Rimor: Towards identifying anomalous appliances in buildings

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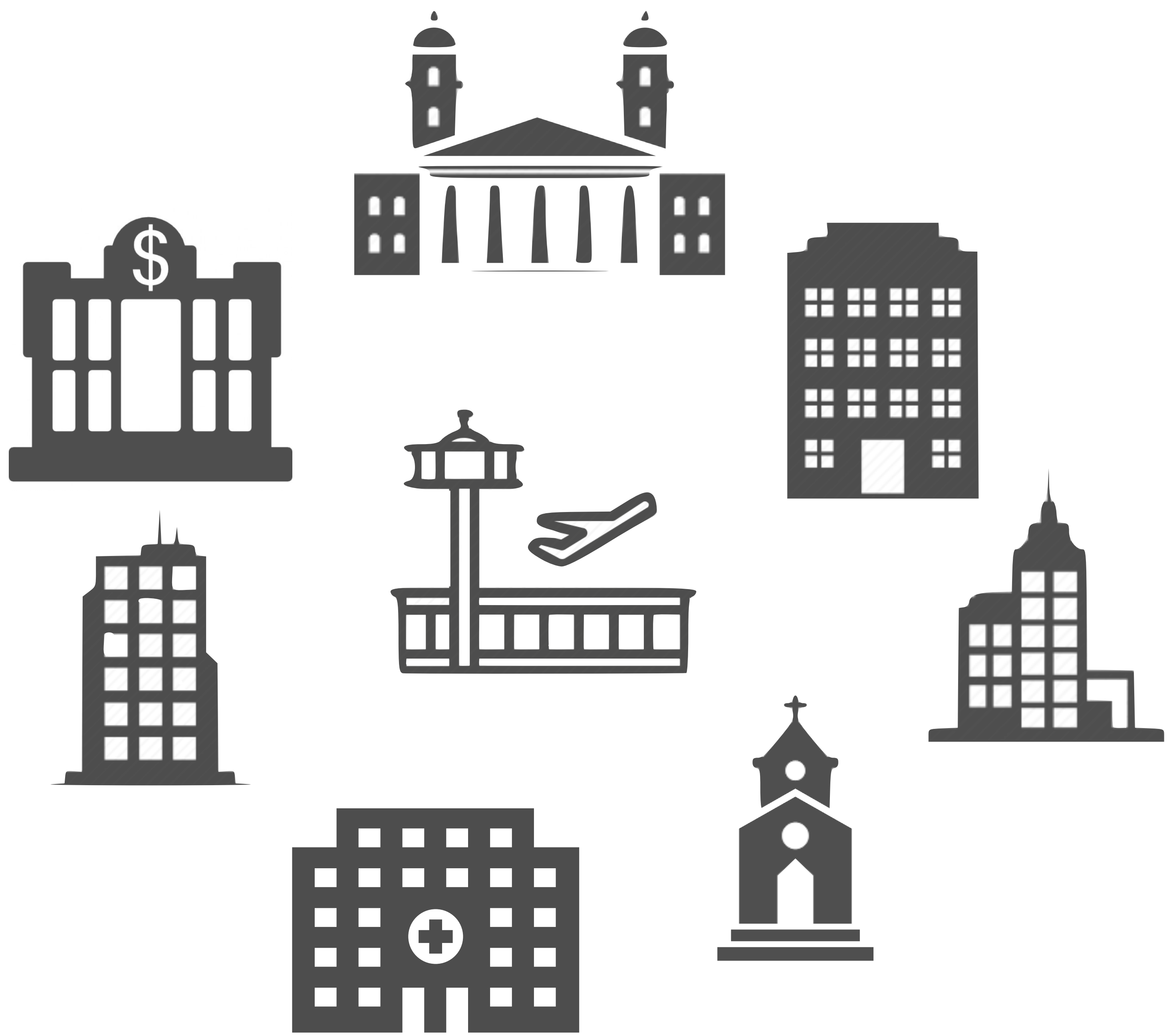
Buildings consume 39% of energy [1]



[1] International Energy Outlook, 2017

Energy wastage ⟶ anomalies

Reasons for energy wastage:

Duct leakage in HVAC

Energy wastage → anomalies

Reasons for energy wastage:

Duct leakage in HVAC

Wrong AC settings

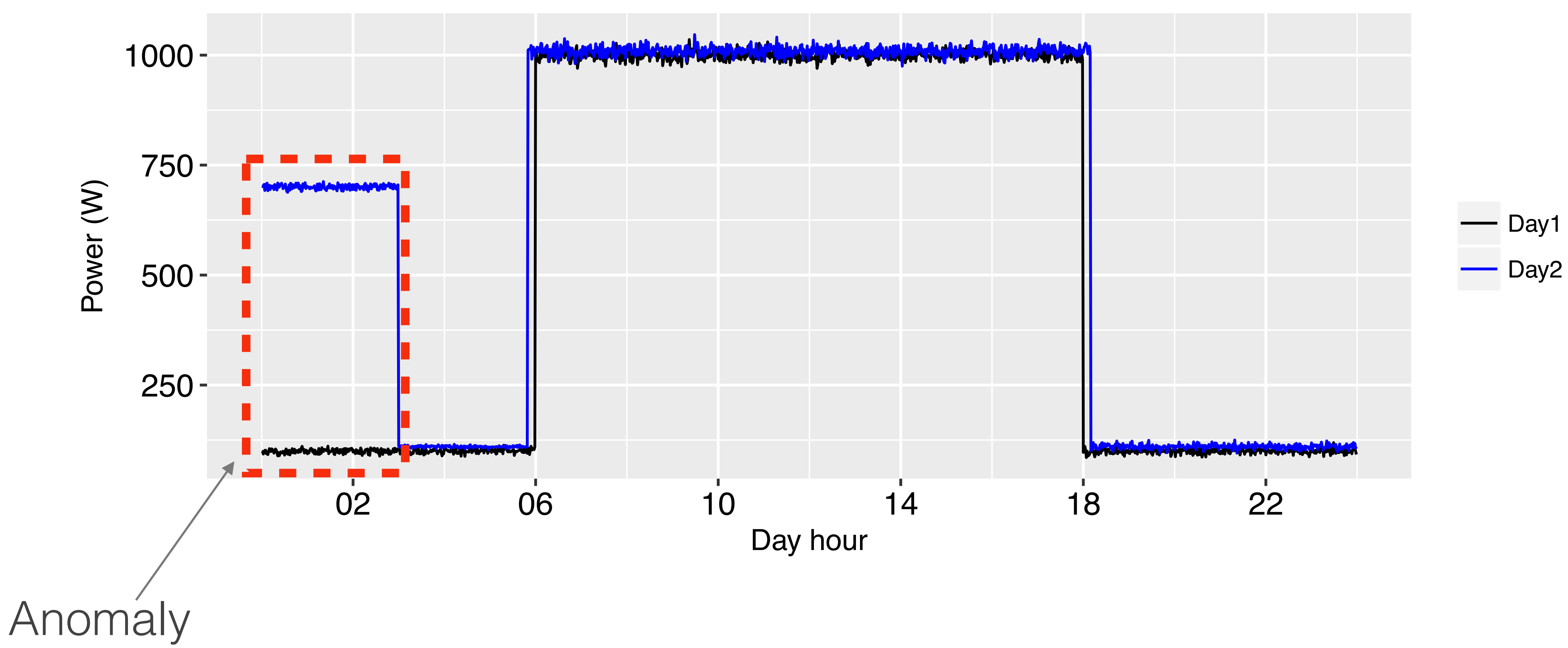
Feedback → energy savings

- Real-time feedback results in 12% energy savings [1]
  - Showing appliance-wise energy consumption to users
  - Providing anomalous energy consumption alerts [2]

[1] Armel et al. Is disaggregation the holy grail of energy efficiency? The case of electricity. Energy policy, 2013
[2] Janetzko et al. Anomaly detection for visual analytics of power consumption data. Computers & Graphics, 2014

Existing approaches [1,2]

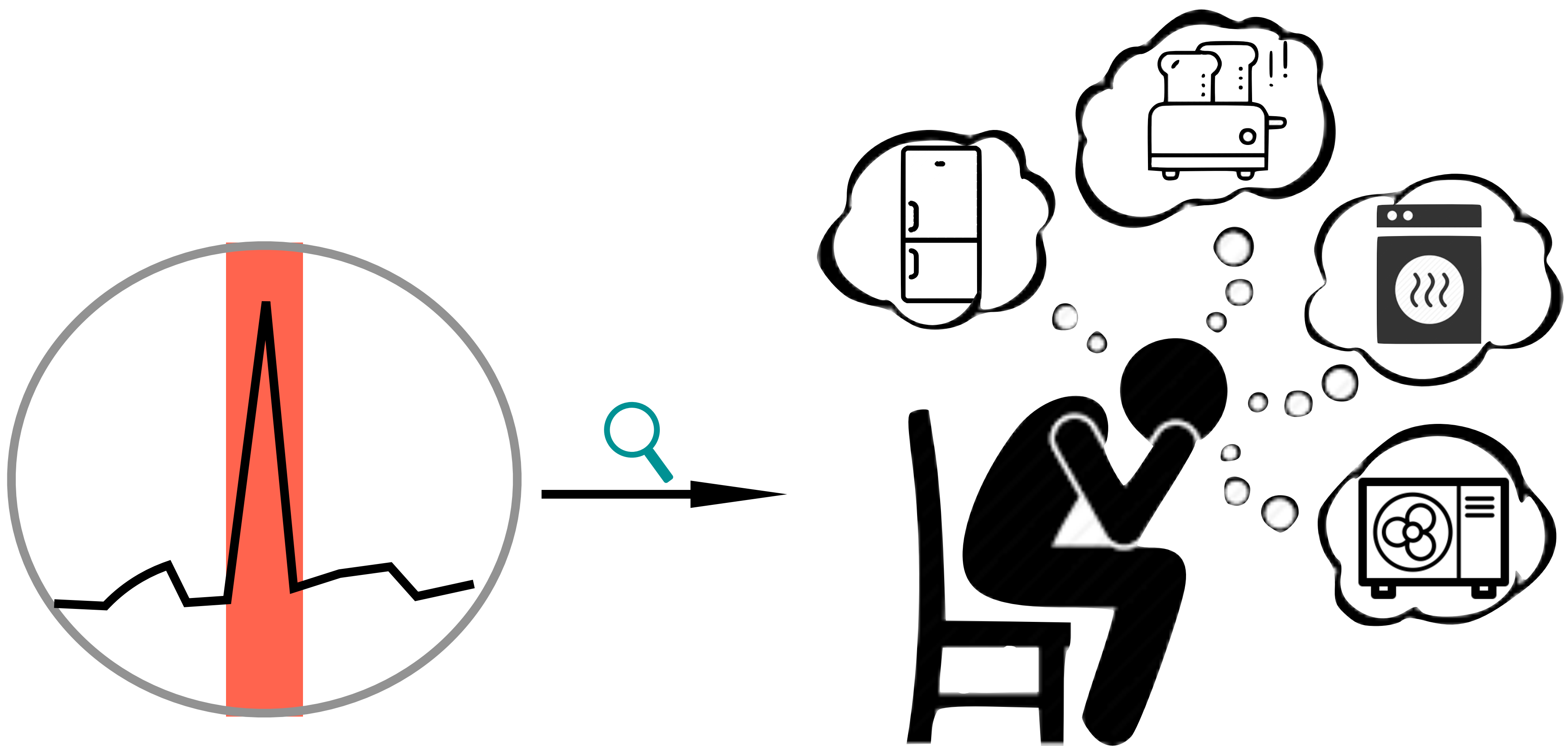
Detect anomalies at the end of the day's consumption



[1] Bellala et al. Towards an understanding of campus-scale power consumption, BuildSys, 2011
[2] Arjuanan et al. Multi-user energy consumption monitoring and anomaly detection with partial context information, BuildSys, 2015

Existing approaches [1,2]

Do not identify the anomalous appliance



Anomalous usage

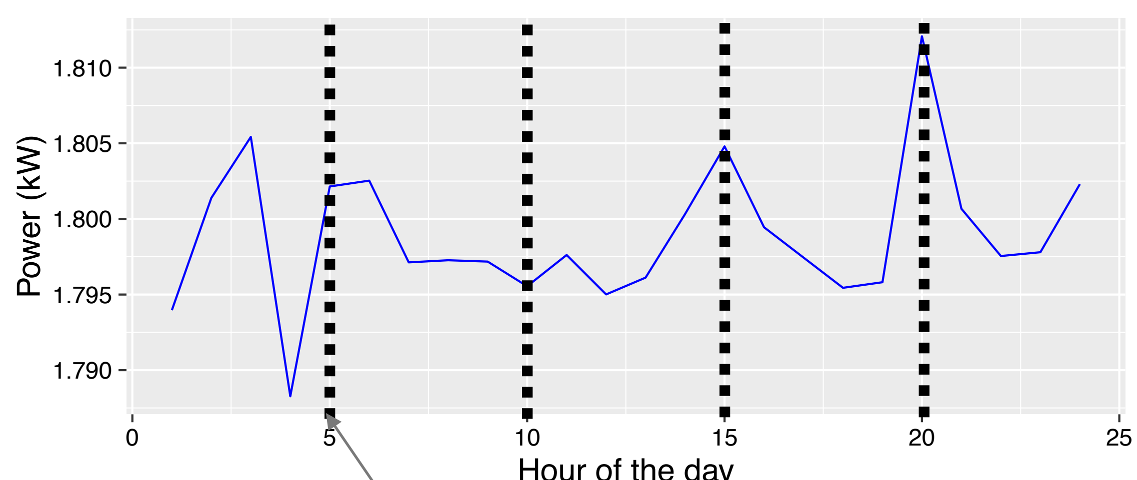
Identify anomalous appliance

[1] Bellala et al. Towards an understanding of campus-scale power consumption, BuildSys, 2011
[2] Arjuanan et al. Multi-user energy consumption monitoring and anomaly detection with partial context information, BuildSys, 2015

Problem statement

Develop an anomaly detection approach which:

can detect anomaly at
user-defined intervals



User-defined time intervals

Problem statement

Develop an anomaly detection approach which:

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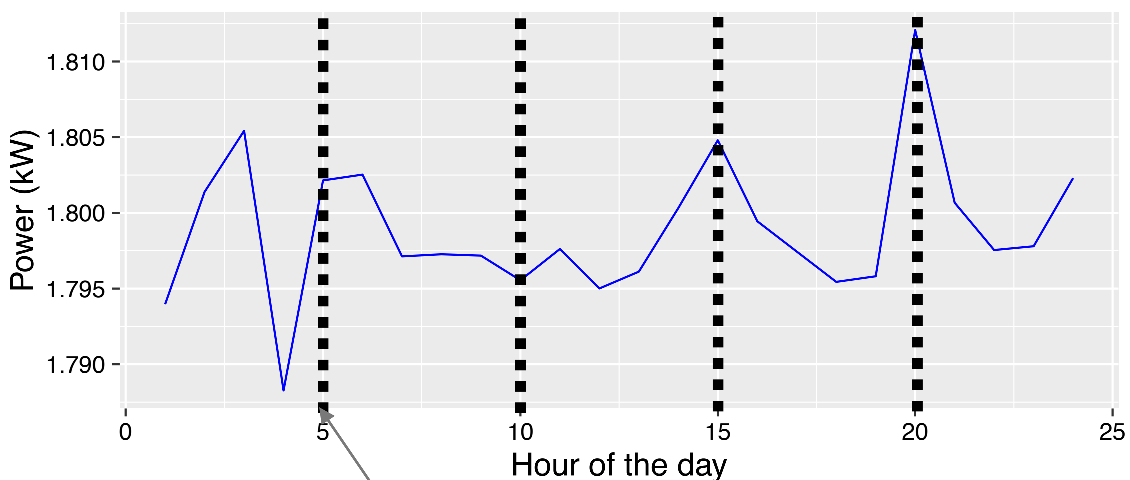
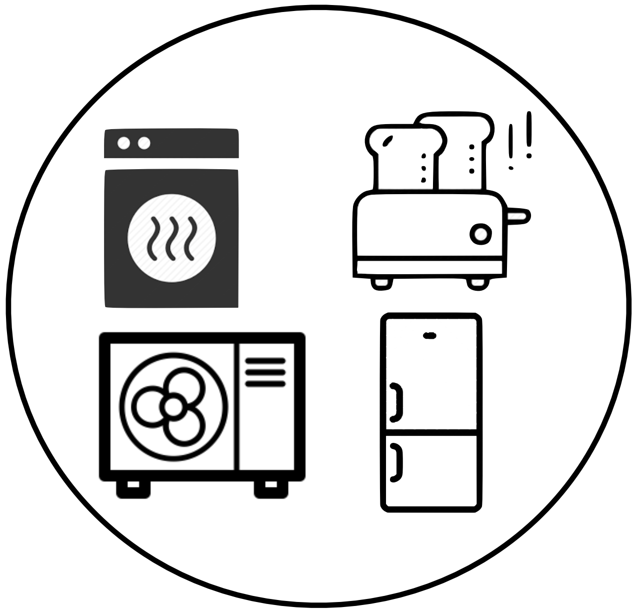


User-defined time intervals



Home appliances

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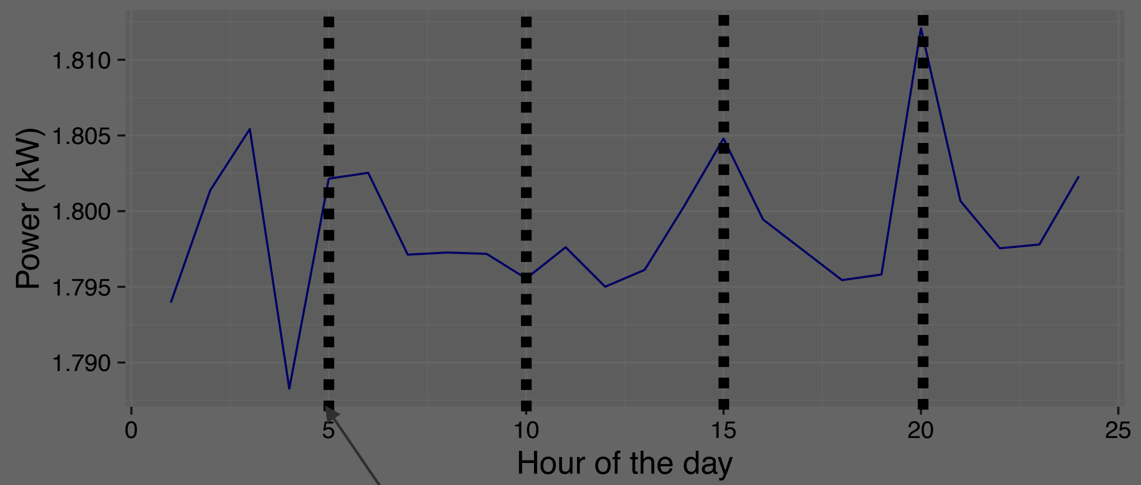
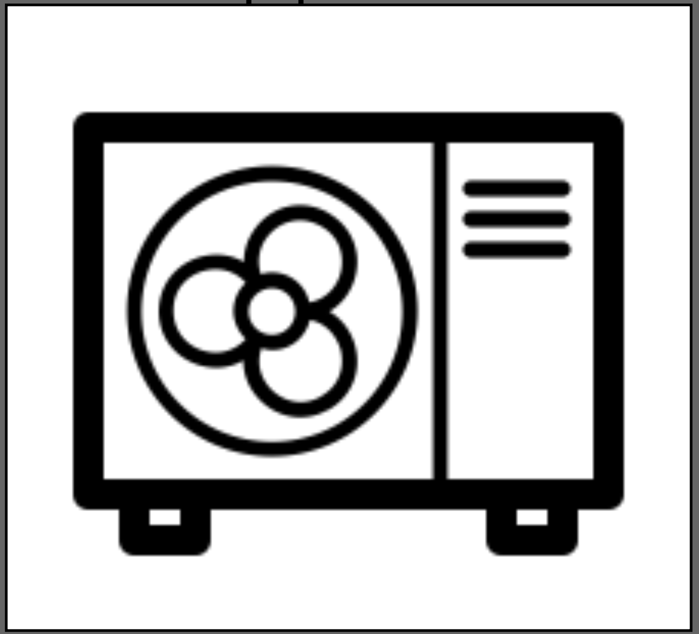


User-defined time intervals



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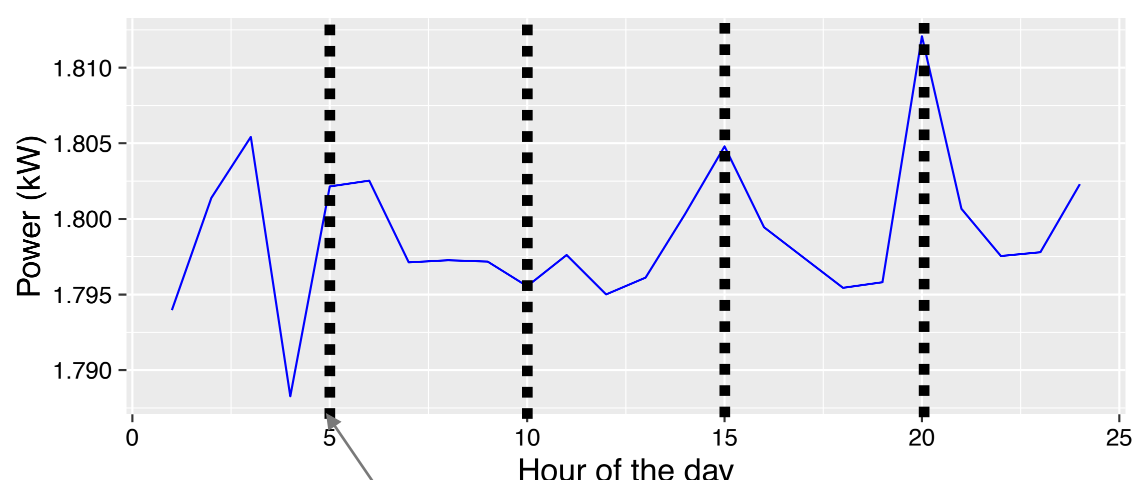
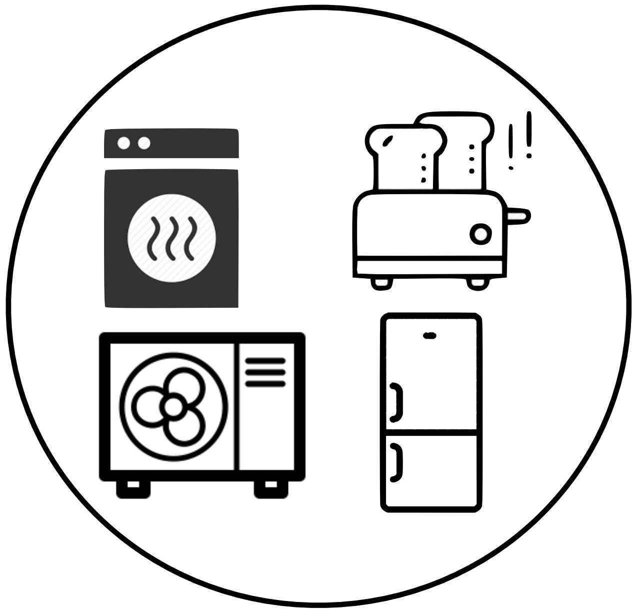


User-defined time intervals

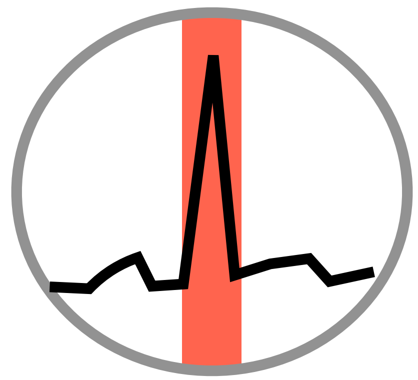
can identify anomalous appliance



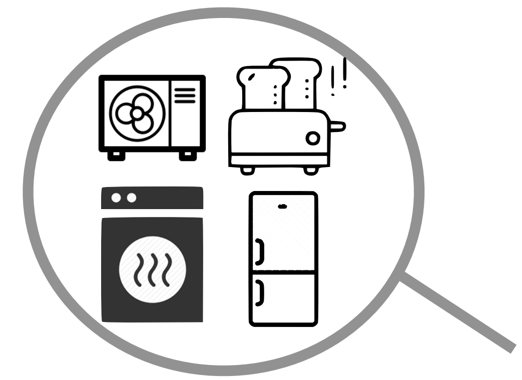
Home appliances

Proposed approach: Rimor

Energy Prediction →

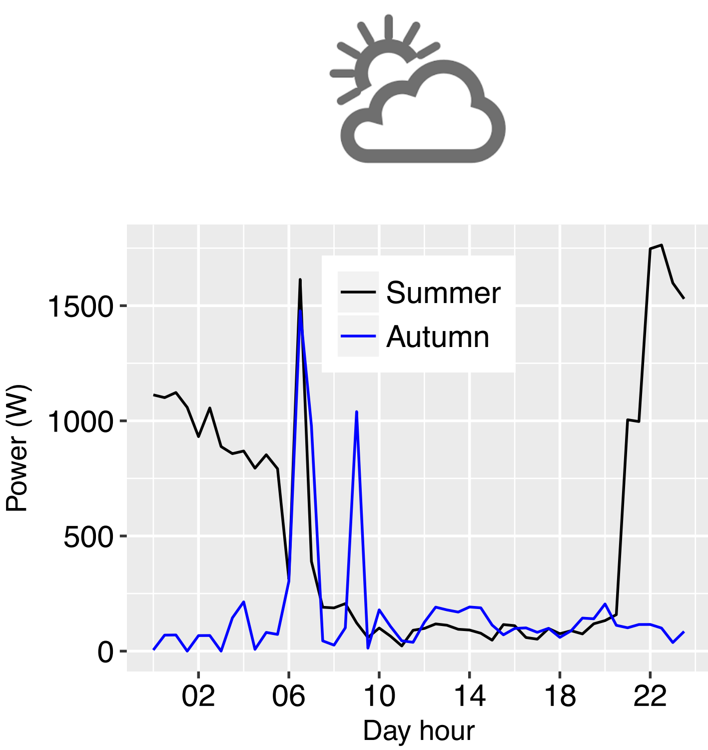


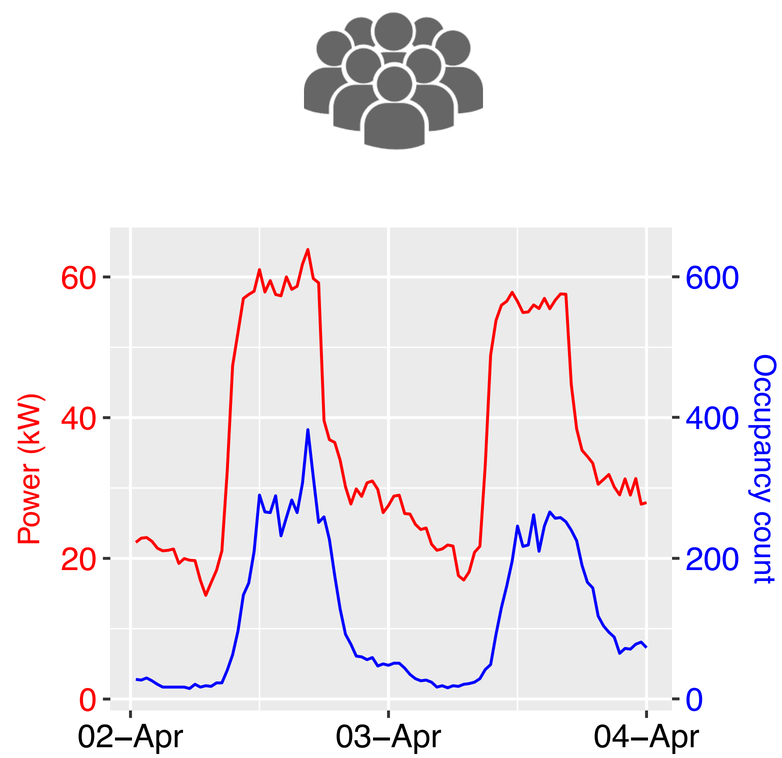
Anomaly Detection →

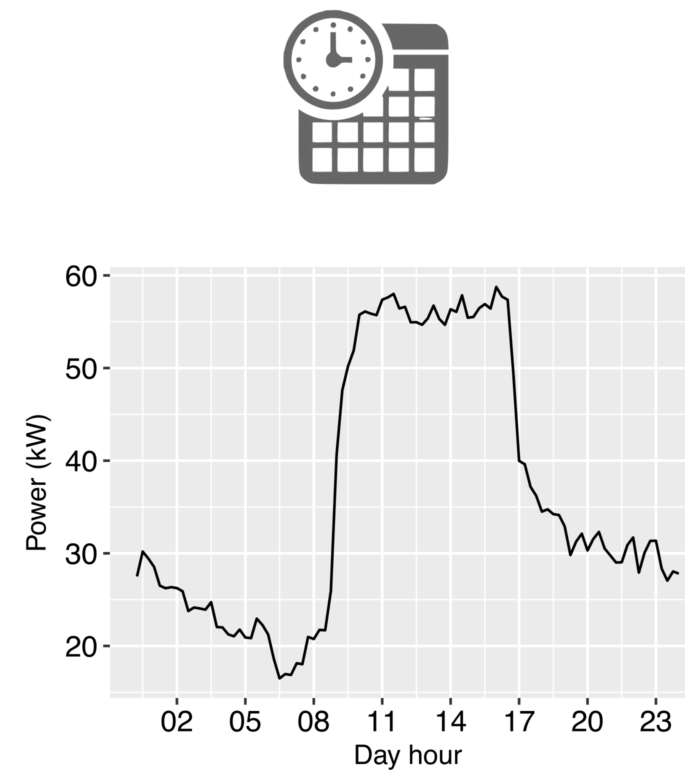


Appliance Identification

Prediction contextual factors



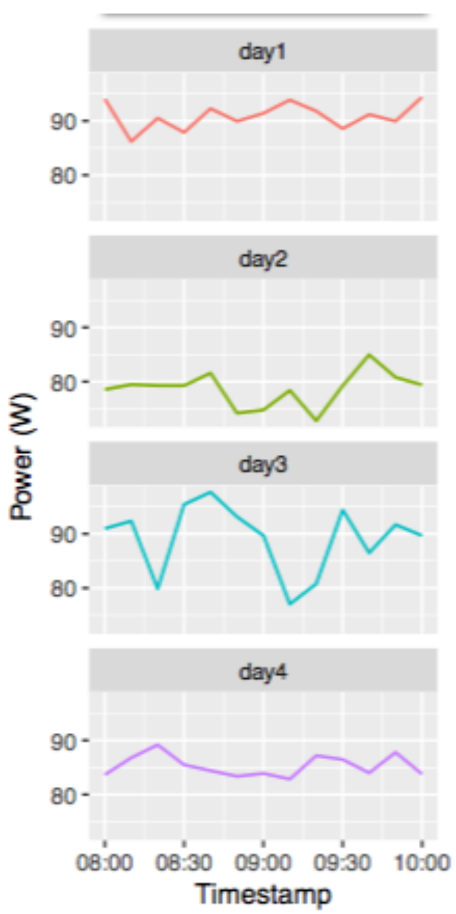




Prediction → *Anomaly detection* → *Appliance identification*

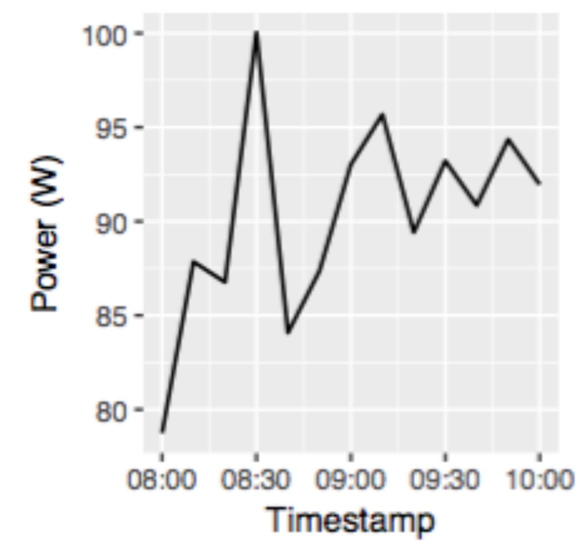
Energy prediction

Historical consumption + **Current day weather** + **Current day-type** = **Predicted Consumption**



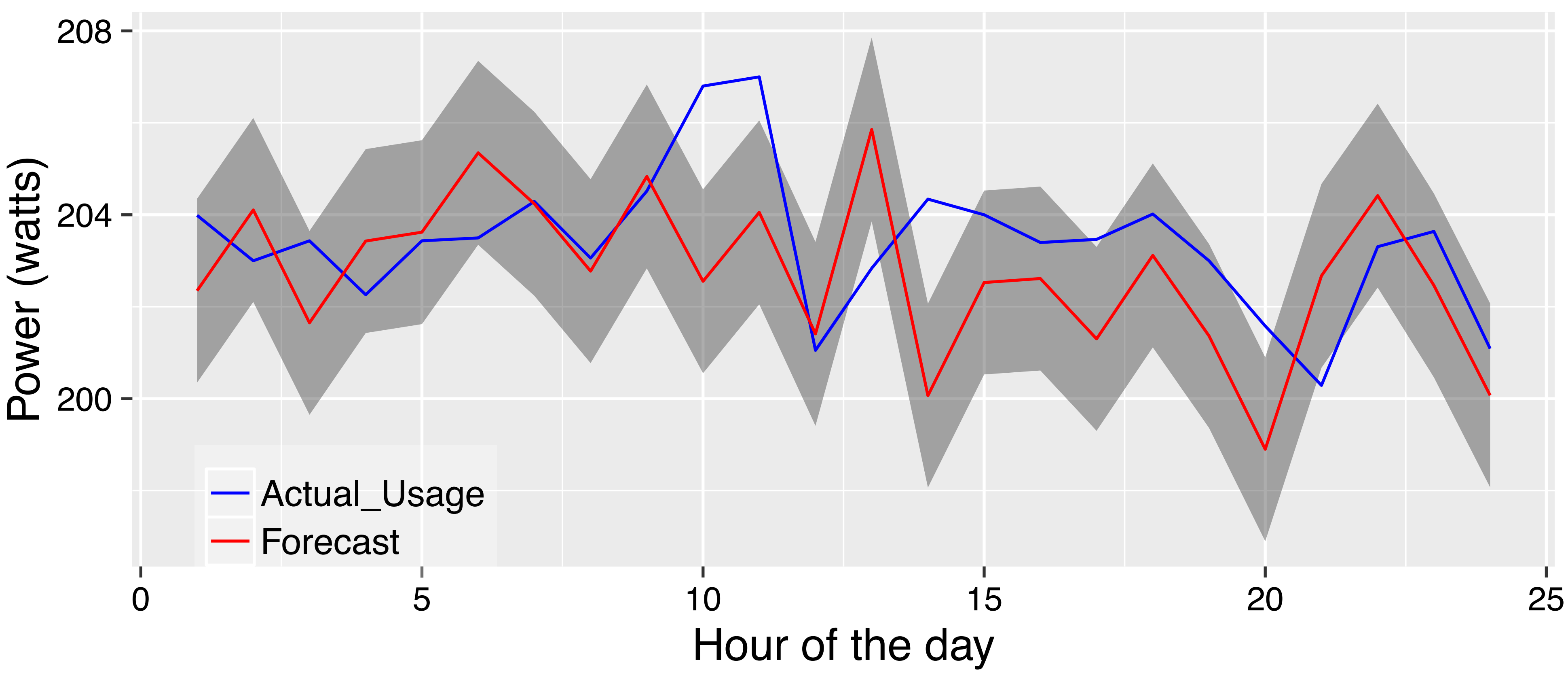
Temperature, Humidity

Weekday, Weekend



Prediction → *Anomaly detection* → *Appliance identification*

Anomaly detection

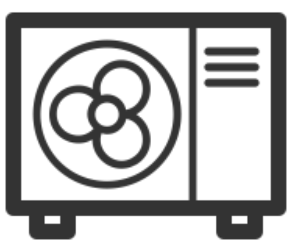


Actual usage found outside the prediction band is flagged as an anomaly

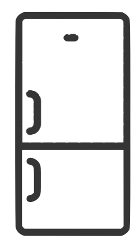
Prediction → **Anomaly detection** → Appliance identification

Anomalous appliance identification

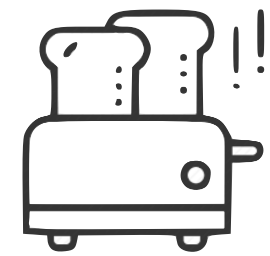
- Typically, each home appliance has different power wattage



1.5 kW



150 W

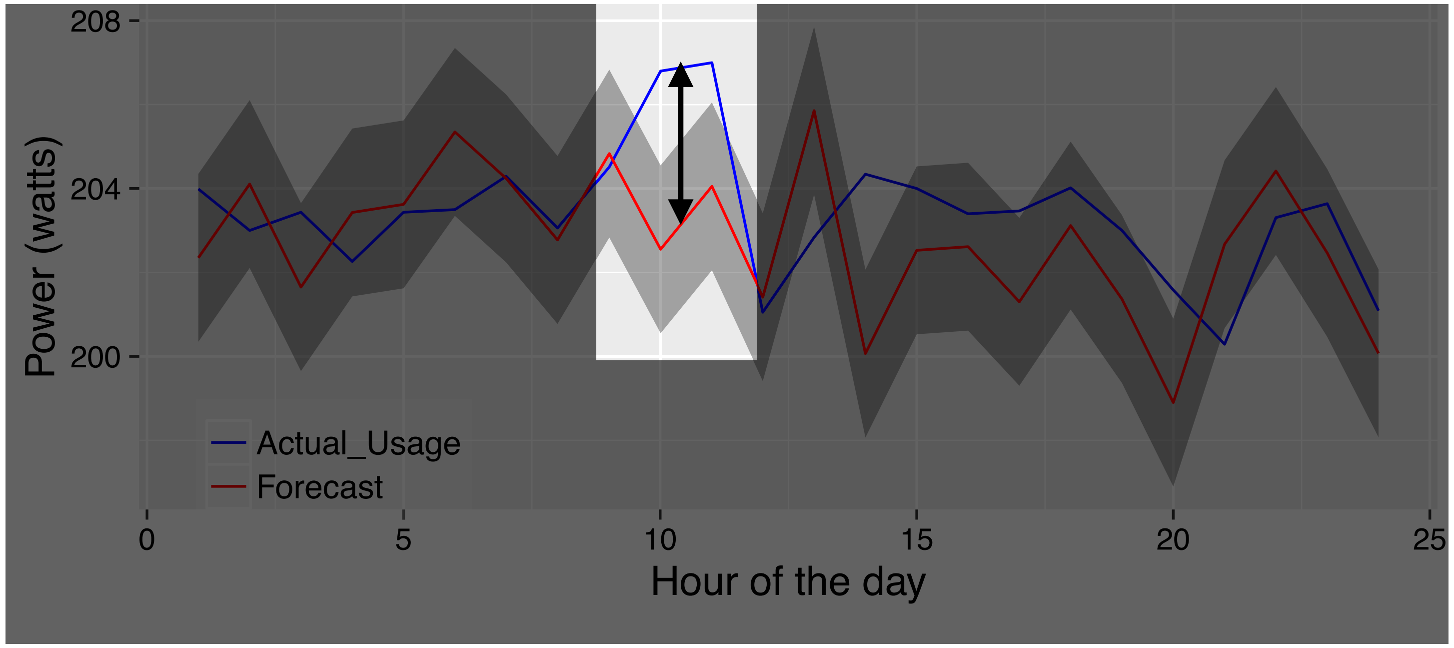


800 W

- Our assumption is anomaly caused by an appliance will be proportional to its wattage

Prediction → Anomaly detection → **Appliance identification**

Anomalous appliance identification



Appliance's wattage minimizing the difference between the predicted and the actual consumption is flagged as anomalous

$$\arg\min_{a_l} \left(abs(\widehat{Y} - Y) - a_l^u\right), \forall l \in \{1, \ldots, n\}$$

Prediction → Anomaly detection → **Appliance identification**

Datasets

Dataset	Dataport	AMPds	ECO	REFIT
Homes	24	1	6	20
Country	USA	Canada	Switzerland	UK

Three months data at 10 minutes sampling rate

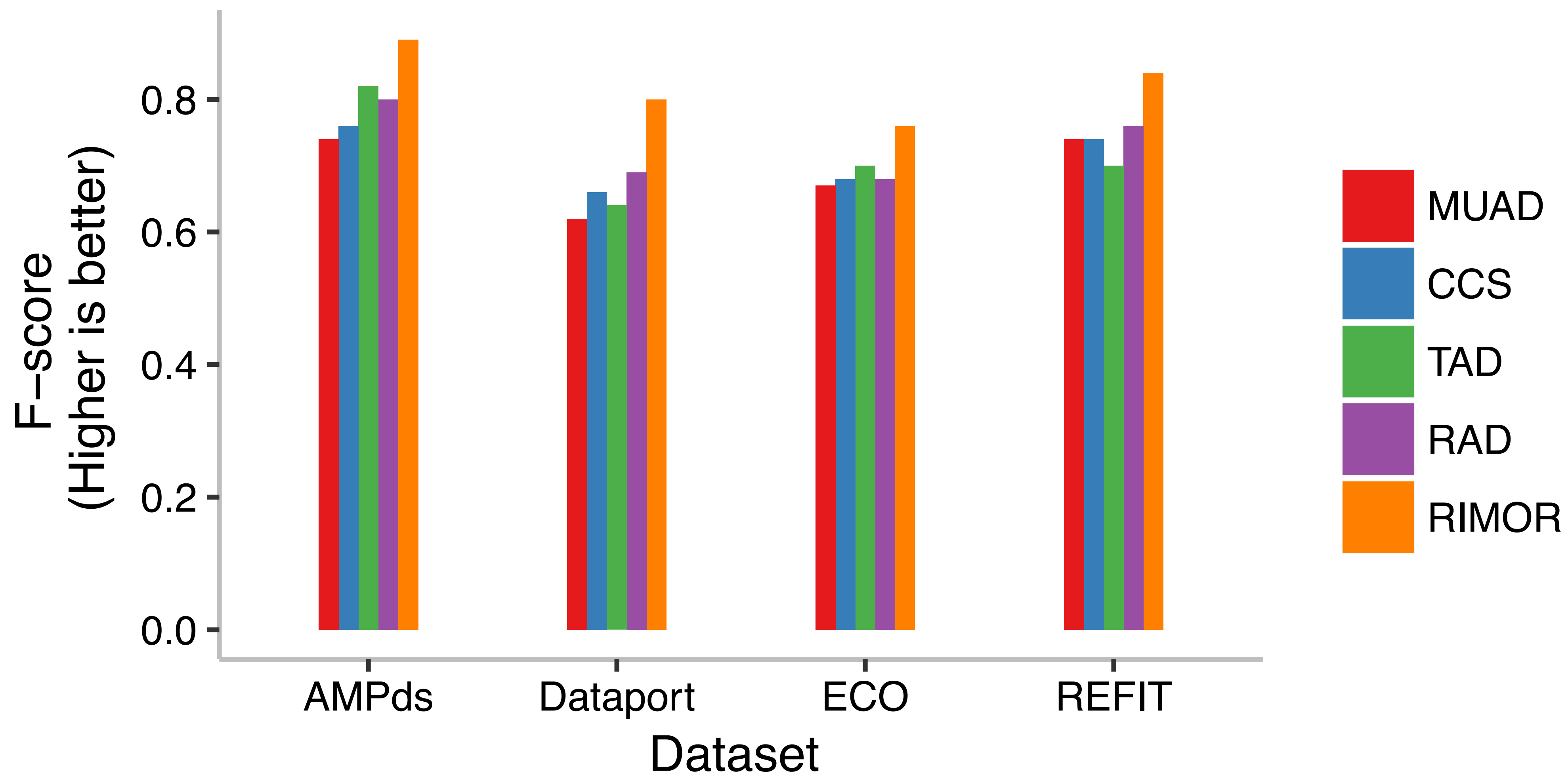
Downloaded temperature and humidity data from Weather Underground service

Calculated appliance wattage from the datasets

Baseline methods

- Multi-user anomaly detection (MUAD) [Buildsys ‘15]
  - Uses clustering to identify anomalies
- Collect, Compare, and Score (CCS) [e-Energy ‘16]
  - Computes density to identify anomalies
- Twitter anomaly detection (TAD) [Hotcloud ‘14]
  - Uses a statistical test to identify anomalies
- Real-time anomaly detection (RAD) [Ren. & Sus. Energy Reviews ‘14]
  - Uses statistical features to identify anomalies

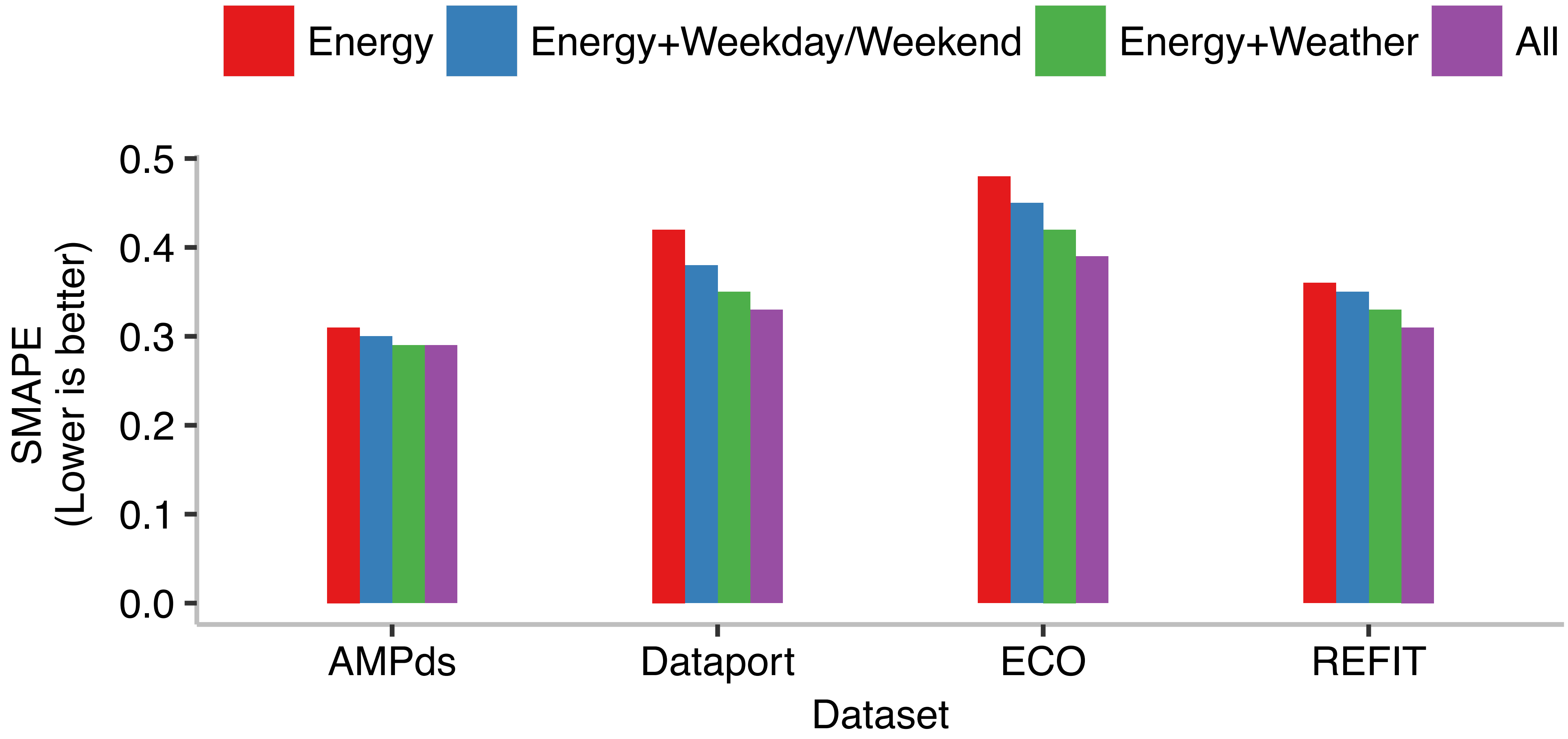
Anomaly detection accuracy



$$\text{F-score} = 2 * \frac{precision * recall}{precision + recall}$$

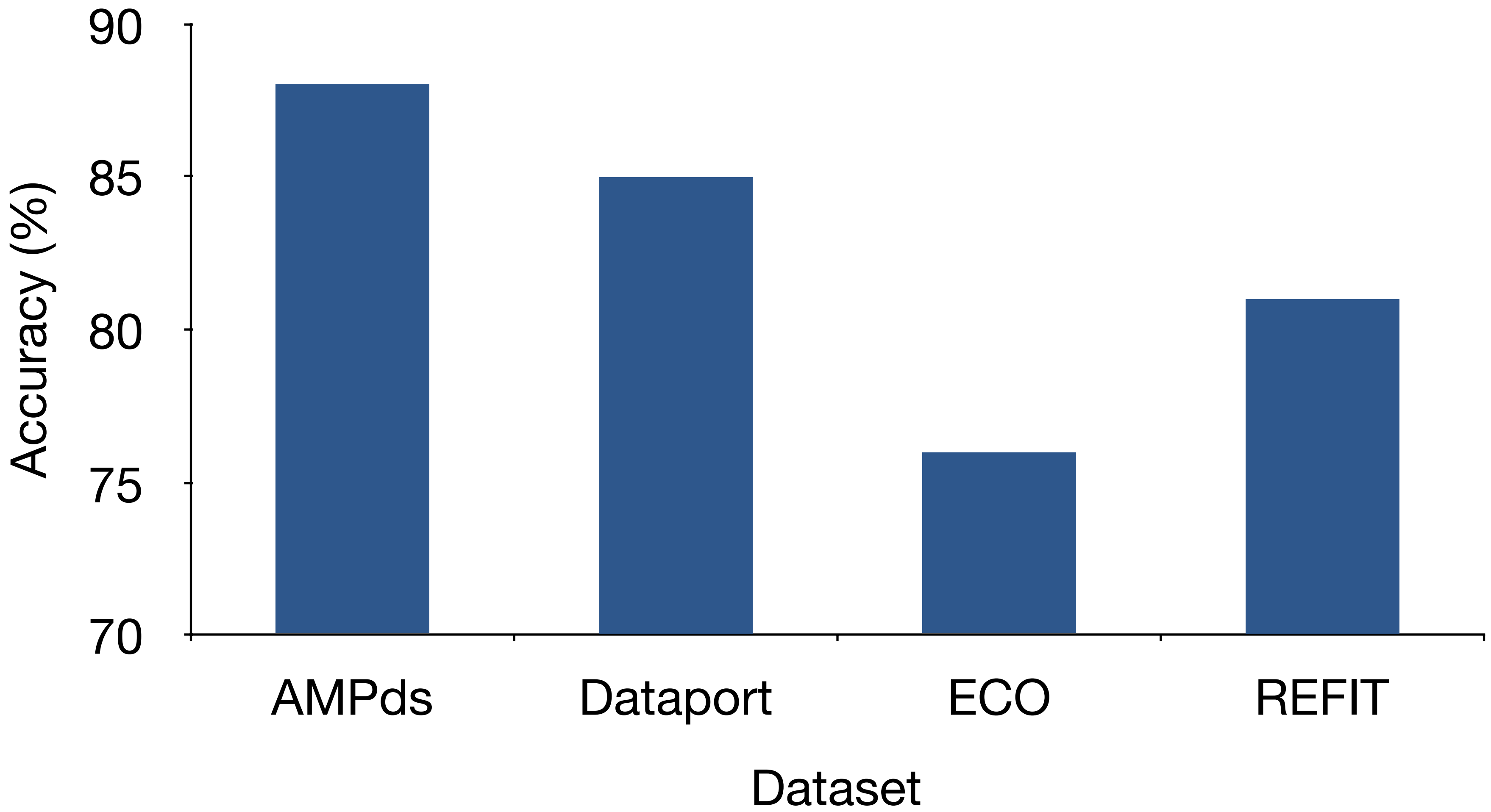
Rimor improves anomaly detection performance by 15%

Effect of contextual features



Adding contextual features decreases SMAPE (error)

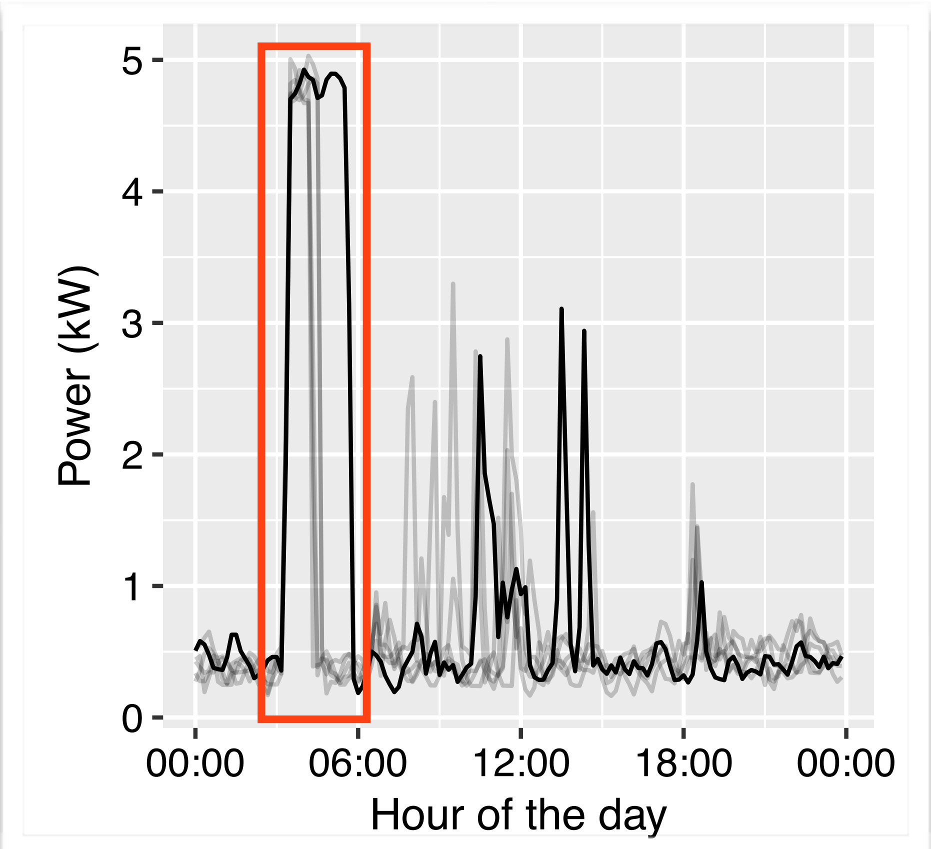
Appliance identification accuracy (%)



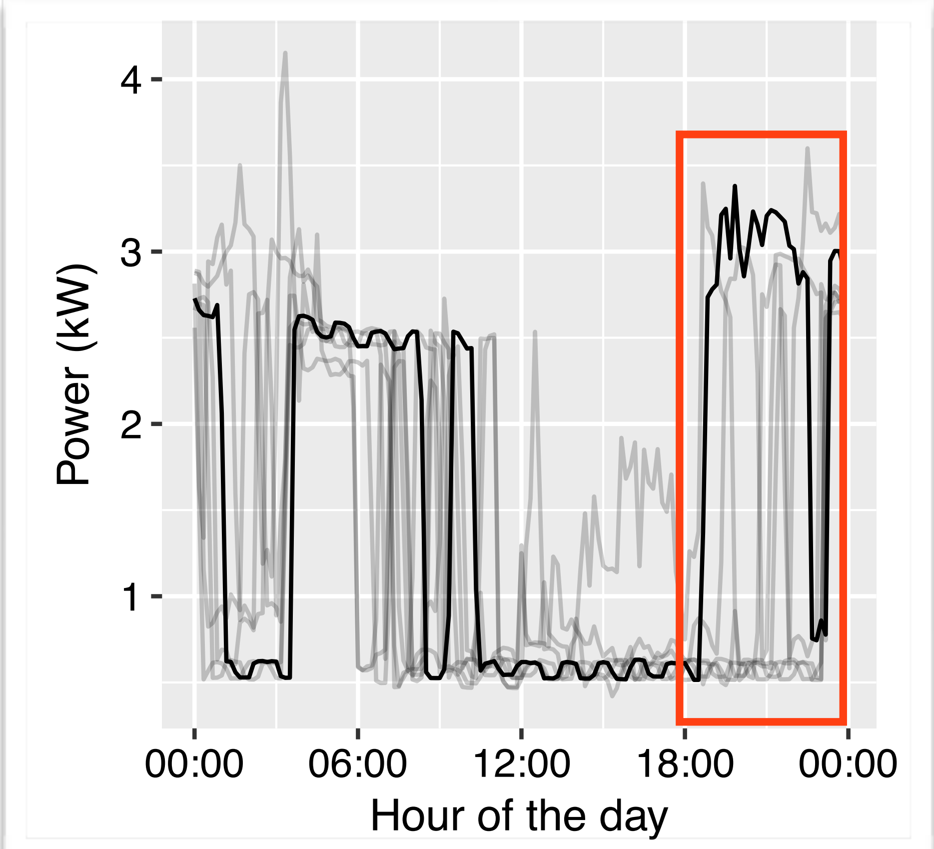
$$Identification\ Accuracy = \frac{Total\ \#\ of\ correct\ identified\ appliances}{Total\ \#\ of\ true\ positive\ anomalies}$$

Rimor reports 82% appliance identification accuracy

Anomalous instances

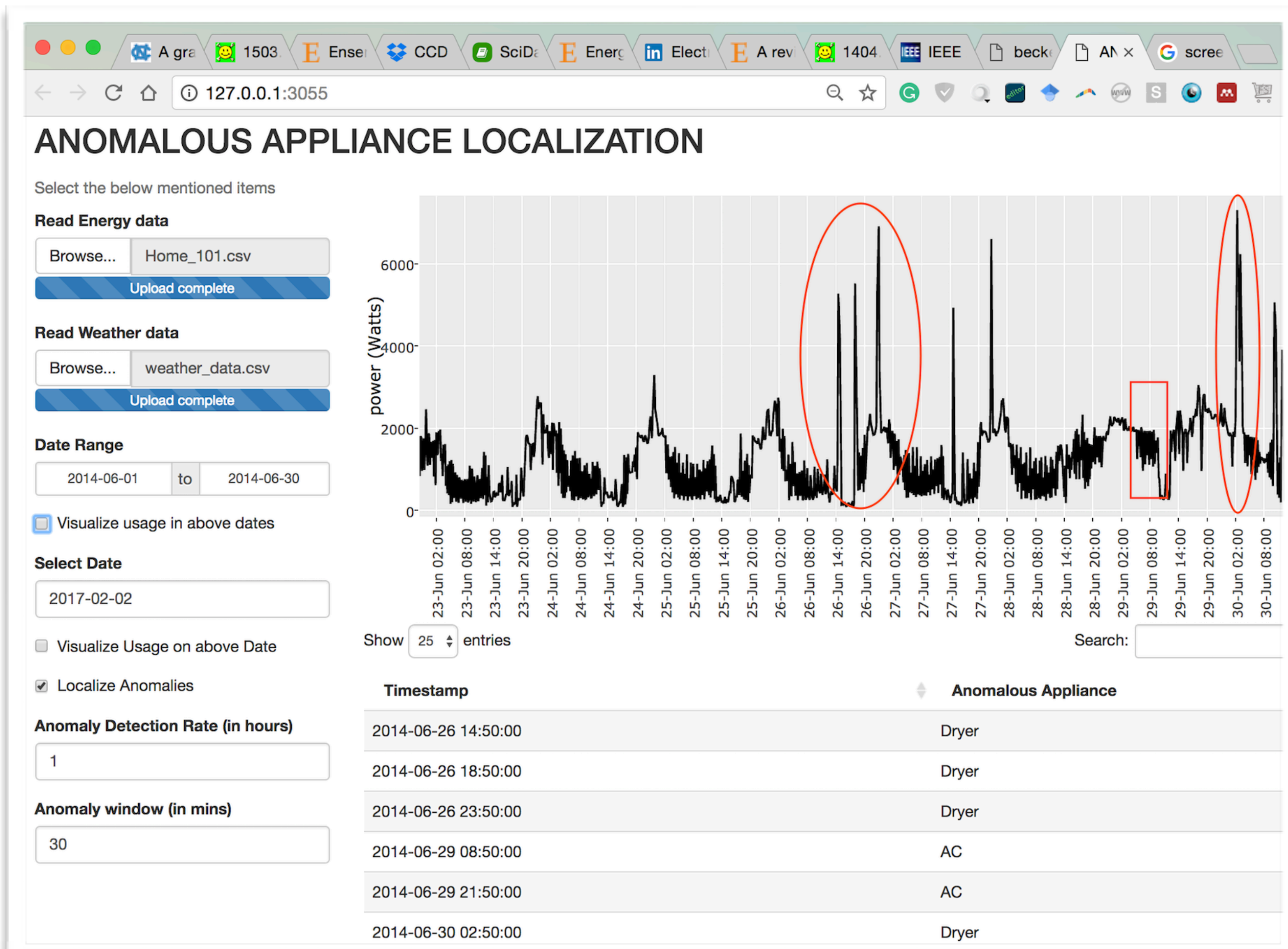


Extended car charging



No compressor cycles

Rimor prototype



https://github.com/loneharoon/AnomAppliance

Future work

- Handle instances with multiple appliances having similar power wattage

Appliances	Dataset	Wattage (W)
Dryer & Microwave	REFIT	450
Cooktop & AC	Dataport	1200
Heatpump & Oven	AMPds	1800

Future work

- Maintaining appliance registry portal

- Differentiate genuine abnormal usage from the actual anomalous usage

Conclusion

- Rimor improves anomaly detection accuracy.
- Adding contextual information helps to improve the anomaly detection accuracy.
- Rimor can be scaled to a large number of homes.

Thank You!

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