy prediction systems. As a first contribution in this direction, we present a multilayer energy forecasting system that includes context data and activities in the forecasting process. Our system acquires raw sensor data from the smart home infrastructure. It adopts complex reasoning algorithms to recognize actions, activities, and tasks from raw data, and a feature extraction algorithm to build feature vectors using a sliding window. A collaborative learning approach is used to anonymously share context-aware energy data. Those data are used for training machine learning algorithms, including classifiers and regressors, to solve different energy prediction tasks. We implemented a prototype of our system, and performed experiments with a large set of real-world data. The experimental results show that our method clearly improves two baseline algorithms.

The rest of the paper is structured as follows. Section 2 illustrates the architecture of our system. Section 3 explains the methods for feature extraction and power load forecasting. Section 4 presents our experimental evaluation and the achieved results. Section 5 concludes the paper.

2. System overview

Figure 1 illustrates an overview of our system. The smart home is instrumented with various sensors to collect data about the inhabitant activities and the environmental conditions. Sensors include position sensors to detect movement of people in the home, and other sensors to detect the interaction with instruments, doors, and items. The infrastructure also includes one power meter that periodically detects instantaneous electricity consumption at the apartment level.

All raw data produced by those sensors are communicated to a ‘semantic integration’ software layer, which is in charge of assigning a semantics to the data according to a sensor vocabulary. That layer relies on a position table, storing the relative position of each sensor in the home, to determine the position of inhabitants based on fired sensors. Raw sensor data preprocessed by the semantic integration layer are called ‘sensor event records’.

A module for activity segmentation and recognition processes the stream of sensor event records for recognizing the activities that are occurring in the home, as well as the actions that compose those activities. That module includes algorithms to segment the activities and identify their start and end time. Indeed, several research efforts have been spent in the last two decades to devise algorithms for activity recognition and segmentation based on sensor data. Different effective solutions to this problem have been proposed, which adopt data-driven [20, 13], knowledge-

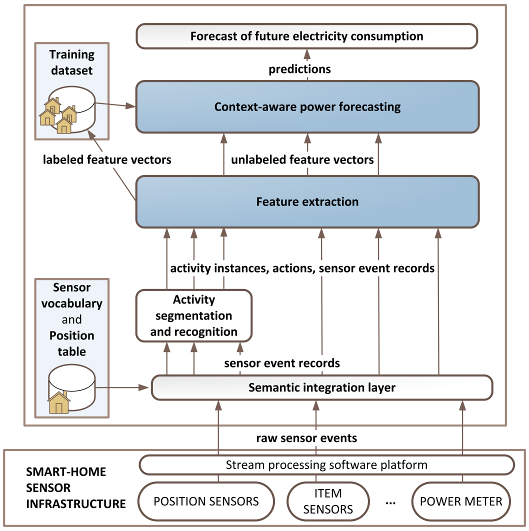


Fig. 1: System overview.

driven [17, 15], or hybrid methods [7, 18]. Since the goal of this work is power forecasting, in this paper we assume the existence of an effective module for action/activity segmentation and recognition, but we do not make any assumption about the actual implementation of that module.

Recognized activities, actions, and sensor event records, including power meter readings, are sent to the module for 'feature extraction', presented in Section 3.1. The latter is in charge of extracting statistical features from the data using a fixed-size sliding window. A feature vector is computed for each window.

Feature vectors are communicated to the 'context-aware power forecasting' module, presented in Section 3.2. That module is in charge of providing a forecast of future electricity consumption in the smart home. To this aim, the module uses a supervised machine learning algorithm trained on an anonymous dataset acquired in different smart homes.

3. Methods

In this section, we present our methods for feature extraction and power load forecasting in smart homes.

3.1. Feature extraction

For each sliding window of x minutes, the module for feature extraction computes the following features:

- Time: the time of the day at the beginning of the window, computed as the number of minutes passed after midnight;
- Temperature: the average temperature registered by a given environmental sensor;
- Activity: for each recognized activity, the number of minutes of that activity execution;
- Presence: for each presence sensor, the number of activations during the window, which is the number of times the sensor has recorded an activity;
- Door: for each door sensor, the number of its activations;
- Action and Task: for each recognized action or task, the number of its executions;
- Trend: the trend of power consumption, computed through linear curve fitting;
- Previous consumption: average electricity consumption during the previous time window;
- Current consumption: average electricity consumption during the current time window.

In addition, the module computes a further value, named 'Future consumption'; i.e., the average power consumption in the following time window. Of course, that value can be computed only with a delay. Feature vectors with future consumption information are communicated to the Training dataset database in anonymous form to enlarge the training set.

3.2. Power forecasting

The power forecasting module adopts a classical machine learning approach to predict future electricity consumption. Indeed, it uses a dataset of feature vectors, computed as explained in Section 3.1 and labeled with the 'Future consumption' value, to train a machine learning algorithm. At run-time, the module uses the trained model to predict future consumption considering unlabeled feature vectors received from the 'feature extraction' module.

The module supports the following kinds of prediction tasks.

- Exact power consumption: in this task, the goal is to predict the average electricity consumption during the next time window. For this task, the module uses a regression machine learning algorithm. More precisely, the module uses the Random Forest technique, an ensemble learning method that combines many decision trees via bagging [4]. It was decided to use 100 trees and 100 predictors for each split, which is the best performing configuration for this model.
- Power change: in this task, the goal is to predict whether the average electricity consumption during the next time window will be larger or smaller with respect to the current one. Being a binary classification task, in this case the module uses a Logistic Regression classifier, namely a logistic regression model with ridge estimator [6].

All experiments were performed using WEKA software.

The prediction of energy consumption in both regression and classification cases would be valuable information in a real world scenario. In fact, it would make it possible to optimise the load of electricity fed into the grid, thus preventing waste and pollution.

4. Experimental evaluation

In this section, we report our experimental evaluation and the achieved results.

4.1. Dataset and experimental setup

We performed our experiments using a dataset acquired and labeled by researchers of the Center for Advanced Studies in Adaptive Systems[1] (CASAS) of Washington State University. The data were acquired from smart home sensors while different categories of people, including persons with cognitive diseases, were carrying out everyday tasks [8]. Since we do not target persons with cognitive disabilities, in our experiments we used only the data acquired from cognitively healthy subjects. Totally, we acquired data from 305 subjects, each performing activities in the smart home for approximately 4 hours. The CASAS smart home is a two-story apartment. The first floor of the apartment consist of a kitchen, living room and a dining area, while bathroom and two bedrooms are located at the second floor. The smart home is equipped with several passive infrared (PIR) motion sensors mounted on the ceiling to track the user's position. It is instrumented with several sensors, including item sensors to detecting the usage of selected kitchen tools, door sensors, burner sensors, hot and cold water sensors, temperature sensors. It also includes a whole-apartment electricity usage meter. In total, the smart-home includes 52 motion sensors, 18 door sensors, 10 item sensors, and one smart meter. The dataset is labeled with the activities, actions and tasks performed by the user.

We have experimented our method using different sizes of the sliding window, ranging from 5 minutes to 150 minutes. For building the feature vectors, we used the raw sensor data and the ground truth annotations of actions,

[1] `http://casas.wsu.edu/`

activities and tasks. We have one feature for time, 5 features for average temperature values in different rooms of the home, 52 features for presence sensors, 18 features for door sensors, 16 features for activities, 13 features for tasks, 12 features for actions, one feature for trend, one feature for previous consumption, and one feature for current consumption.

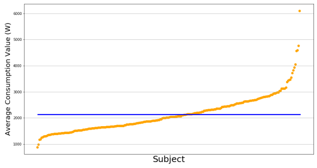


Fig. 2: Average Consumption Values per subject.

We ordered the feature vectors according to the start time of the corresponding sliding window; we used the first half of them as the training set, and the second half as the test set.

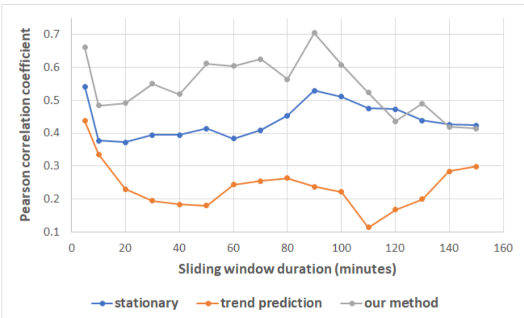
The Figure 2 represents the average energy consumption for each user, the horizontal line in blue indicates the average value of all averages. It seems evident from the graph that the consumption values are distributed rather evenly.

4.2. Results

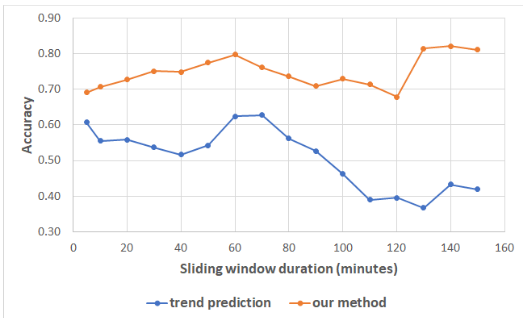
We have compared our method with two baselines. The first one, named 'stationary', assumes that the average power consumption in the next time window is exactly the same of the current one. The second baseline, named 'trend prediction', assumes that power consumption in the home follows a linear trend. Hence, with this baseline, we forecast the average consumption in the next time window based on the linear interpolation of the power consumption readings of the current window. For the sake of this paper, we do not apply feature selection techniques.

The experimental results are shown in Figure 3. The results of the 'Exact power consumption' task, shown in Figure 3a, are expressed in terms of Pearson correlation coefficient [14].With this evaluation metric it was possible to see how well the algorithm estimated the energy consumption trend, not just the exact consumption value. The results show that our method clearly outperforms the baselines with time windows of 100 minutes or less. With longer time windows, the 'stationary' baseline achieves results close to the one of our methods.

The results of the 'Power change' task, shown in Figure 3b, are expressed in terms of accuracy; i.e., the percentage of correctly classified labels. Accuracy is an adequate metric in our case, since classes ('increase' vs 'decrease') are balanced. For this experiment, we did not use the 'stationary' baseline, since it could not predict neither an increase or a decrease of power consumption. Results show that our method clearly outperforms the 'trend prediction' baseline.



(a) Exact power consumption



(b) Power change

Fig. 3: Experimental results

5. Conclusion and future work

In this paper, we have presented a preliminary context-aware system for energy consumption forecasting in smart homes. Our system acquires context data from heterogeneous smart homes sensors. Those data are processed by artificial intelligence algorithms to recognize current activities, actions, and tasks. We collect the raw and inferred data using a sliding window approach, and we extract feature vectors including power consumption information. Those data are shared in anonymous form to train machine learning algorithms, which are used for energy forecasting tasks. An experimental evaluation with real world data shows that our approach is promising.

The current work can be extended and improved in several directions. Feature selection methods could be applied to reduce overfitting and reduce the computational cost of our methods. Activity forecasting methods could be introduced to improve the system accuracy. Experiments with long-term observations in different smart homes, as well as comparison with other approaches, should be performed to better assess the effectiveness of our system.

Acknowledgements

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