Neural network approaches and dataset parser for NILM

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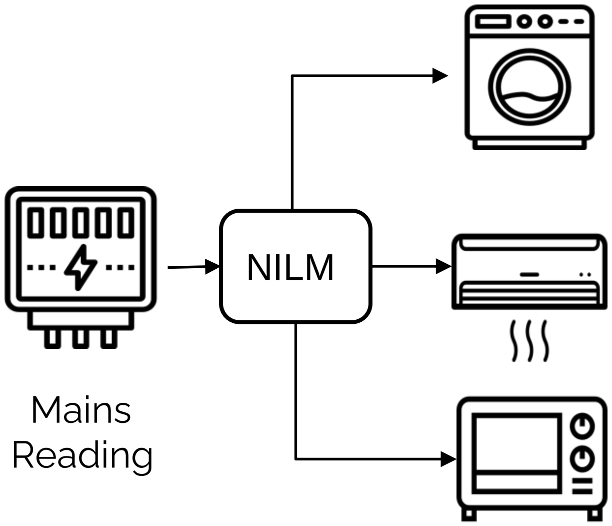
Non Intrusive Load Monitoring (NILM)

- Non-intrusive load monitoring is a task of estimating the power consumption by the appliances given the aggregate power consumption.



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NILM toolkit

- NILM toolkit was created to enable reproducible NILM research.
- Provided baseline NILM algorithms.
- Multiple datasets in common format.

State of the Art in NILM

Towards reproducible state-of-the-art energy disaggregation

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ABSTRACT

Non-intrusive load monitoring (NILM) or energy disaggregation is the task of separating the household energy measured at the aggregate level into constituent appliances. In 2014, the NILM toolkit (NILMTK) was introduced in an effort towards making NILM research reproducible. Despite serving as the reference library for data set parsers and reference benchmark algorithm implementations, few publications presenting algorithmic contributions within the field went on to contribute implementations back to the toolkit. This paper describes two significant contributions to the NILM community in an effort towards reproducible state-of-the-art research: i) a rewrite of the disaggregation API and a new experiment API which lower the barrier to entry for algorithm developers and simplify the definition of algorithm comparison experiments, and ii) the release of NILMTK-contrib; a new repository containing NILMTK-compatible implementations of 3 benchmarks and 9 recent disaggregation algorithms. We have performed an extensive empirical evaluation using a number of publicly available data sets across three important experiment scenarios to showcase the ease of performing reproducible research in NILMTK.

CCS CONCEPTS

• **Computing methodologies → Machine learning algorithms.**

KEYWORDS

energy disaggregation; non-intrusive load monitoring; smart meters

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1 INTRODUCTION

Non-intrusive load monitoring (NILM) or energy disaggregation is the task of separating a building's energy measured at the aggregate level into constituent appliances. The problem was originally studied by Hart in the early 1980s [9] and has seen a renewed interest in recent years owing to the availability of larger data sets, smart meter rollouts, and amidst climate change concerns.

Despite more than three decades of research in the field, three factors primarily affected reproducibility, and therefore empirical comparison of NILM algorithms: i) it was hard to assess generality of NILM approaches as most works were evaluated on a single data set, ii) there was lack of comparison using the same benchmarks due to the lack of availability of open-source benchmark implementations, and iii) different metrics were used based on the use case under consideration. The open source non-intrusive load monitoring toolkit (NILMTK) [3] was released in early 2014 against this background to enable easy comparison of NILM algorithms in a reproducible fashion. The main contributions of the toolkit were: i) NILMTK-DF (data format): the standard energy disaggregation data structure used by NILMTK; ii) parsers for six existing data sets; iii) implementations of two benchmark NILM algorithms; iv) statistical and diagnostic functions for understanding data sets; v) a suite of accuracy metrics across a range of use cases. Later in 2014, NILMTK v0.2 was released [12] which added support for out-of-core computation, motivated by release of very large data sets such as Dataport data set [18].

Since these two releases, NILMTK has become the energy disaggregation field's reference library for data set parsers and reference benchmark algorithm implementations. However, few publications presenting algorithmic contributions within the field went on to contribute implementations back to the toolkit. As a result, new publications generally compare a novel algorithm with a baseline benchmark algorithm instead of the state-of-the-art within the field. Consequently, it is still not possible to compare the performance of state-of-the-art algorithms side-by-side, therefore limiting progress within the field.

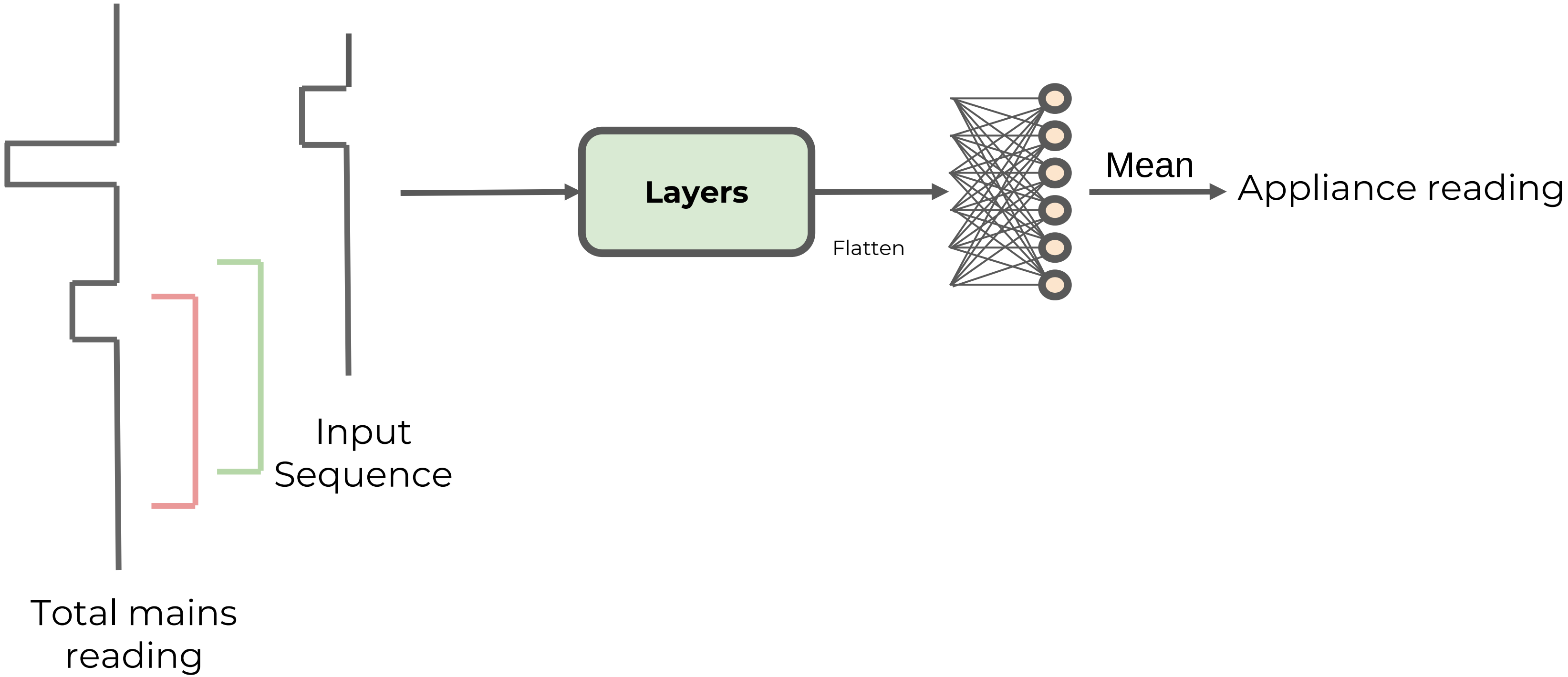
Algorithms	Fridge	Air Conditioner	Electric Furnace	Washing Machine
Mean	63.3±07.7	224.8±16.4	81.5±01.6	5.07±00.8
Edge detection	41.1±18.1	86.8±30.5	30.2±11.2	4.8±01.3
CO	65.7±42.3	98.5±85.7	56.9±55.4	105±19.0
DSC	78.4±56.5	71.5±36.0	39.1±17.9	6.5±05.7
ExactFHMM	66.7±23.5	45.5±44.6	95.3±110.5	59.9±17.5
ApproxFHMM	63.8±08.0	139.9±130.2	**26.5±12.0**	30.7±21.3
FHMM+SAC	59.2 ±05.7	97.0±40.3	35.1±19.0	3.8±00.7
DAE	32.2±11.8	39.3±27.9	29.4±15.3	3.1±01.6
RNN	38.4±07.9	46.6±30.6	33.9±20.6	3.5±01.2
Seq2Seq	28.1±09.5	32.3±25.2	27.9±15.3	**2.3±01.2**
Seq2Point	**23.5±12.1**	**24.8±20.9**	27.5±15.0	2.4±00.9
OnlineGRU	28.8±11.4	25.3±17.1	34.5±15.0	3.0±01.4

Table 1: MAE Mean ± Std. Error: train/test on different set of buildings, same data set

Contributions in the paper

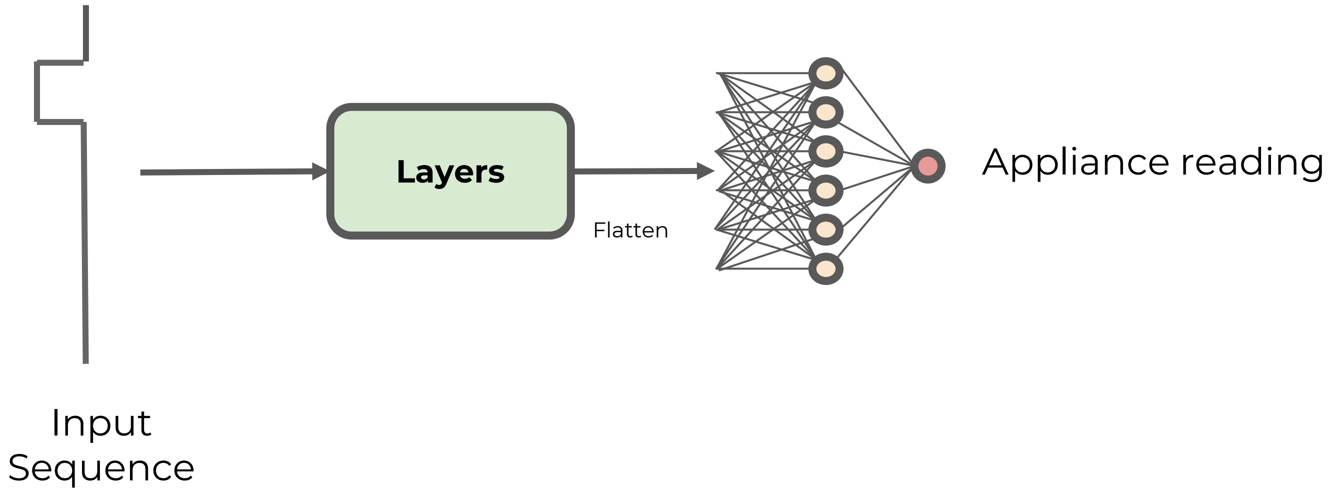
- Implementation of five new neural networks for NILM task.
- Parser for publicly available IDEAL dataset.
- Empirical comparison of five proposed neural networks against state-of-the-art implementations.

Current neural network approaches



SEQ2SEQ MODEL

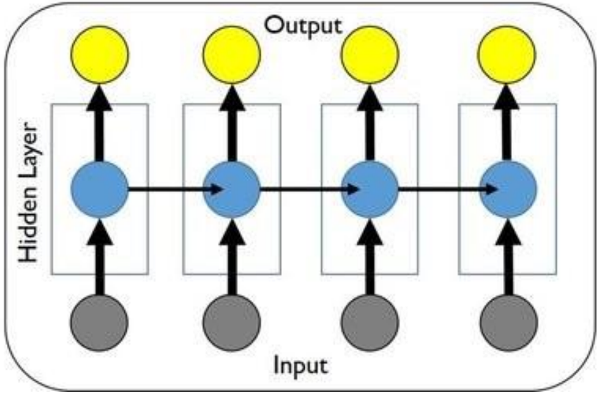
Current neural network approaches



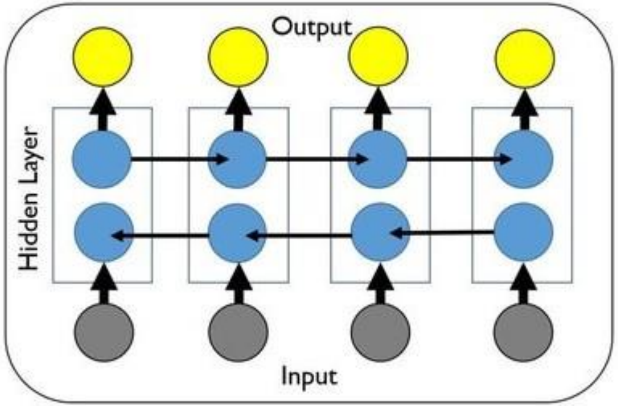
SEQ2POINT MODEL

Bidirectional Long Short-Term Memory (BiLSTM)

- BiLSTM considers the future readings of aggregate data along with past while training and predicting the appliance reading.



LSTM

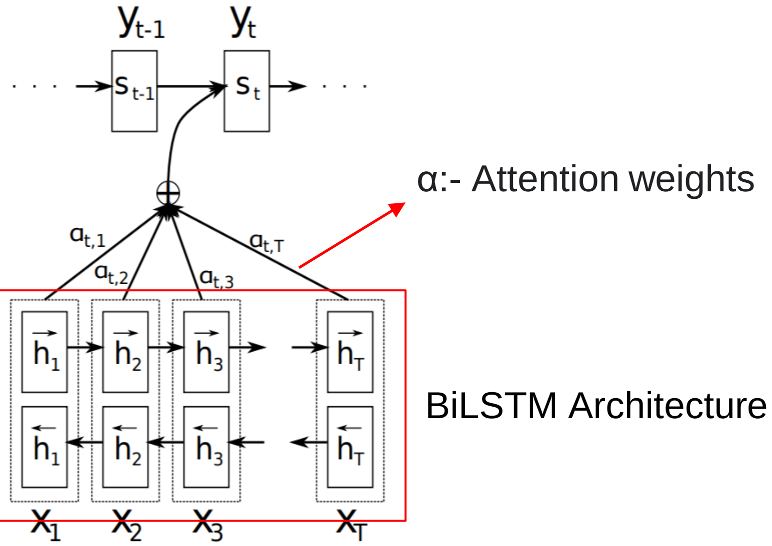


BiLSTM

Image Reference:-https://www.researchgate.net/figure/LSTM-and-BiLSTM-Architectures_fig2_324769532

BiLSTM Model with attention weights

- Attention to each position of the aggregate signal, which can be linked to state-change of the target appliance.



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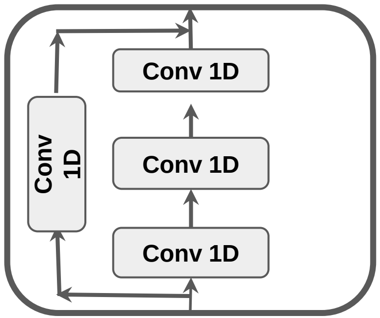
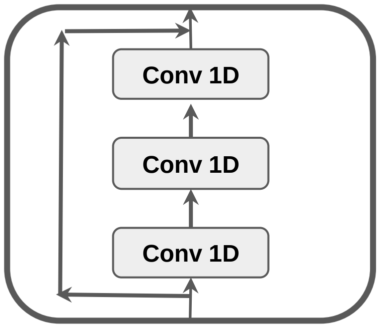
Residual Neural Network (ResNet)

- Skip connections preserve information of previous layer.



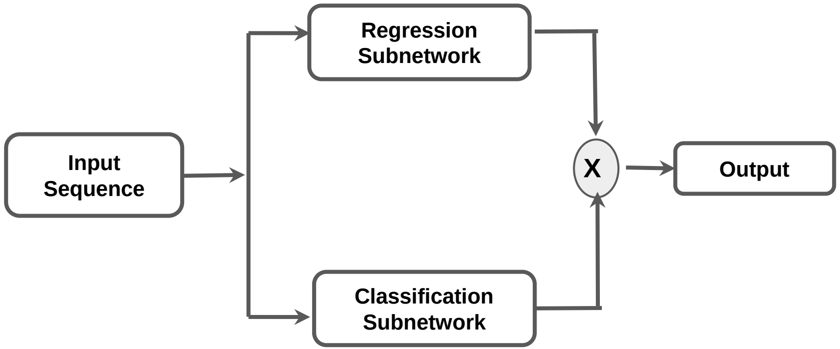
(a). Convolutional Block



(b). Identity Block

Classification Subnetwork

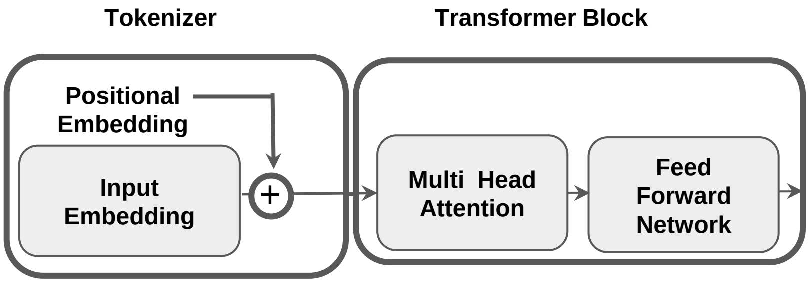
- Considers state of the target appliance along with regression subnetwork while training and testing.



Model with regression subnetwork and classification subnetwork

Bidirectional Encoder Representation from Transformer (BERT)

- BERT adds attention locally to the aggregate reading to understand the context of the current window sequence.



Tokenizer and Transformer block in BERT model

Parser For IDEAL Dataset

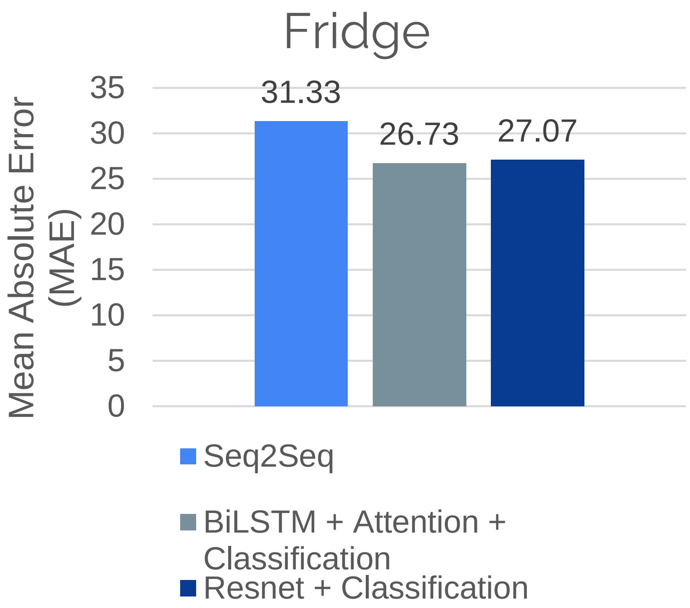
- IDEAL dataset contains data from 255 UK homes and among which 39 homes have appliance data.
- IDEAL dataset is largest publicly available dataset.
- The dataset parser is created using NILM metadata format.
- This dataset parser is contributed to open-source repo NILMtk for simplified usage of NILM toolkit for IDEAL dataset

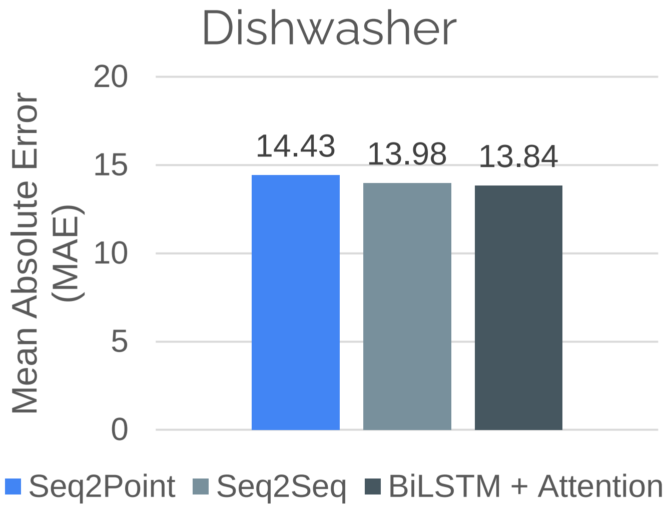
Experimental Settings

- Leave one home out cross validation.

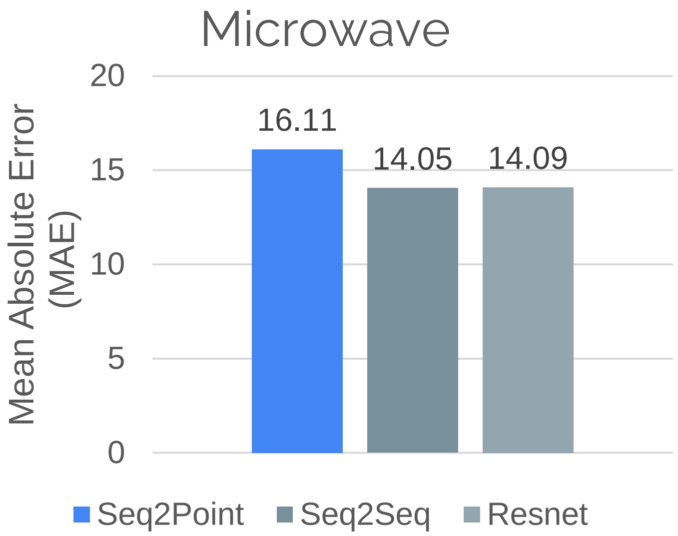
DATASET	REDD	IDEAL
Sequence Length	99	99
Appliances	Fridge, Dish Washer, Microwave, Washer Dryer	Fridge, Washer Machine
Metric	Mean Absolute Error (MAE)	Mean Absolute Error (MAE)

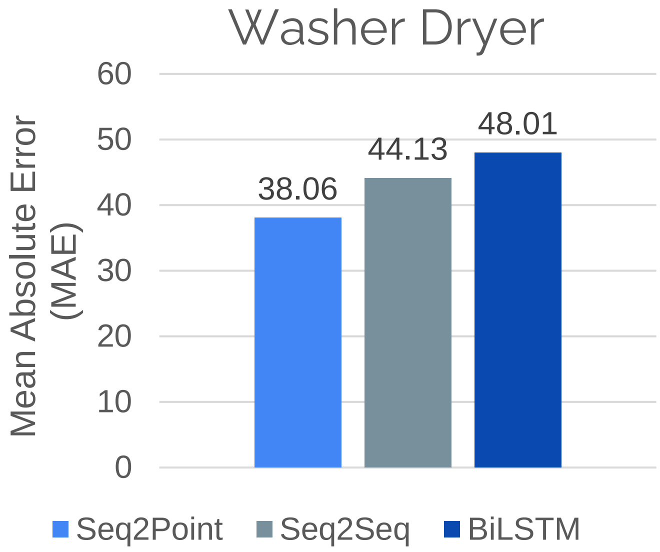
Comparison of algorithms on REDD Dataset



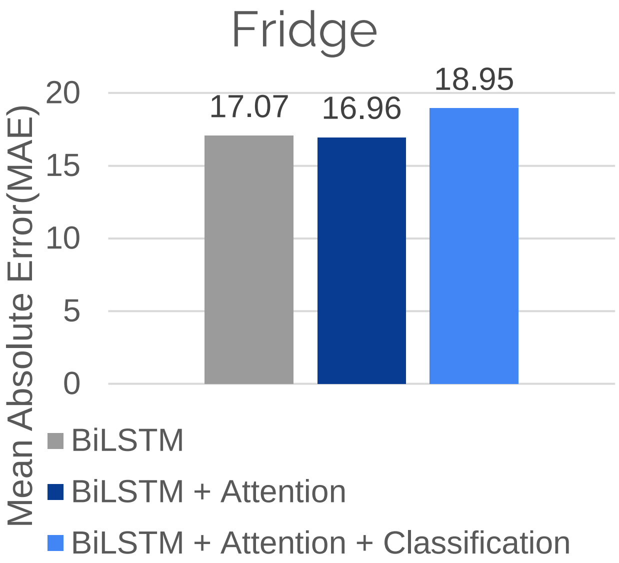


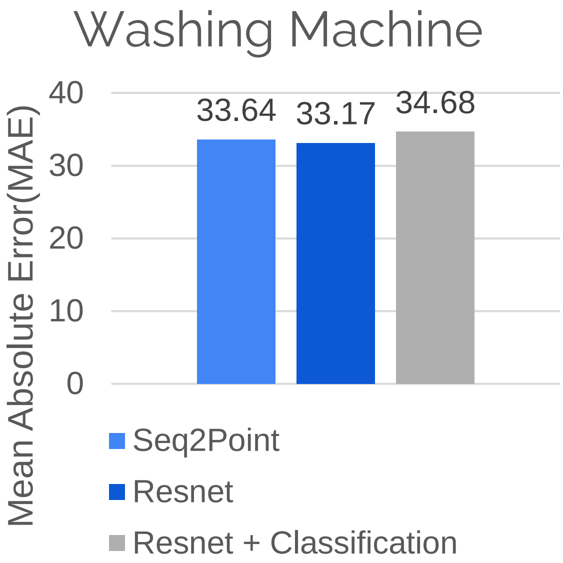
Comparison of algorithms on REDD Dataset





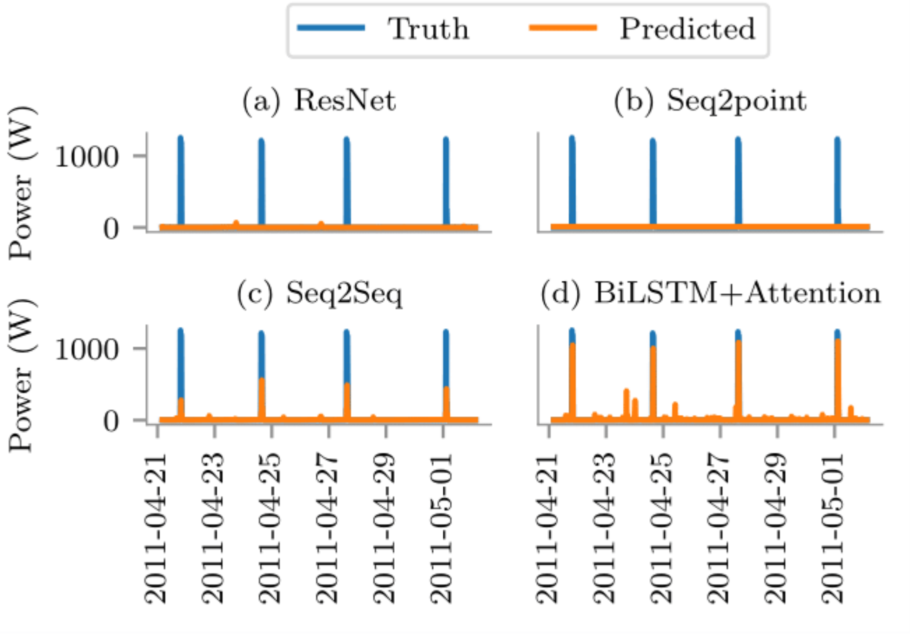
Comparison of algorithms on IDEAL Dataset





Analysis

- BiLSTM predicts accurately in comparison with baselines with some false positives.



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Limitations and Future Work

- Compared newly implemented algorithm on two dataset, we are trying to expand it on more number of datasets across different countries.

- Explanation for better performance of new models.

Summary

- Implemented five new neural network algorithms for NILM task.
- Contributed dataset parser for IDEAL dataset.
- Qualitative and quantitative comparison of newly implemented algorithms with baseline.
- New neural networks performed comparable or better than the state-of-the-art.

Thank You!!

Applying for MS in EECS/CS for Fall 2022

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