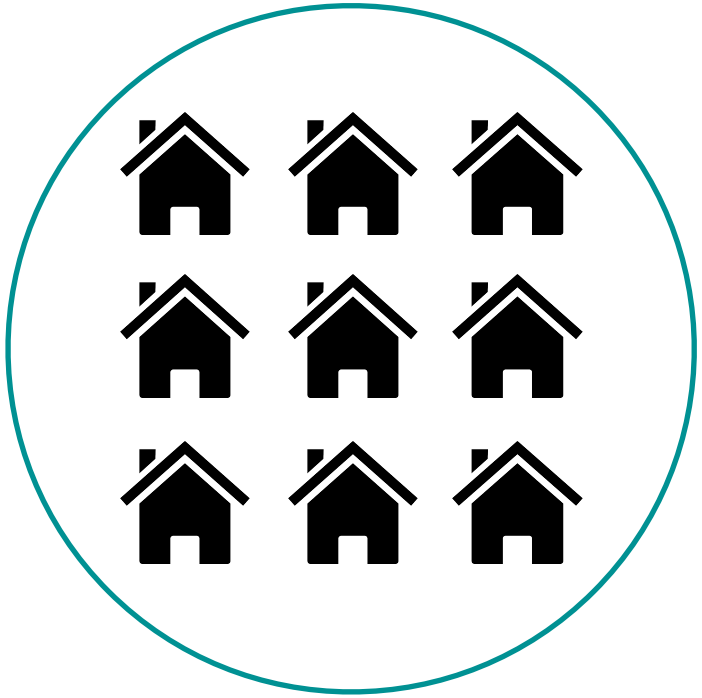
Monitor: An Abnormality Detection Approach for Buildings Energy Consumption

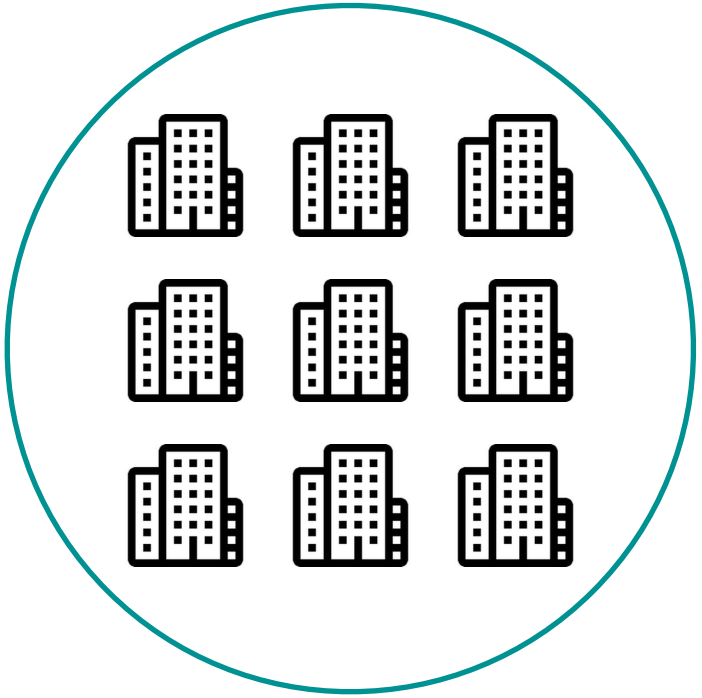
Haroon Rashid
Pushpendra Singh

INDRAPRASTHA INSTITUTE *of*
INFORMATION TECHNOLOGY **DELHI**

Buildings consume 39% of energy



Residential buildings

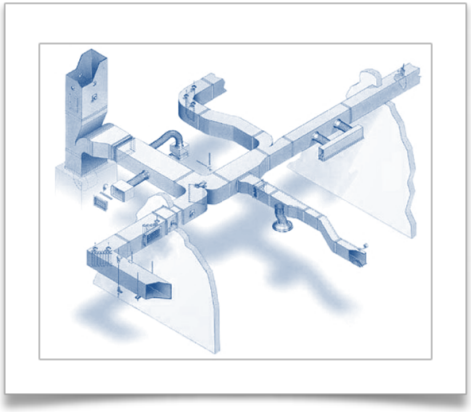


Commercial buildings

Source: International Energy Outlook, 2017

Energy wastage → abnormalities

Reasons for energy wastage:

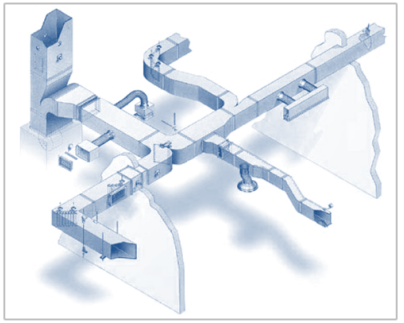


Duct leakage in HVAC

Source: Google Images

Energy wastage → abnormalities

Reasons for energy wastage:



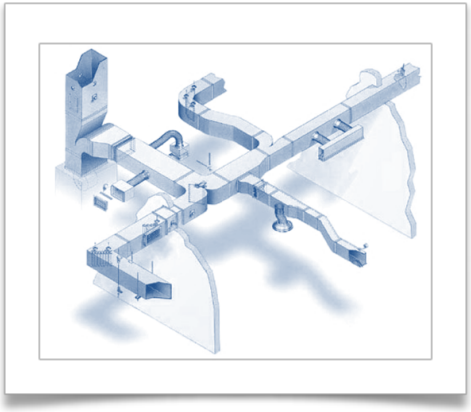
Duct leakage in HVAC

Lights ON during day hours

Source: Google Images

Energy wastage → abnormalities

Reasons for energy wastage:



Duct leakage in HVAC

Lights ON during day hours

Wrong AC settings

Source: Google Images

Energy wastage results in abnormalities

Reasons for

- Applia
- Forge
- Applia

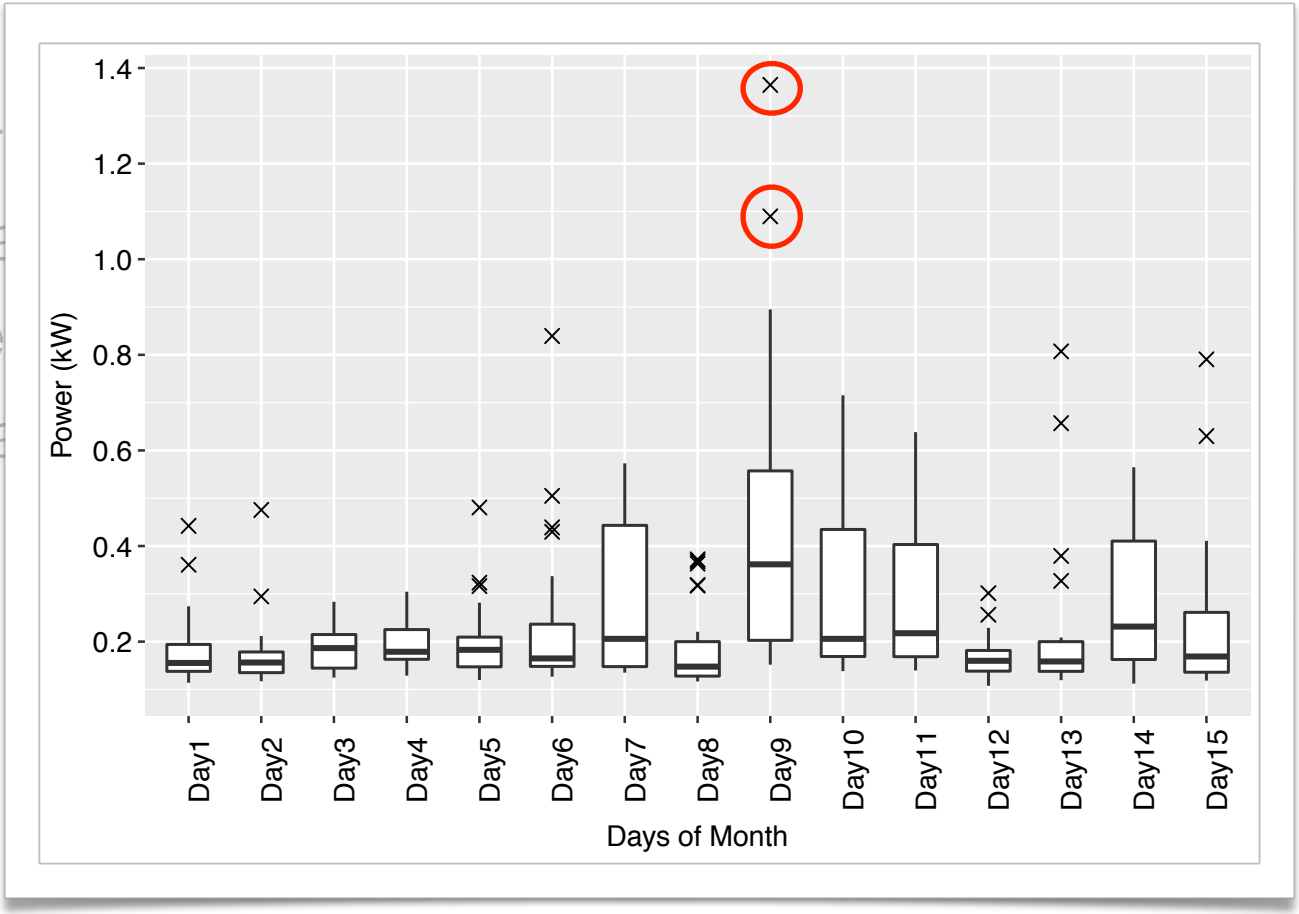


Fig: Box plots on hourly power consumption of a home for 15 days

Using smart meters for abnormality detection

- Allows real-time communication between grid and the meter
- Allows logging of different energy parameters such as voltage, current, power factor, etc.

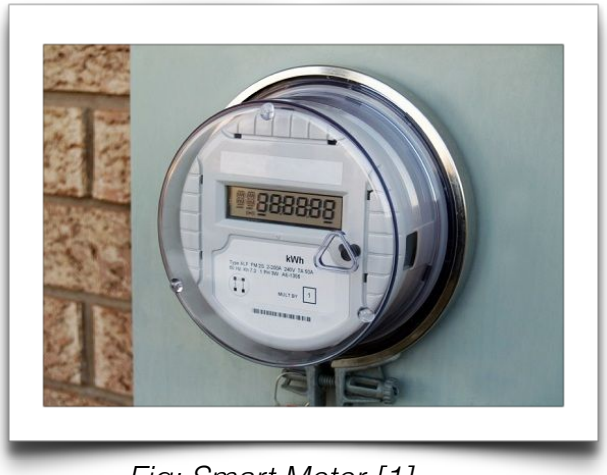


Fig: Smart Meter [1]

Half of US customers have smart meters installed [2]

[1] Source: Google Images
[2] International Energy Outlook, 2017

Issues with existing approaches

Lower abnormality detection accuracy

- Simple thresholding methods result in false positives [1]

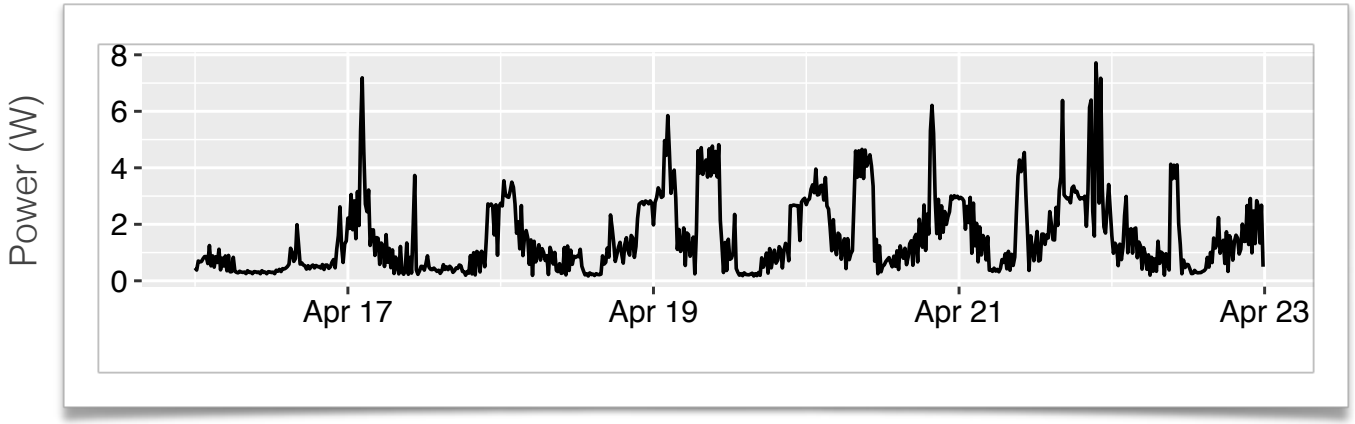


Fig: Every day follows a different energy consumption

- Ignoring contextual information [2]

[1] Balakrishnan et al. Data driven investigation of faults in HVAC systems with MCC, BuildSys, 2014
[2] Bellala et al. Towards an understanding of campus-scale power consumption, BuildSys, 2011

Issues with existing approaches

- Evaluated on either residential or commercial buildings [1]

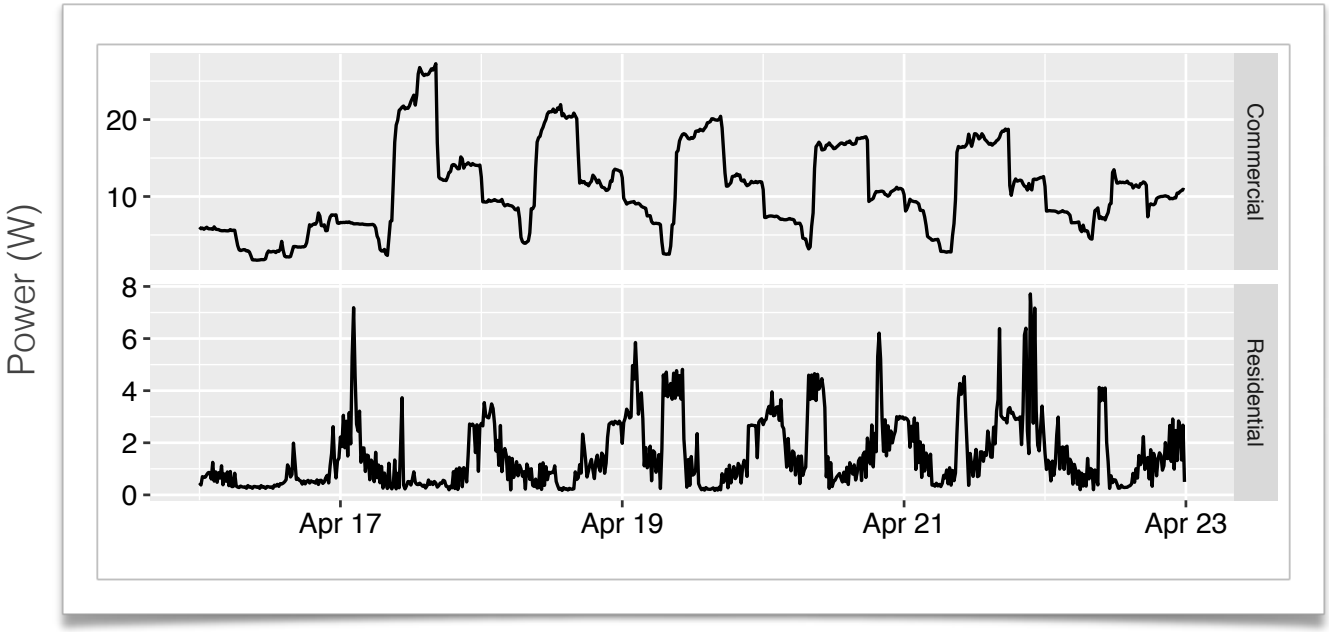


Fig: Energy consumption signature of commercial & residential buildings

[1] Bellala et al. Towards an understanding of campus-scale power consumption, BuildSys, 2011

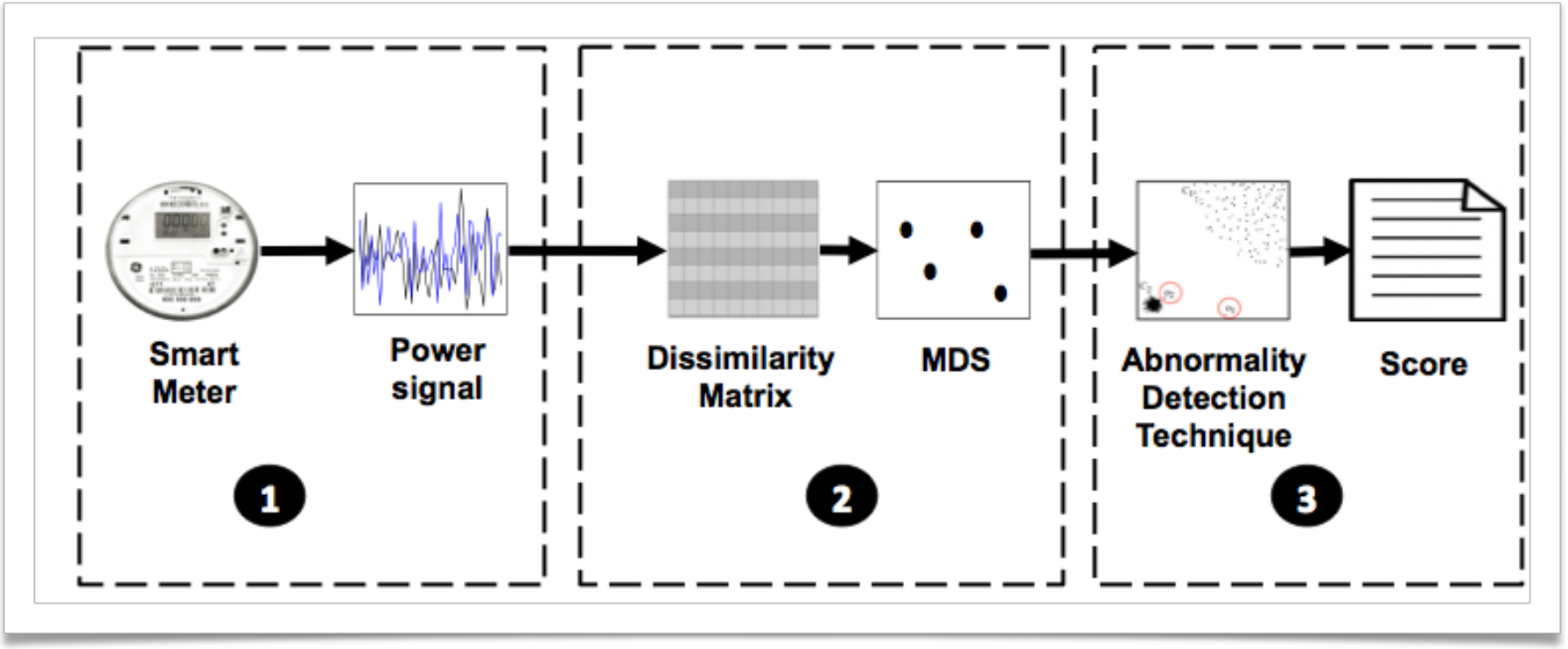
Problem statement

Develop an abnormality detection approach that will:

- Improve abnormality detection accuracy

- Work in both residential and commercial buildings

Proposed method: Monitor



Data Input → *Dimensionality reduction* → *Abnormality flagging*

Dimensionality reduction

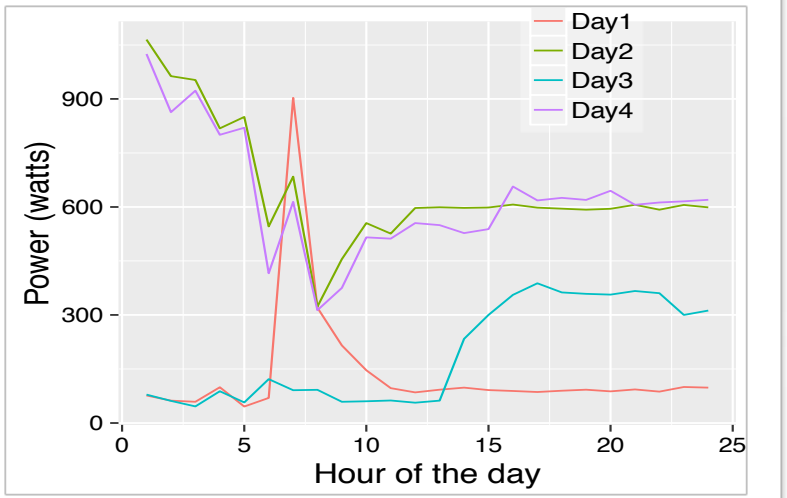


Fig: Hourly power consumption of four days

Multidimensional Scaling →

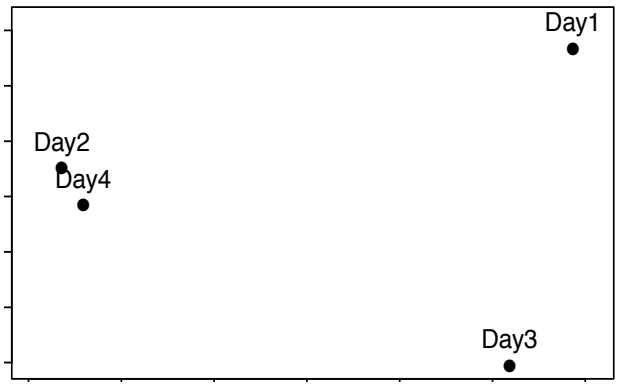


Fig: Lower dimensional representation

Data Input → **Dimensionality reduction** → Abnormality flagging

Abnormality flagging

- Compute density for each day's consumption with Local Outlier Factor (LOF)[1]
- Normalize density values in the range of 0 to 1.

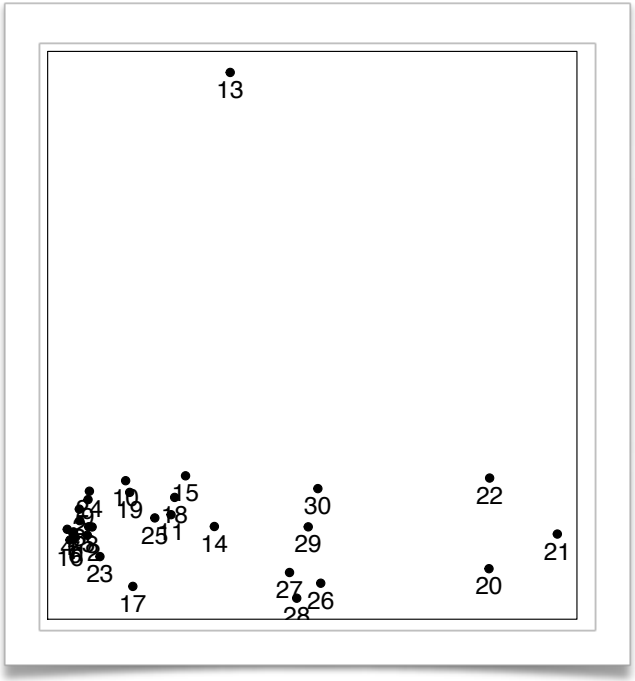


Fig: Lower dimensional representation

Data Input → Dimensionality reduction → **Abnormality flagging**

[1] M. M. Breunig et al. Identifying density-based local outliers. 2002

Dataset: IIIT-D energy dataset

16 weeks of data at hourly average sampling rate

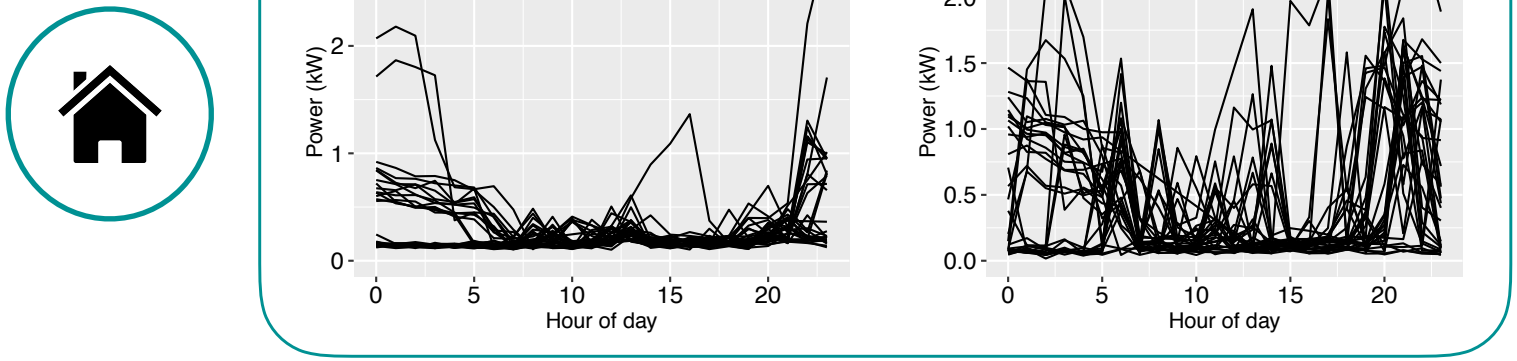
Two faculty apartments

- Size: Three bedrooms, a hall and a kitchen
- Family size: Four (at max.)
- Appliances: Fridge, AC, lighting and cooking appliances

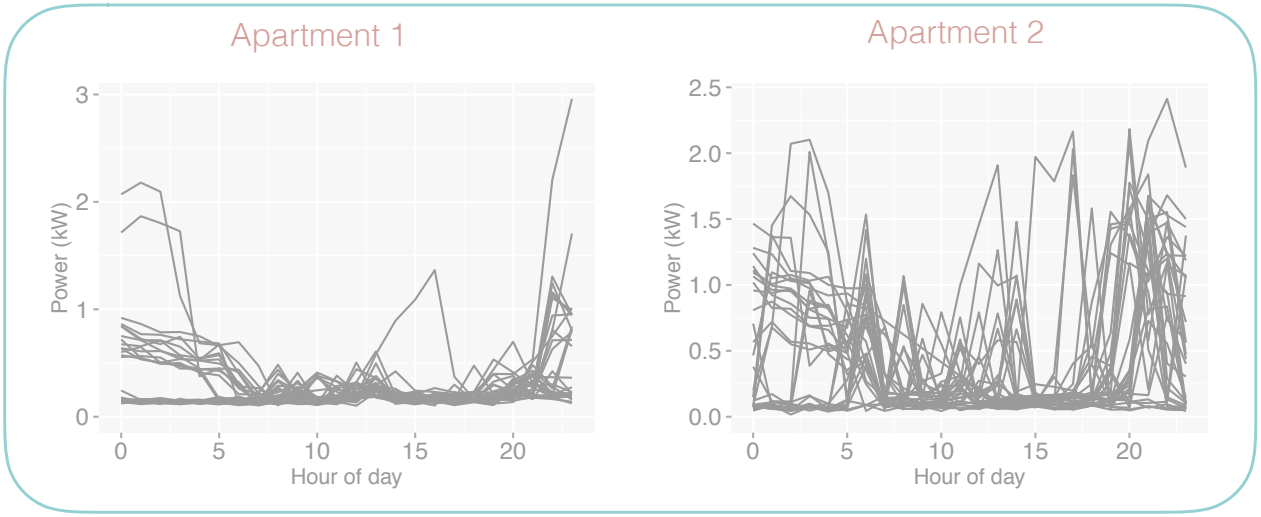
Lecture block & HVAC chiller

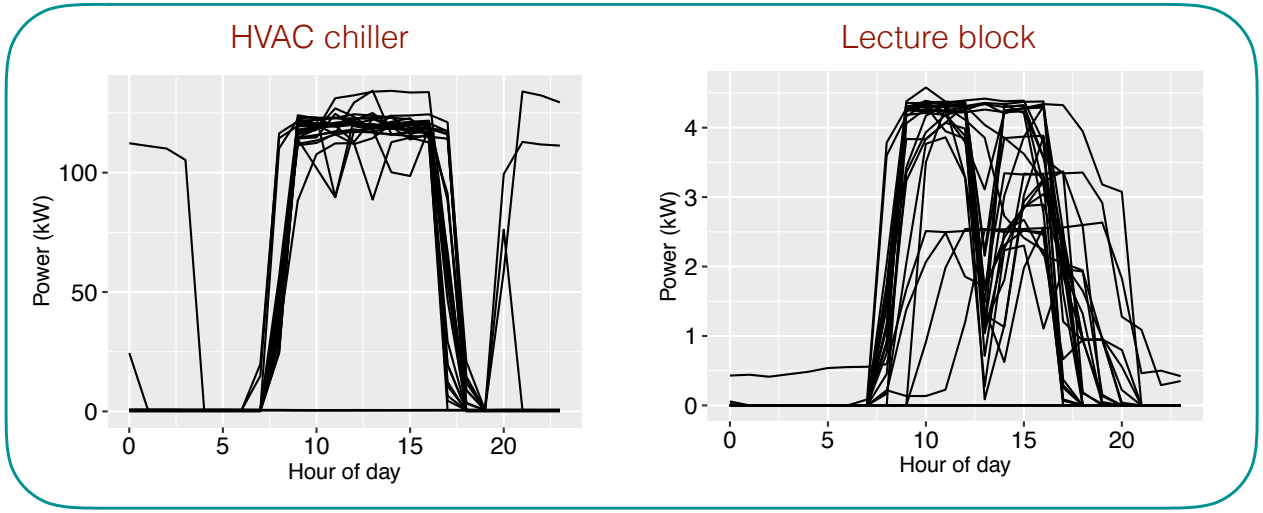
- Lecture block: 12 classrooms having lights, fans and HVAC equipment
- HVAC chiller: A 100kW equipment for removing heat from the circulating water of HVAC system

Power consumption patterns in the used dataset



Power consumption patterns in the used dataset

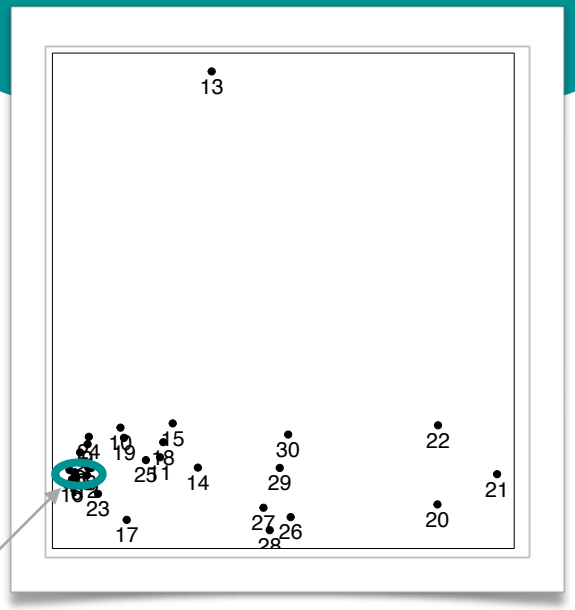




Baseline methods

- **ADM-I** [1]

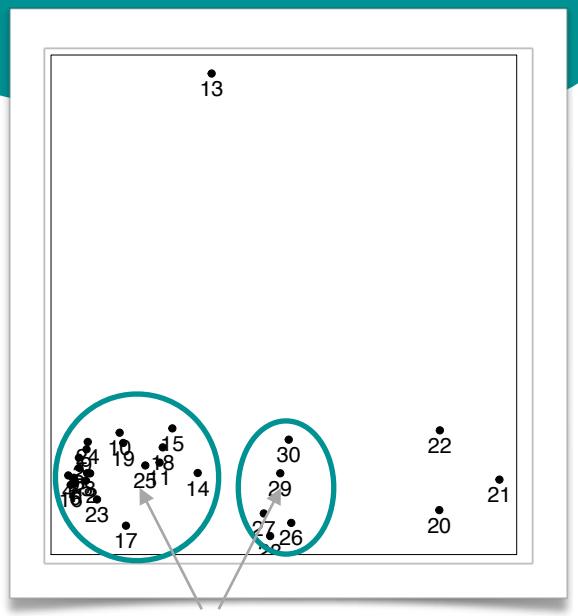
Computes abnormality score for all days with respect to one day having highest density



Day with highest density

- **ADM-II** [2]

Computes abnormality score for each day with respect to the centers of all the clusters



Cluster centers

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

Results

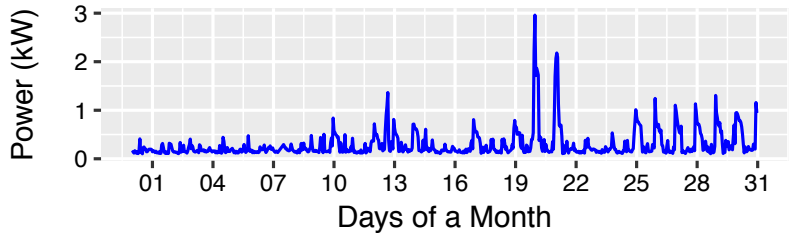


Fig: Power signature of an apartment for one month

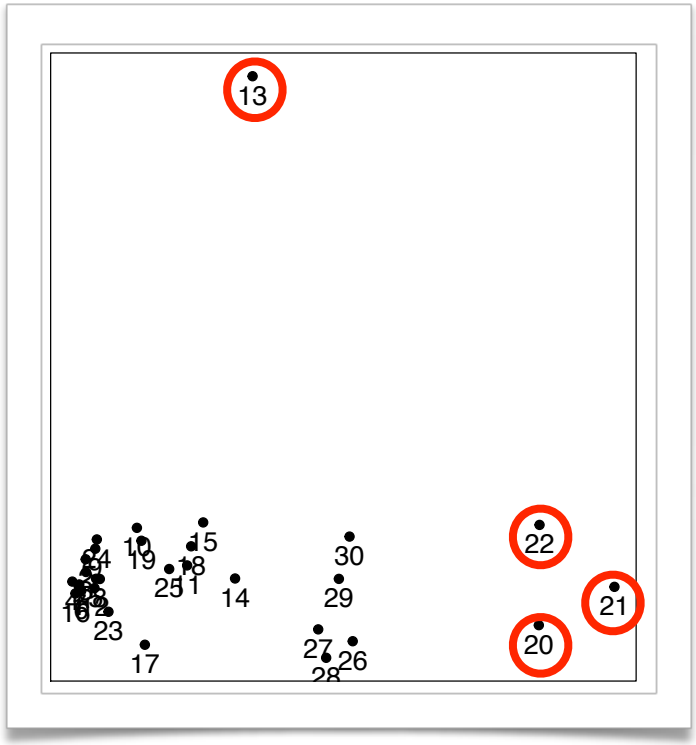


Fig: Lower dimensional representation of one month data

Results

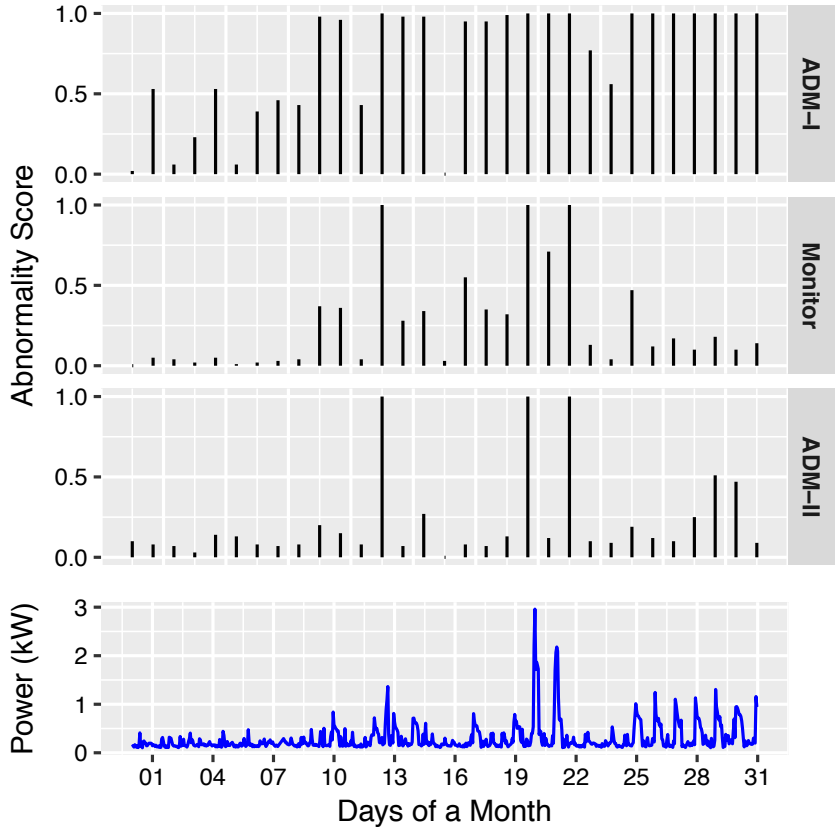


Fig: Power signature of an apartment for one month

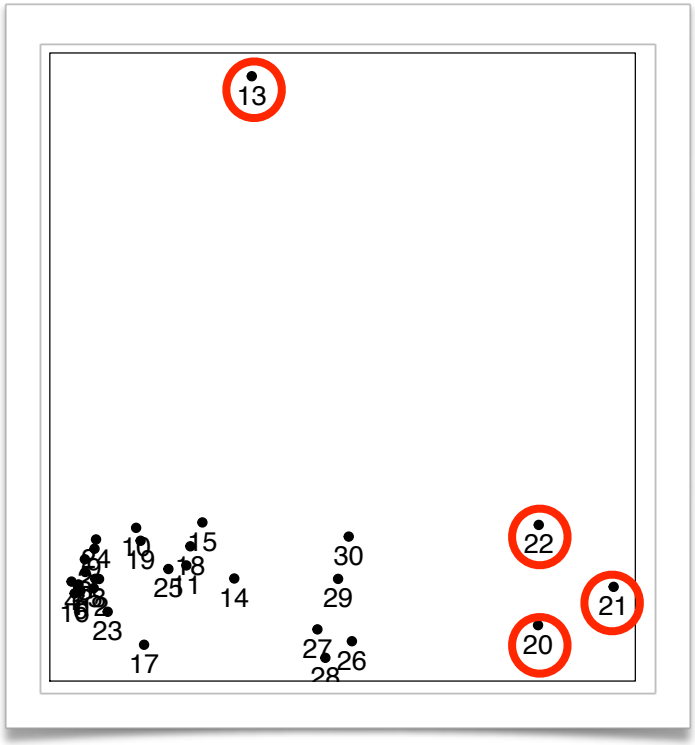
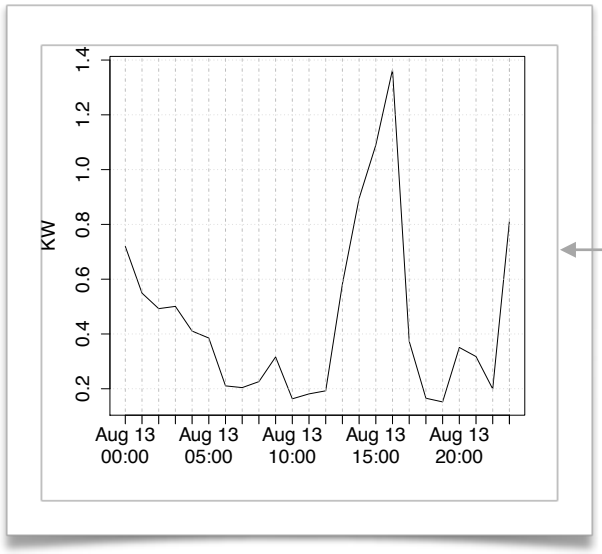
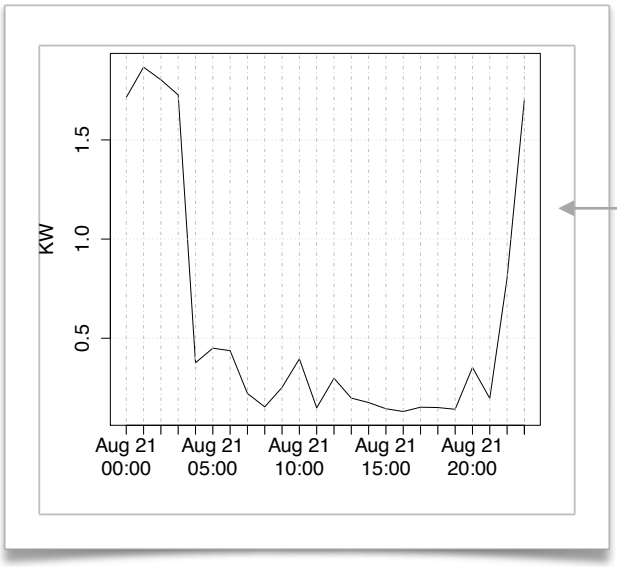


Fig: Lower dimensional representation of one month data

Results





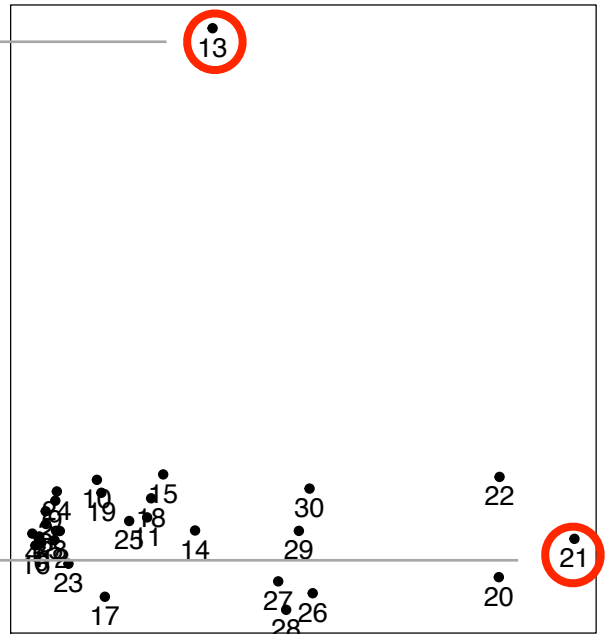
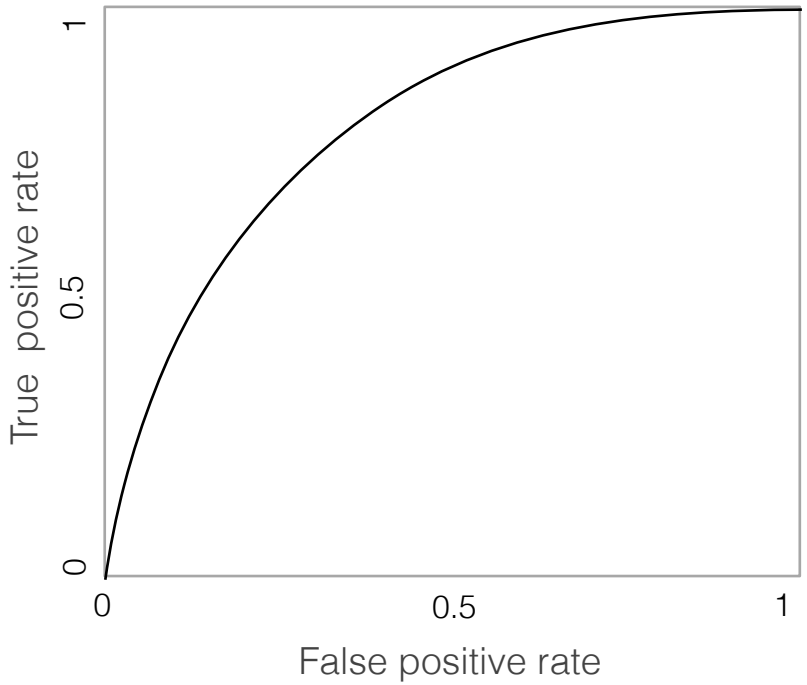


Fig: Lower dimensional representation of one month data

Accuracy metric: ROC curve → AUC

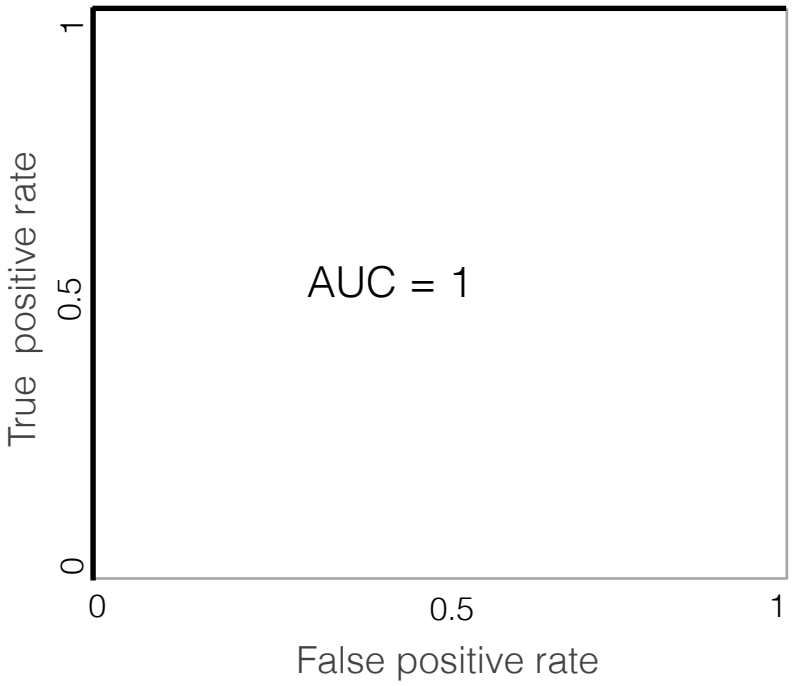


$$TPR = \frac{TP}{TP + FN}$$

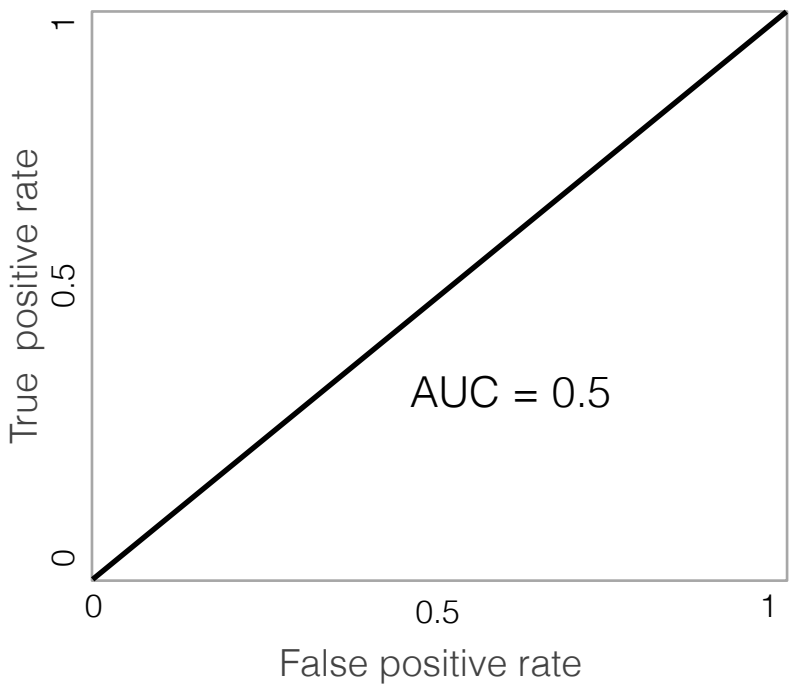
$$FPR = \frac{FP}{FP + TN}$$

ROC curve gives a single value called as Area Under the Curve (AUC)

Accuracy metric: ROC curve → AUC



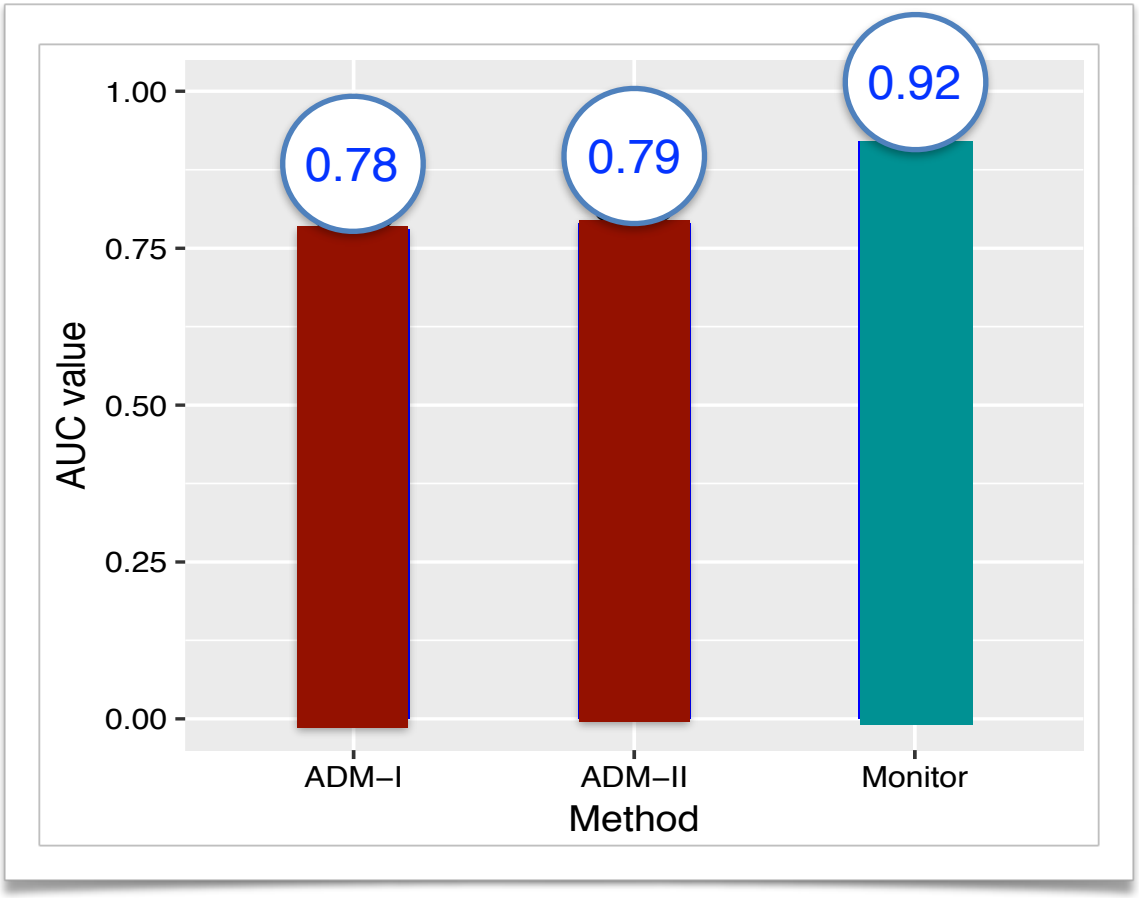
Best



Worst

AUC value ranges between 0 and 1

Monitor increases AUC by 17%



The higher the AUC, the better is the performance

Monitor reduces false positives (+)

Method	A1	A2	Lecture block	Chiller
ADM-I	15	9	7	20
ADM-II	0	1	2	2
Monitor	0	2	0	0

Table: False positives with different methods

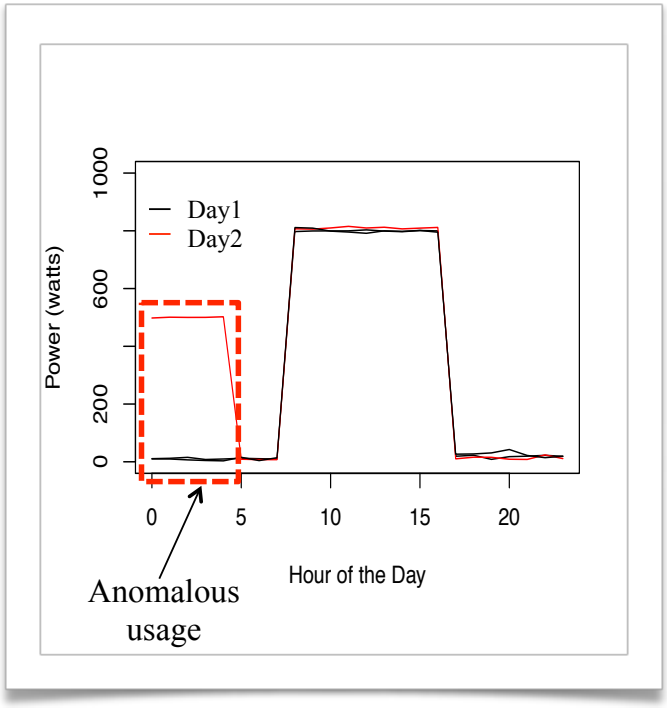
Monitor has more false negatives (-)

Method	A1	A2	Lecture block	Chiller
ADM-I	0	0	2	0
ADM-II	1	1	2	2
Monitor	1	1	3	1

Table: False negatives with different methods

Limitations

- Anomaly detection not in real-time



- Manual anomaly search

timestamp	power
2013-02-24 00:10:00	533.8
2013-02-24 00:20:00	666.4
2013-02-24 00:30:00	1052.9
2013-02-24 00:40:00	1048.8
2013-02-24 00:50:00	1189.5
2013-02-24 01:00:00	1145

Conclusion

- Improves abnormality detection accuracy
  - Reduces false positives by a large margin
- Works for both residential and commercial scenarios

Thank You!

haroonr@iiitd.ac.in | https://loneharoon.github.io