Machine Learning Engineer Nanodegree

Capstone Proposal

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A. Domain Background

Up to 60% of the world's electricity consumption is contributed by both residential and commercial buildings according to the United Nations Environment Programmes Sustainable Building and Climate Initiative (UNEP-SBCI). However, the conventional energy monitoring only captures the aggregate of all the electrical loads in a building. An accurate and real-time monitoring of the appliance-level consumptions offers actionable feedback and insight into effective energy saving behaviour, significantly stimulating the reduction of the overall energy demand. The current approach deploys sensors that monitor the individual appliance consumption in buildings. This approach is both cumbersome and costly among other limitations and has therefore, together with the introduction of smart energy meters, led to the consideration of energy disaggregation techniques.

Energy disaggregation (also known as nonintrusive load monitoring or NILM) is a computational technique that breaks down the single point source data, recognizes the load appliances running in a building, and estimates their individual power consumption. Simply, NILM takes a building energy signal from a single monitoring point and separates it into its component appliances. George W. Hart started the research into residential energy disaggregation at MIT in the 1980s, proposing the first NILM event-based approach using the state transition edges (corresponding to on/off events) in appliances power signals to cluster them. Several NILM methods have been proposed which include combinatorial optimisation (CO), factorial hidden Markov models (FHMM), non-negative matrix factorization (NMF), and Deep Neural Networks. In addition, recent approaches have explored different features and hyper-features of the alternating current waveforms and used complex device models with multiple states.

B. Problem Statement

The increasing need for energy saving, as well as the accelerating computing power and the advancement in machine learning, has led to the popularity in research on NILM using machine learning techniques. However the promising value of energy disaggregation and the popularity of this field, none of the approaches have proven to successfully solve the real-life disaggregation problem; there is no precise, reliable and general method that can practically be deployed in a household, hence, the need for performance improvements in the algorithms. While it may be too ambitious to develop a new algorithm that solves this problem in this project, exploring and comparing the performance of the NILM algorithms by changing the pre-processing (such as sample rate, normalization using voltage, and using reactive power) and fine-tuning the hyper-parameters, seeking to get better performance for practical solution proves to be worthwhile.

C. Datasets and Inputs

This project will use the Reference Energy Disaggregation Data Set (REDD) (available:http://redd.csail.mit.edu), a publicly available data set containing power usage information for several homes. This reference dataset is aimed to be the benchmark data set to energy and sustainability domain such as the MNIST digit recognition in machine vision domain, specifically targeting the task of energy disaggregation.

REDD contains measurements of both whole-home and appliance-level electricity consumptions of some real houses over a period of several months. Each house measurements include the whole-home electricity signals (both current and voltage) recorded at a high frequency of 15 kHz; 24 individual appliances signals at 0.5 Hz, each labeled with its category; and 20 plug-level measurements recorded at 1 Hz, to cater for appliances that are grouped and powered from the same wall socket outlet. Overall, there are 10 monitored homes and total of 119 days of data (across the homes).

D. Solution Statement

This project aims at contributing to the search of practical NILM techniques by investigating the effects of data set pre-processing and hyper-parameters fine-tuning on the performance of the one or more of the benchmark NILM algorithms: combinatorial optimisation, factorial hidden Markov model (FHMM using exact inference), and maximum likelihood estimation.

E. Benchmark Model

In this project, two benchmark disaggregation algorithms implemented in nonintrusive load monitoring tool kit (NILMTK) (available:http://nilmtk.github.io/) are used: an approach based on combinatorial optimisation and an approach based on the factorial hidden Markov model. The NILMTK allows easy empirical comparisons of these two algorithms across different existing data sets or between raw and pre-processed data sets.

F. Evaluation Metrics

For empirical evaluation of NILM algorithms and fair performance comparison between different approaches, it is important to define the evaluation standards. Several metrics are used to evaluate energy disaggregation algorithms. NILMTK offers a suite of evaluation metrics such as accuracy, F_Score, fraction-of-energy-assigned-correctly, mean-normalized-error-power, and rms-error-power.

G. Project Design

This project will extensively use the toolkit, NILMTK, specifically designed for energy disaggregation. This toolkit is similar to the various toolkits for generalized machine learning tasks such as the scikit-learn. NILMTK includes the tools such as data set parsers, benchmark algorithms, and evaluation metrics specific for the energy disaggregation domain. This toolkit does not replace the existing general toolkits rather it extends them, similar to the way scikit-learn adds machine learning functionality to the numpy API for Python. Fig 1.0 highlights the NILMTK pipeline from data sets import to the evaluation of algorithms.

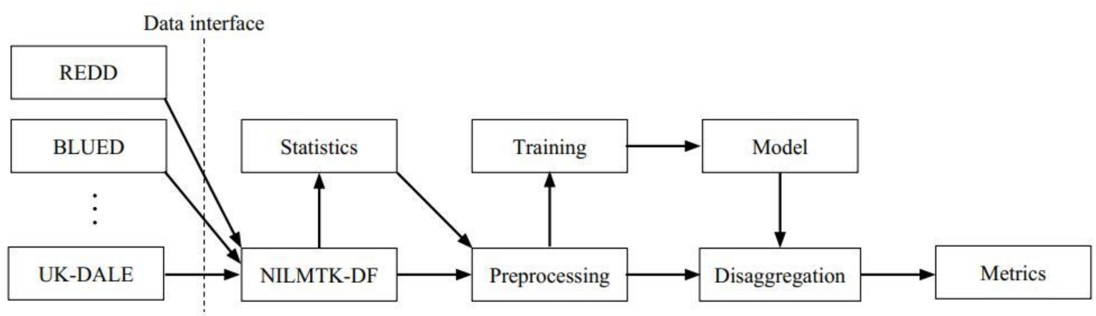

Fig 1.0: NILMTK Pipeline [source: http://nilmtk.github.io]

I. Data set Import and Data Format: The REDD data set is imported and converted into the NILMTK HDF5 format. The data is then saved in this format and loaded from disk into memory for further operations. It is good to note that at multiple stages in the NILMTK processing pipeline, the data can be saved and loaded to allow other tools to interact with NILMTK.

II. Data set statistics: Insights into the data set structure will be explored and the data summary be presented.

III. Pre-processing: This is the focus of this project. It will explore different pre-processing such as changing the sample rates, normalization using voltage, and using reactive power component. This phase of the pipeline will resample the data, filter out erroneous readings, and find gaps in the readings.

IV. Algorithms: The two popular benchmark algorithms will be trained on the vanilla and preprocessed data set. The first is combinatorial optimisation and the second, factorial hidden Markov model (FHMM). This pipeline phase will explore different hyper-parameters tuning for the learning algorithms.

V. Disaggregation/Prediction: In this phase, the trained models will make predictions on both seen and unseen data samples.

VI. Evaluation and metrics: This phase finds the proportion of energy submetered, calculates F1 score etc etc. in each of the algorithms across different preprocessings. These metrics will be compared against the implementations in the benchmark algorithms on the vanilla data set.