Non-Intrusive Load Monitoring Using Prior Models of Appliance Usage

12752 Project Proposal

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1 Introduction

Non-intrusive load monitoring (NILM) is aimed to estimate the electricity consumption of each appliance from the aggregate consumption, without installing any additional sensors. [1] Because of the rapid growth in smart meter deployments all over the world—which provides an ideal platform for collecting electricity consumption data and communicating with consumers [2, 3]—we can expect NILM will be of great importance in the future for the management of the power system. [2]

Many approaches have been proposed to solve the NILM problem. Even though the methods of those solutions are very different from each other, most of them relies heavily on the power load data to train the model. For example, Parson et al. used the aggregated power load data to learn the transition matrix and the emission matrix for each appliance in the setting of a hidden markov model; [3] Hart et al. used a model to detect and attribute the significant changes in the power load. [1] However, given the rise of *smart cities*, we could have a lot more information that can help us to build a better model. For example, we may use the income information of a person to predict the number of appliances and the types of those appliances he/she has and tweak our model with that; we may use the traffic flow data to predict the time that a person will return back home and start using appliances. Thus, for this project, we would like to explore the feasibility of building a NILM solution with *not only the power load and the data for the power system, but also the ambient information and the information of the residents.*

2 Data

The data set we are going to use is the Dutch Residential Energy Dataset (DRED). [4] The data set contains the appliance level consumption data, the ambient information (indoor and outdoor temperatures, wind speed, humidity and precipitation) and the room-level occupancy information of one household. We will split the data set into a training set and a test set because we could not find a similar data set from another household.

3 Methods

We will use the hidden markov model to decode the states of appliances. First, for each appliance we will build models for estimating the transition probabilities from one state to another state and the emission probabilities of the power consumption of one state, with the temperature, occupancy and time features. We plan to use a softmax regression model for this. Then, we will apply iterative Viterbi algorithm to find the most likely state chain for each appliance, which is the same as the method proposed by Parson et al. [3]

4 Expected Results

We expect to have a method for NILM based on HMM but with information from various sources. With this method, the HMM model can be *built* efficiently and accurately for each household based on the data other than the power load.

References

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