Usage Disaggregation of Smart Meter Data of Japanese Commercial Customers Using Machine Learning

August 26th, 2019

16th European Conference Ljubljana

Minao Watanabe, Kenta Ofuji

The University of Aizu

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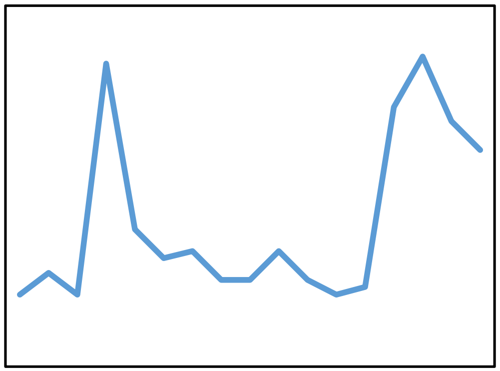
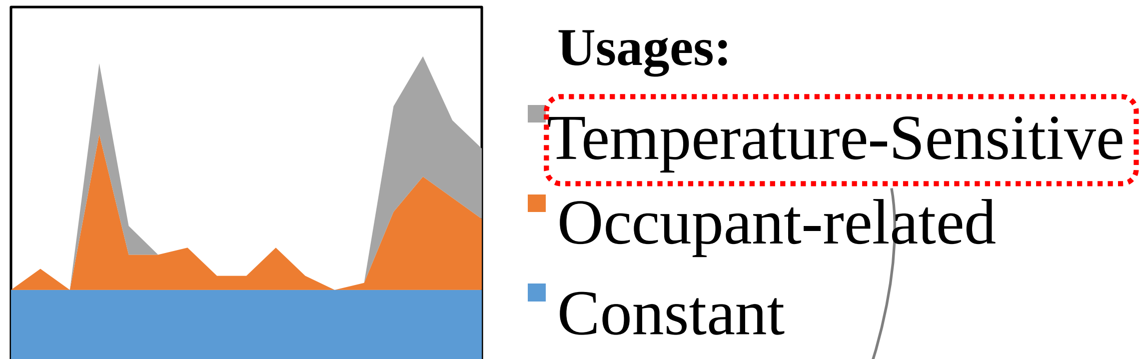
1. Approach and method of “Disaggregation”
2. Evaluation of intra-building by random forest regression
3. Evaluation of across-building by lightGBM

What is Disaggregation for?

- Disaggregate into several usage data from only whole-building smart meter data



Whole-building demand



Disaggregated by usages

Helps understand
- **peak occurrences** and
- **usage composition**

Data

- Japanese commercial buildings smart meter open data
  - Collected under Japanese government-aided energy efficiency projects
  - Covers 16 business types (Restaurants, Hospitals, Schools, ...), approx. **6,000** buildings across Japan
    - ✓ Use only "Supermarket" data
  - 1 hour granularity x 1 year (8,760 hours)
  - Data items:
    - ✓ Business Attributes

      E.g.: Industry, Location, Floor Area, …
    - ✓ **Six distinct usages** + Whole-building demand

- **Air Conditioning**
- **Freezing/Cooling Energy**
- Lighting, Power, ….

Disaggregate by :

- Random Forest regression (RFR)
- lightGBM algorithms

Motivation to disaggregate A/C versus Freezing/Cooling demand

- Both temperature-sensitive but with different underlying equipment
- **Of greatest magnitude** within gross building demand

Temperature-sensitive demand

Air Conditioning	Freezing / Cooling
e.g. Package air conditioning units	e.g. Freezer / Chiller

Forecasting model strategy

Explanatory Variables

Feature Matrix

X

RFR
lightGBM

Target Variable

Demand

y

- **Air Conditioning**
- **Freezing / Cooling**

<u>Feature Values used:</u>

1-1. Whole-building demand

1-2. 1-hour previous value of *y* → Auto Regressive(1) model

2-1. Hour of day (1 - 24)

2-2. Day of the week (Sun. – Sat.)

3. Proxy temperature (of nearby city)

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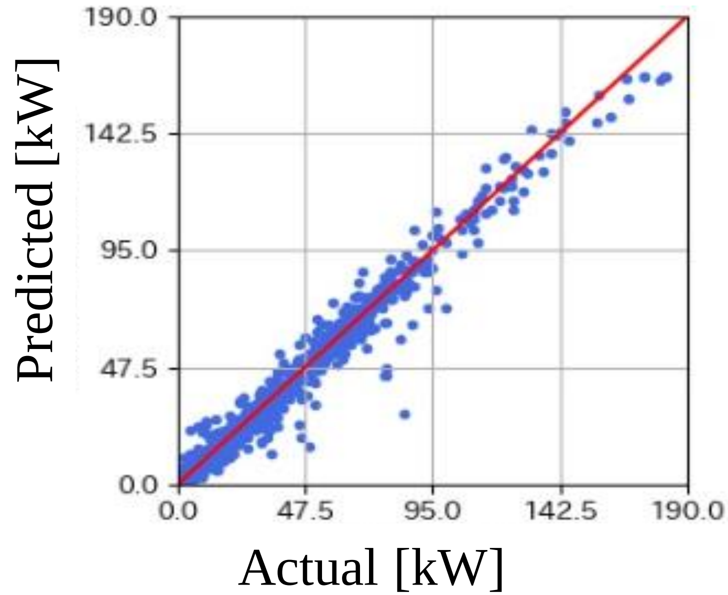
Results for one building : Air Conditioning , using RFR

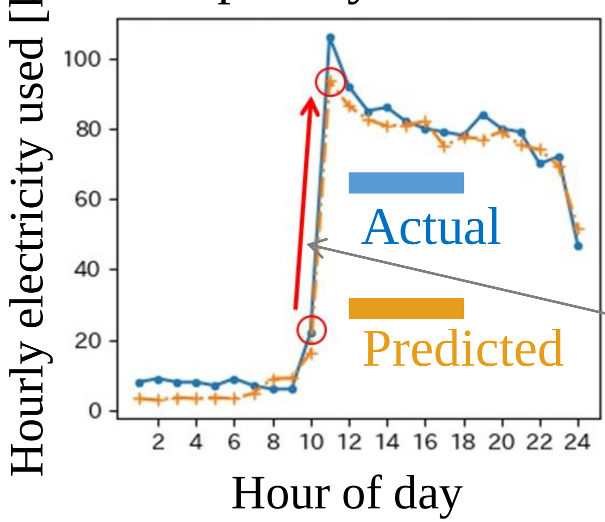
- Target: 30% in a year

  Mean Sq. Errors = 19.7 [%]

  (MSE)



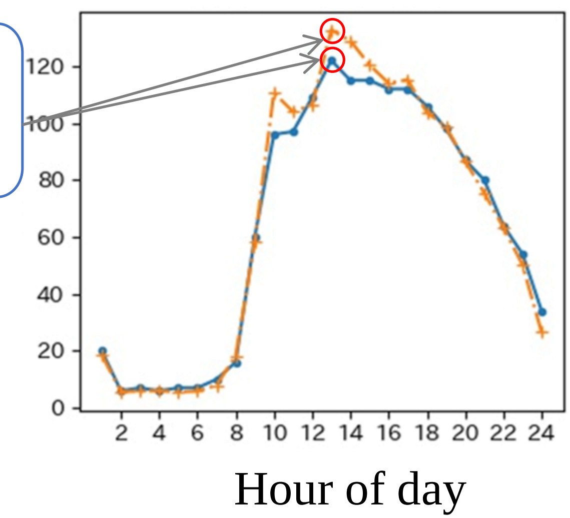
Sample day in **Winter**



Prediction error only10kW in peak hour

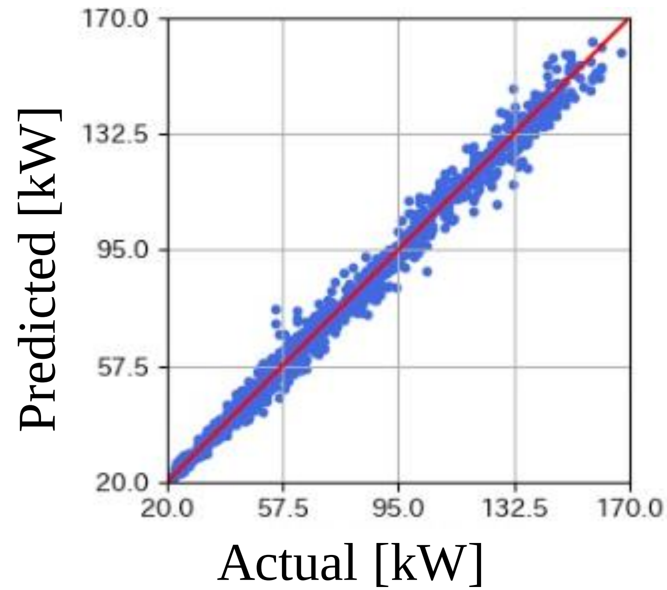
Cannot keep up with **sudden surge**

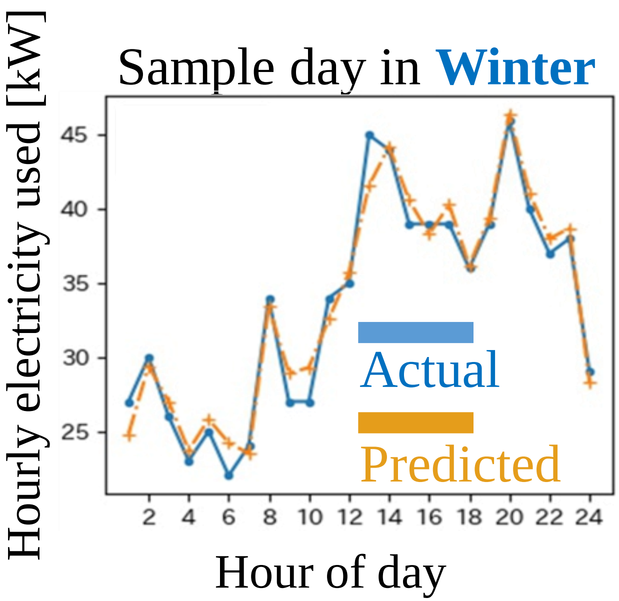
Sample day in **Summer**



Results for one building : Freezing / Cooling , using RFR

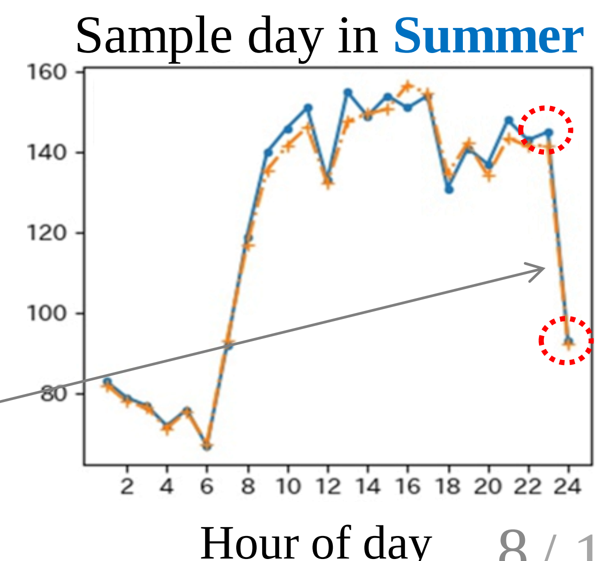
- Target: 30% in a year
  - MSE = 10.9 [%]
    - ➢Better prediction than A/C





Absolute energy smaller in winter, due to lower outside air temperature

Can keep up with **sudden sag**



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Across building forecast : Cross validation plan

215 Supermarkets *

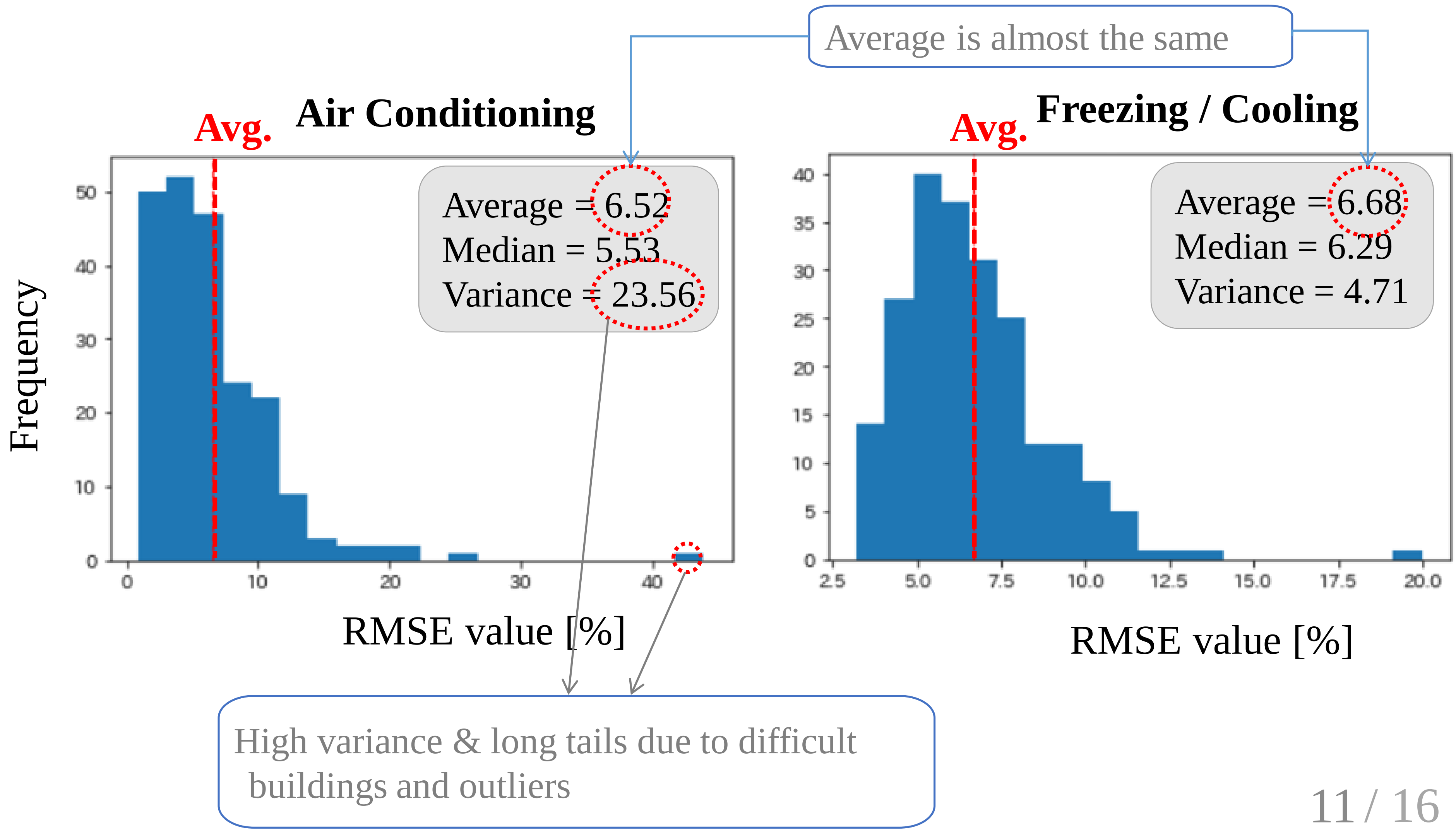
Number of CV iterations

i = 1	Evaluation 8760 x 43	Learning 1 8760 x 43	Learning 2 8760 x 43	Learning 3 8760 x 43	Learning 4 8760 x 43
i = 2	Learning 1 8760 x 43	Evaluation 8760 x 43	Learning 2 8760 x 43	Learning 3 8760 x 43	Learning 4 8760 x 43
i = 3	Learning 1 8760 x 43	Learning 2 8760 x 43	Evaluation 8760 x 43	Learning 3 8760 x 43	Learning 4 8760 x 43
i = 4	Learning 1 8760 x 43	Learning 2 8760 x 43	Learning 3 8760 x 43	Evaluation 8760 x 43	Learning 4 8760 x 43
i = 5	Learning 1 8760 x 43	Learning 2 8760 x 43	Learning 3 8760 x 43	Learning 4 8760 x 43	Evaluation 8760 x 43

* Used samples that had measurements of both A/C and Freezing/Cooling energy

Results for across-building: Root Mean Sq. Errors, by lightGBM

- Building-wise RMSE
  - ➢Many buildings fall between 0 and 10 [%] RMSE



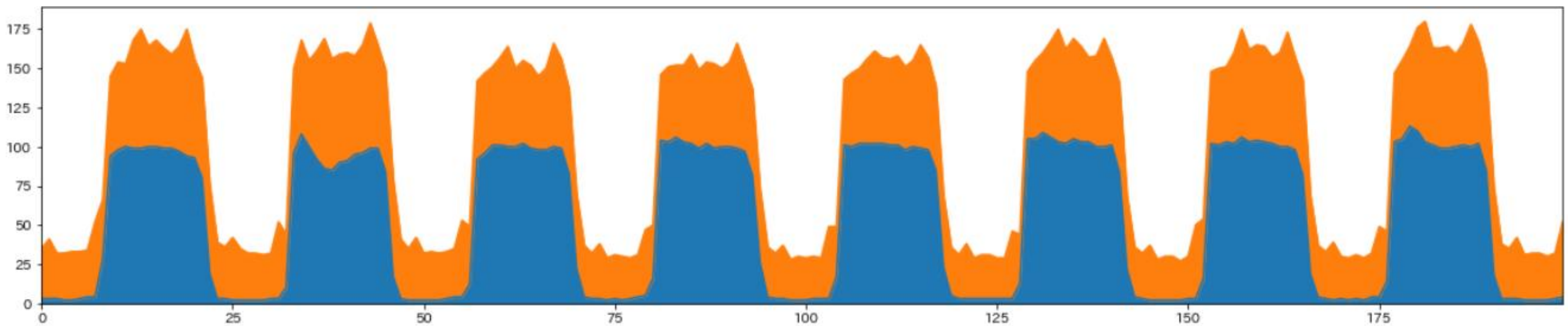
Example predicted time-series, across-building lightGBM

Air Conditioning

Freezing / Cooling

Actual

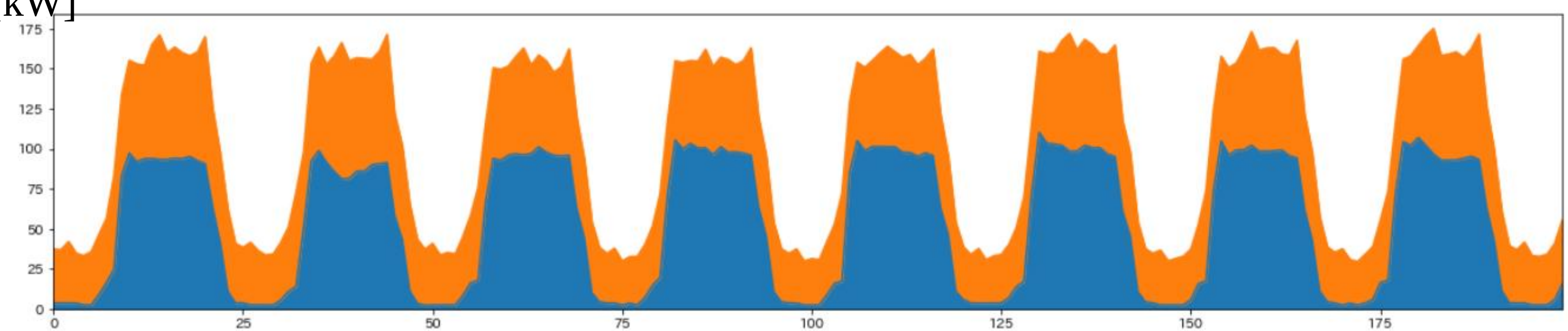
[kW]



Hour

Predicted

[kW]

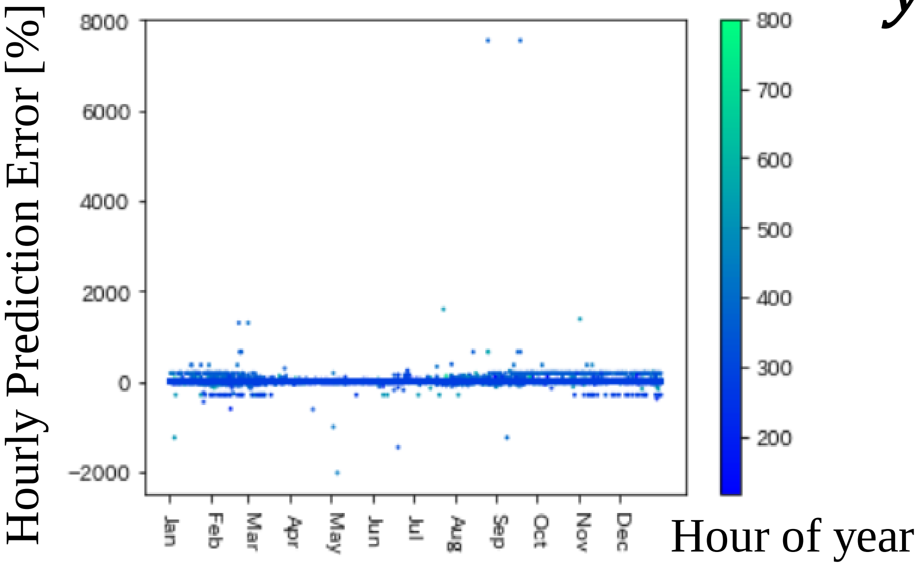


Hour

Prediction errors, across-building lightGBM

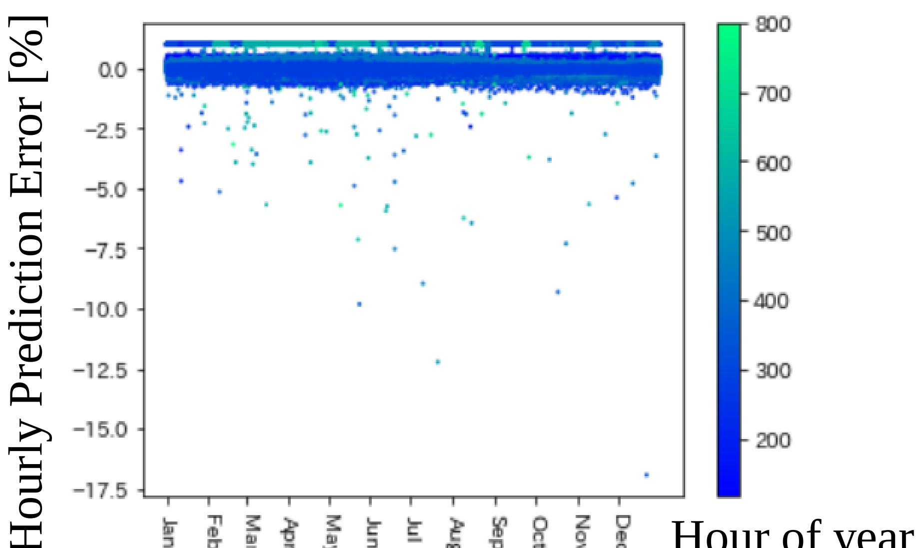
$$y_{error} = \frac{y_{real} - y_{pred}}{y_{pred}}$$

- Air Conditioning



- A little percent prediction points are anomaly error

- Freezing / Cooling



- Over 99 percent prediction points fall within +/-5% range

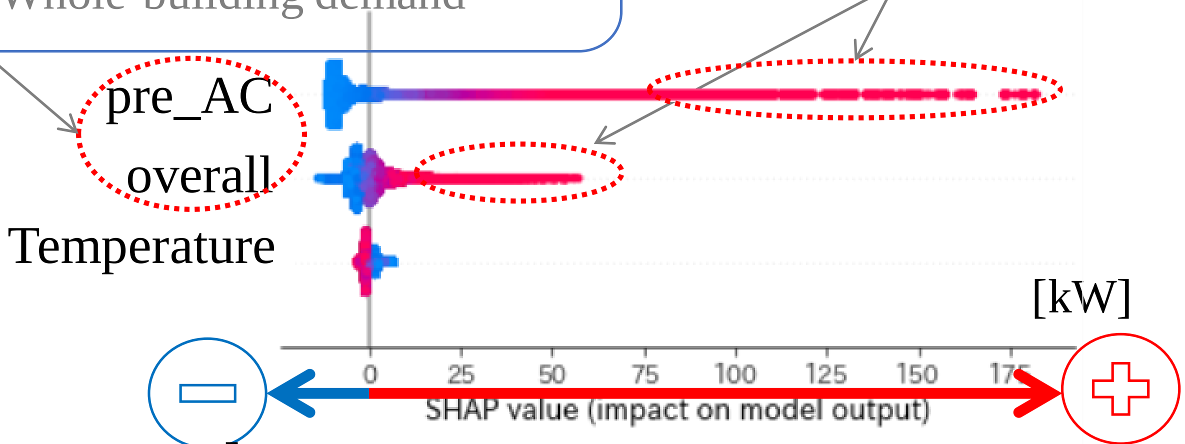
- only 10 points out of +/-5% range

SHAP figure : Feature importances, across-building lightGBM

- Air Conditioning

Highest impact on forecasted values from :
- pre_AC: 1-hour-before target value
- overall: Whole-building demand

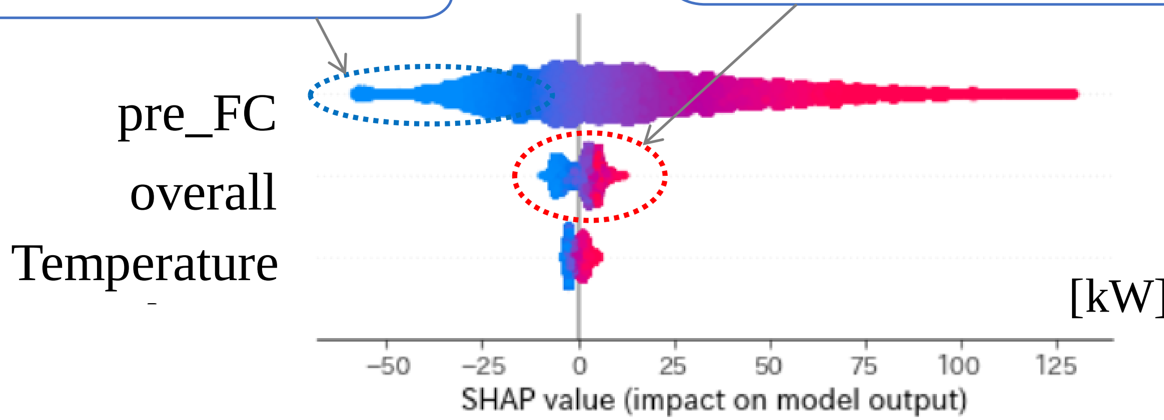
If these values are large:
- positive impacts to predicted values
- the greater these values, the greater the effect

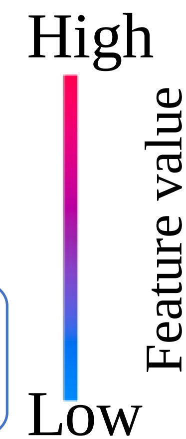


- Freezing / Cooling

Stronger negative impact

Less prominent impact of “overall”





Conclusions

- Successful disaggregation:
  - Temperature-sensitive demand was disaggregated between Air Conditioning and Freezing/Cooling
  - Made possible by lightGBM model trained with different buildings, capturing differences between A/C and Freezing/Cooling

- Possible application:
  - Demand side
    - ✓ potentially detect equipment fault
    - ✓ find peak timing in a year
  - Supplier side
    - ✓ Make energy without excess

Future work

- Problems and possible improvements
  - ➢ Air conditioning resulted to relatively less accurate prediction due to some difficult buildings and outliers
  - ➢ Better model tuning
    - ✓ Better parameter choice
    - ✓ Proper choice of training data

- Next steps
  - ➢ Want to extend to other types of industry
  - ➢ Try to predict with non-AR(1) model