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A machine learning-assisted building electricity consumption profiling for anomaly detection

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ABSTRACT

We propose a novel framework to address the problem of detecting anomalies in building electricity consumption profiles. Our method is based on two sequential steps, which combine machine learning clustering and regression methods. The first step separates weekly anomalous consumption profiles from regular ones, for a selected timespan. This is achieved through an unsupervised machine learning clustering method applied on a representation of weekly profiles in a two-dimensional space. The results of the clustering method are used to train a regression model which predicts the future behavior of the time series. Any measured consumption which deviates from the predicted value of the regression model is flagged as anomalous, and this could potentially trigger an alarm in the system. Results are discussed and performances are compared with respect to a simple regression model. Possible applications of this method for real-time anomaly detection are briefly discussed.

Keywords: Anomaly Detection, Unsupervised Machine Learning, Buildings Electricity Consumption, Time Series

NOMENCLATURE

Abbreviations	
ARMA	Auto-Regressive-Moving-Average
LSTM	Long Short-Term Memory algorithm
RF	Random Forest algorithm

Symbols	
t	Time step of a time series
t-n	*n-th* past time step of a time series
t+1	Future time step of a time series
E(t)	Value of the electricity consumed at the time step t

1. INTRODUCTION

Anomaly detection problems are common in many practical applications, ranging from identifying bank frauds, medical records or fake news. In this work we focused on anomaly detection in electricity consumption time series of supermarkets. The goal is to identify measured values which deviate from what can be considered as a typical consumption pattern. The main difficulty in addressing such a problem is the lack of any labels defining typical and anomalous consumption patterns. This makes supervised learning tools not directly exploitable. Other difficulties might arise from the heterogeneity of the data across different buildings and the non-stationarity of energy consumption patterns. Being anomaly detection a broad topic, several attempts exist in the literature. Popular anomaly detection techniques include density-based models (like *k*-nearest neighbours and isolation forests) [1], one-class support vector machines [2], and neural networks [3]. For what concerns anomaly detection in time series, typical approaches involve the fit of an Auto-Regressive-

Moving-Average (ARMA) model or the training of a Long Short-Term Memory (LSTM) neural network. The optimal parameters of ARMA models can be estimated via Box-Jenkins method [4], but this type of algorithm requires an ad hoc case-by-case tuning, thus preventing to build a general model, applicable to any pattern. Similarly, LSTM algorithms suffer from the necessity of a training set which does not contain anomalies, and thus not blindly applicable to the recorded timeseries.

Inspired by the interactive labelling approach proposed in [5], we present a machine learning-assisted workflow to detect anomalies in electricity consumption time series. We showed as a linear regression model (Section 2.1) trained to predict the value at a certain time step, learning from past lags, cannot be used to generalize the detection. In fact, if an anomaly occurs in the past, this information would bias the prediction of future values. We circumvent the problem by using a pipeline which first separates anomalies at week granularity ('normal' weeks versus 'anomalous' ones), by means of an unsupervised clustering method (Section 2.2) and then identifies point-wise anomalies in time after training a regression model (Section 2.3) only on weekly patterns classified as 'normal' during the previous step.

2. DATA AND METHODS

The original dataset contains time series of water, electricity and heating consumption of supermarkets and small shops located in Switzerland. The measurements, taken at intervals of 15 minutes for a total of 68555 time-steps between January 2018 and November 2019, are made available by OPIT Solutions AG. We focused on the electricity consumption patterns of buildings, retaining only those time series with a mean value of consumed electricity over the year larger than 10 kWh/m^2, thus excluding small stores. This resulted in the selection of 105 different buildings and of their corresponding consumption patterns. In this paper, We choose a single building to evaluate and display the performance of the proposed model. Since its name and location cannot be disclosed, we referred to it generically as *Building 2*.

2.1 Baseline model

The underlying objective is to forecast the value of consumption at a future time step and then to flag any deviation from the measured values as an anomaly. As baseline, a simple linear regression model is used. Our data follow an underlying periodic weekly pattern. Two kinds of features are explored: numerical, in the form of values of the electricity consumption at the *t-n* time steps of the preceding weeks (*lags*) and categorical, represented by the day of the week, the month of the year, and a binary value to distinguish between working days and holidays. The target *E(t)* of the regression model is the electricity consumption value measured at a certain time step *t*. Once trained, the model predicts the value E(t+1).

Subsequently, in order to flag an anomaly, a threshold on the absolute residual between the predicted and measured value at each time step is defined: if the residual exceeds this threshold then the measurement is detected as anomalous. Such threshold is derived in a deterministic way for each building, setting it to 20% of the 90th percentile of the measured values.

2.2 Clustering

For the first step of our pipeline, we used a similar approach to [6]. We map weekly profiles into points in a two-dimensional space. The idea behind is that points exhibiting a typical consumption pattern will form dense clusters in such space while points representing anomalous weekly patterns will lie outside the detected clusters. In order to map the weekly patterns into the two-dimensional space we proceed as follow. We measure the distance between two weekly profiles of electricity consumption along the year using the Euclidean norm (or *l2*-norm) between the frequency spectrum of two time series. We consider the magnitude of the spectrum only, as this already contains all the necessary information to characterize the time series. A squared matrix *M* contains information on the *l2*-norm distances between magnitudes of each *i*-th weeks' spectrum (Y_i), such that $M_{ij} = |Y_i - Y_j|^2$. We applied Singular Vector Decomposition (SVD) and Principal Component Analysis (PCA) on the elements of M, to reduce the number of features needed to characterize each week. We found that two features are enough to explain 80% of the total variance. The density-based clustering algorithm DBSCAN [7] is then used to group points (weeks) in the two-dimensional features plane. Two parameters characterize this algorithm: minimum number of points in a cluster (MinP) and maximum distance for two points to be considered as neighbours (ε). We performed a grid search with the goal of tuning these two parameters. The best values of the model parameters were found to be MinP=9 and $\varepsilon=0.012 \cdot S1$, where $S1$=2867.5 is the first singular value of *M*.

2.3 Features selection and regression model

In order to prevent the model from learning from anomalous weeks we need a training set as regular as possible. Weekly profiles detected as regular during the previous step are averaged by extracting the mean at each time step and a reference timeseries is created to be used in the training. In such timeseries, point-wise anomalies can still be present. However, since we excluded from the previous step weeks containing systematic anomalies, the remaining ones exhibit an underlying regular pattern.

For predicting the time series behaviour at the time step t+1, we train a linear regression model on the past lags of this reference timeseries. In order to maximize the performance of a regression model, it is a known practice to first select the relevant set of features, and to tune the hyper-parameters of the model. A peculiarity of the Random Forest algorithm (RF) [8] is to rank input features by their importance in predicting the target. We used RF to select the most relevant features for the task among those mentioned in Section 2.1. The RF builds *N* independent regression trees, splitting the data at each node. The features considered to perform each splitting are a random subset of the total number of features. The results obtained for the *N* trees are then averaged to provide a model output. At the growth of *N*, the performance improves. However, the convergence rate was shown to saturate quite fast [9] and thus we fixed the number of trees to N=200. The optimal maximum number of features to be used at each splitting has an optimal value which lies between 11 and 15, given by the empirical formula *P/3* suggested in [10], where P=39 is the number of total features. We rank the importance of each feature as provided by the algorithm, deciding to retain only those features whose score was higher than $5 \cdot 10^{-4}$. They are listed in Table 1.

Table 1. List of retained features from the RF feature importance

Feature name	Type	Value
Electricity consumption at previous *n*-th lag	numerical	E(t-671),E(t-672),E(t-673), E(t-1343), E(t-1344), E(t-1345), E(t-2015),E(t-2016), E(t-2017),E(t-2687), E(t-2688)
Month of the year	categorical	[1-12]
Day of the week	categorical	[1-7]
Holiday	binary	{1,0}

Features extracted from the reference time series in output from the step described in Section 2.3 are used to train a linear regression model which predicts electricity consumption at t+1.

3. RESULTS AND DISCUSSION

The results obtained by applying the baseline model described in Section 2.1 are shown in the upper part of Figure 3. The figure shows that the model is not predicting well the series behaviour. As expected, the model predictions are far from the real measured value also in time steps which do not exhibit an apparent anomalous behaviour. The predictions are not accurate for two main reasons: (i) weeks with unexpected closure days blow up the forecasting accuracy for the following week; (ii) day-wise anomalies in time (spikes or drops) are 'learnt' by the model, thus biasing the forecasting.

Figure 1 shows the outcome of the first step of our

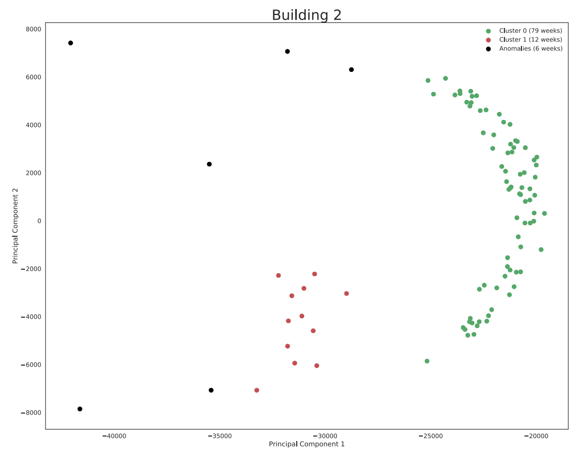
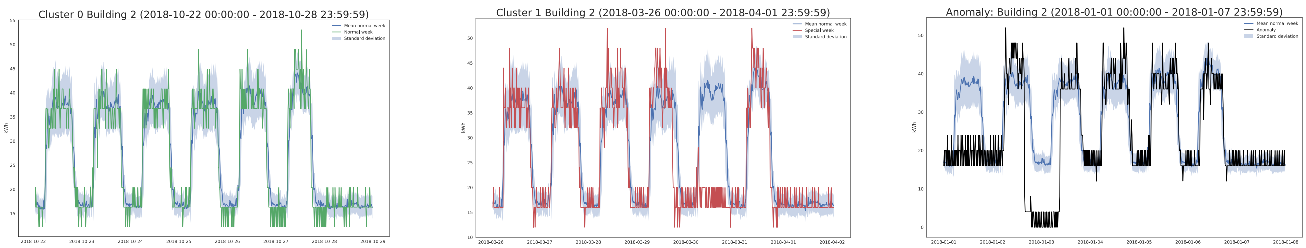


Fig 1. Result of the unsupervised clustering algorithm in classifying the weekly electricity consumption patterns. In green the weeks with a standard trend, in red weeks with a special trend and in black weeks which are not classified in none of the previous and thus considered as anomalous ones.

pipeline (unsupervised clustering) described in Section 2.2 for Building 2. Noticeably, there is a visual separation between points representing non-conventional weekly patterns and standard ones in the two-dimensional space (the two coordinates are the features resulting from PCA). Interestingly, the algorithm localizes a third group of weeks which do not belong neither to the standard nor to the group of outliers. Figure 2 shows three weeks extracted from each cluster, superimposed to the average of the standard weeks for Building 2. The non-standard week is likely a week where an infra-week closure day has been observed by the shop, whereas the anomalous one shows a clear drop in the consumed electricity during the night between the second and third day. To validate the results of the clustering method, we ask the energy managers of Building 2 to manually identify ten anomalous weeks according to their experience and criteria. As a result, the algorithm is able

Fig 2. Three examples of weeks (green = standard, red = non-standard, black = anomalous) superimposed to an average standard week (blue) resulting from the mean over the standard weeks at each time step and its standard deviation.



to classify eight of them in as outliers (anomalies, black), while the other two are classified in the non-standard cluster (red). The lower part of Figure 3 shows the result of a linear regression model trained on the normal weeks in output from the clustering step. The value E(t) is predicted for each time step of two weeks, and the corresponding measurement of the time series is

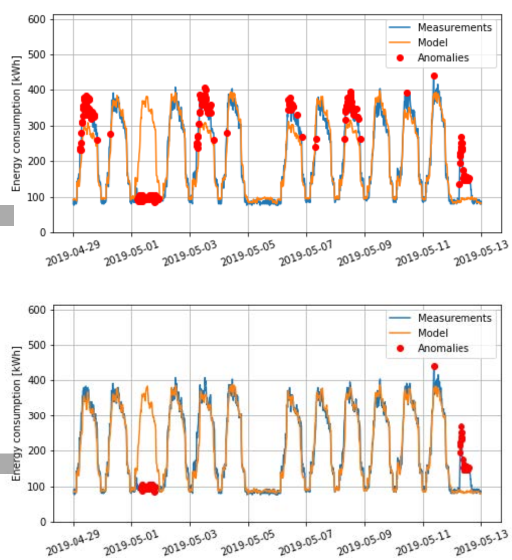


Fig 3. Upper: results of the baseline model. Lower: results of the linear regression algorithm trained after the clustering of normal weeks. The forecasting is shown in orange, the actual values of the time series in blue, and the anomalies detected are highlighted in red.

labelled as anomalous if it differs from the prediction.

The thresholds to define a point-like anomaly are quantified in multiple ways. For the initial and final part of working days, which exhibit the steepest slopes, a fixed threshold is applied, to avoid triggering of false anomalies. For the central part of the working days, corresponding to the supermarket opening hours, a building-dependent threshold is used. The threshold is computed as 2σ, where σ is obtained through the standard deviation of the working hours' electricity consumption. Out of nearly 70 hourly anomalies identified by the baseline approach in the two weeks shown in Figure 3, only 25 are flagged as such as a result of the pipeline.

4. CONCLUSION

A qualitative check of the result obtained for all the buildings reveals that a two-step approach made of unsupervised clustering-based categorization of weeks and a subsequent regression model with a feedback mechanism that exploits the regularity of standard weeks is able to successfully identify anomalies in building electricity consumption time series. The highlighted qualities of this approach make it applicable to the interesting challenge of real-time anomaly detection. Once the model is trained for a specific building, it can be used to forecast the expected value of energy consumption at the next 15 minutes. In this way, as soon as the real measurement becomes available, real-time anomaly classifications are possible. The wall clock time for each prediction is few milliseconds. This makes the method suitable for data sampled at much higher frequency. The model does not need to be retrained, unless the underlying weekly pattern starts to considerably deviate from the one learnt in the training.

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