Monitor: An Abnormality Detection Approach for Buildings Energy Consumption

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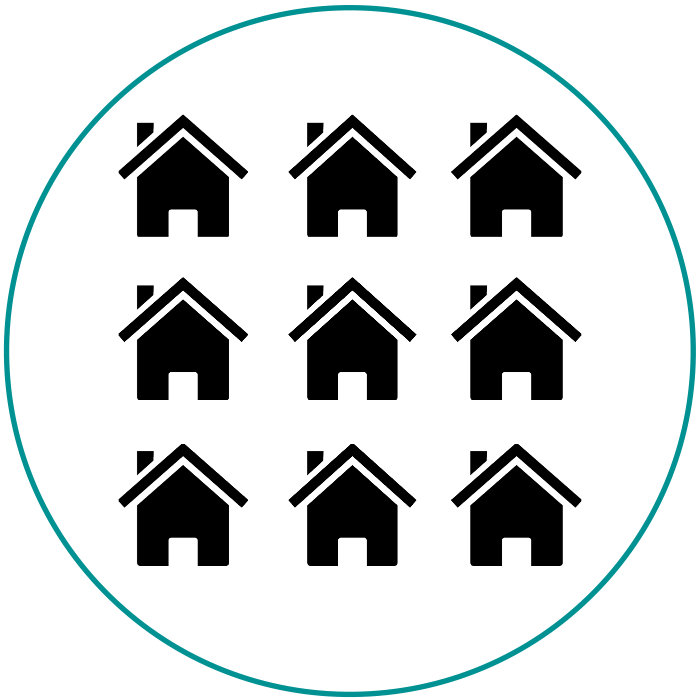
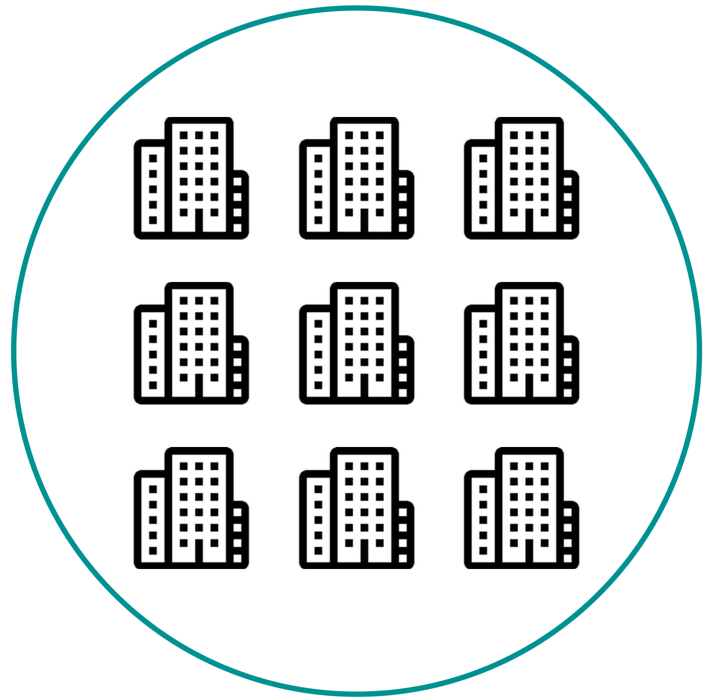
Buildings consume 39% of energy



Residential buildings

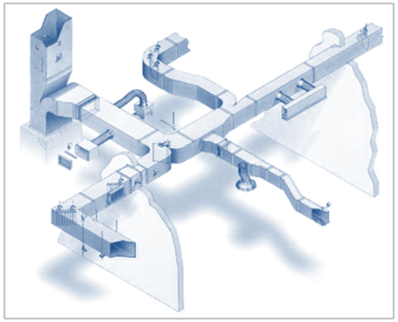


Commercial buildings

Source: International Energy Outlook, 2017

Energy wastage → abnormalities

Reasons for energy wastage:



Duct leakage in HVAC

Source: Google Images

Energy wastage → abnormalities

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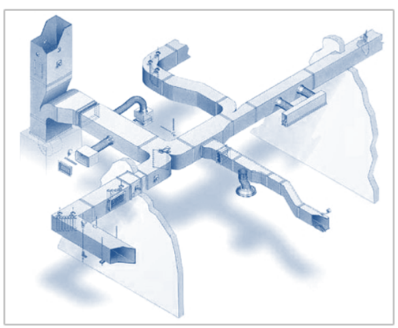


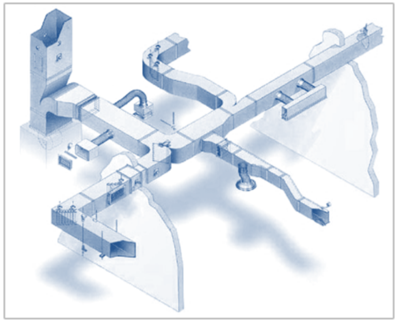
Duct leakage in HVAC

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

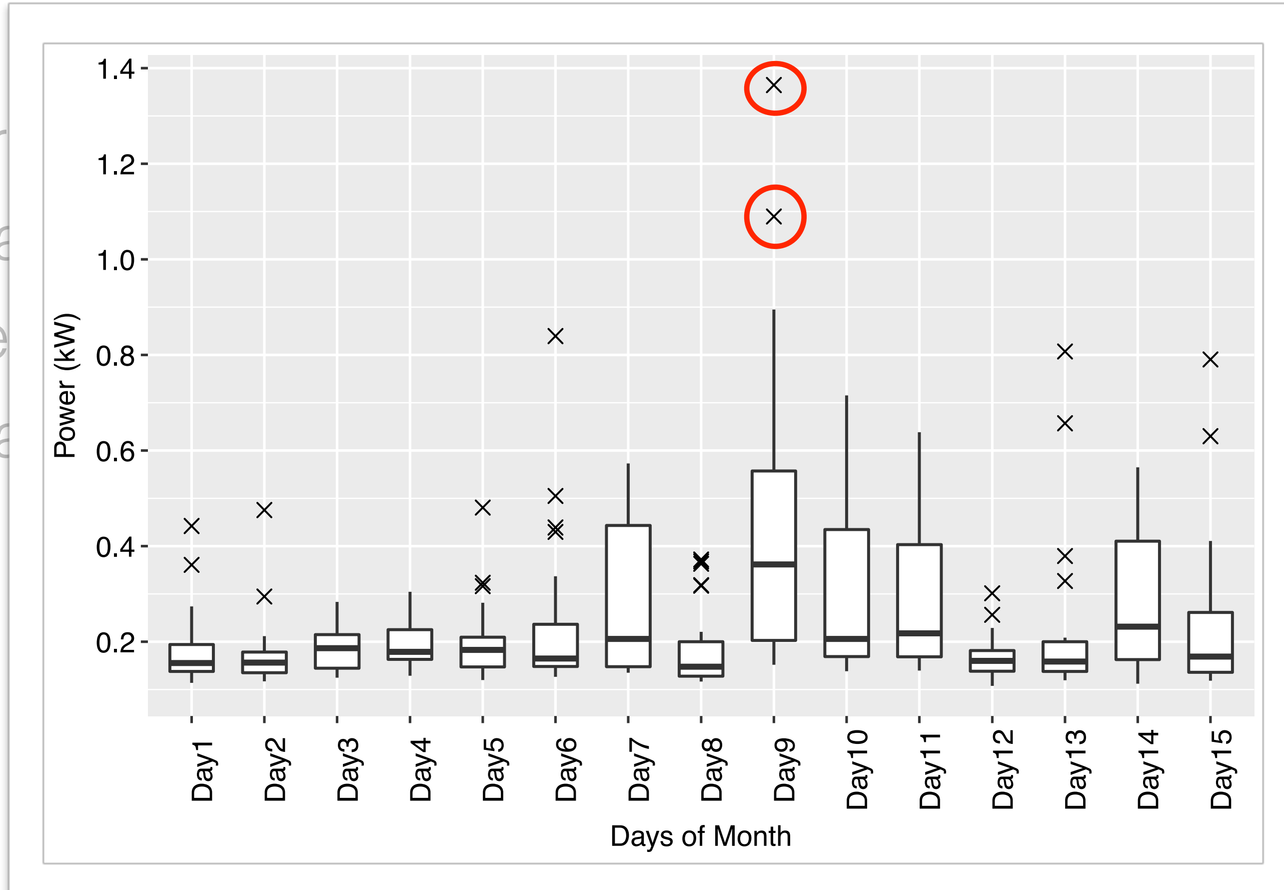


Fig: Box plots on hourly power consumption of a home for 15 days

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]

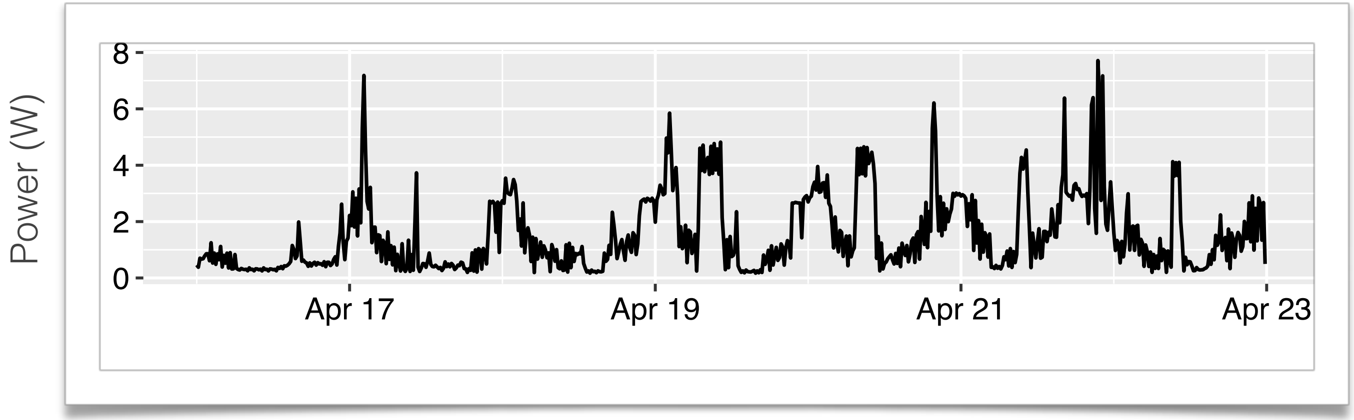


Fig: Every day follows a different energy consumption

- 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]

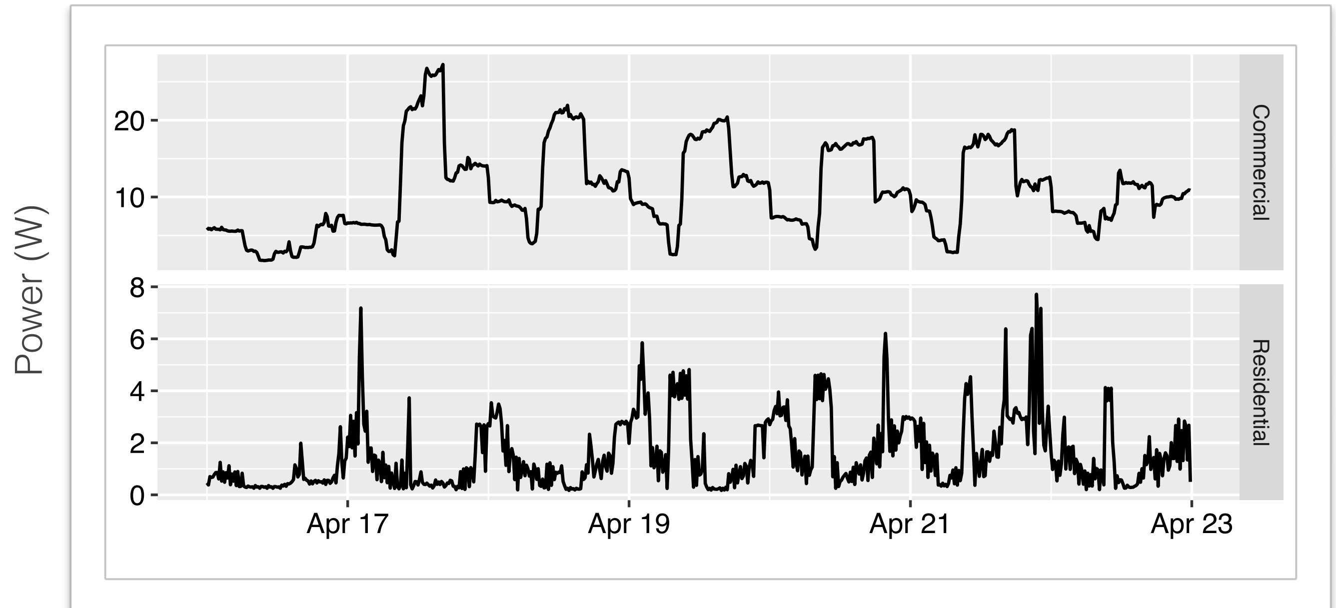


Fig: Energy consumption signature of commercial & residential buildings

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

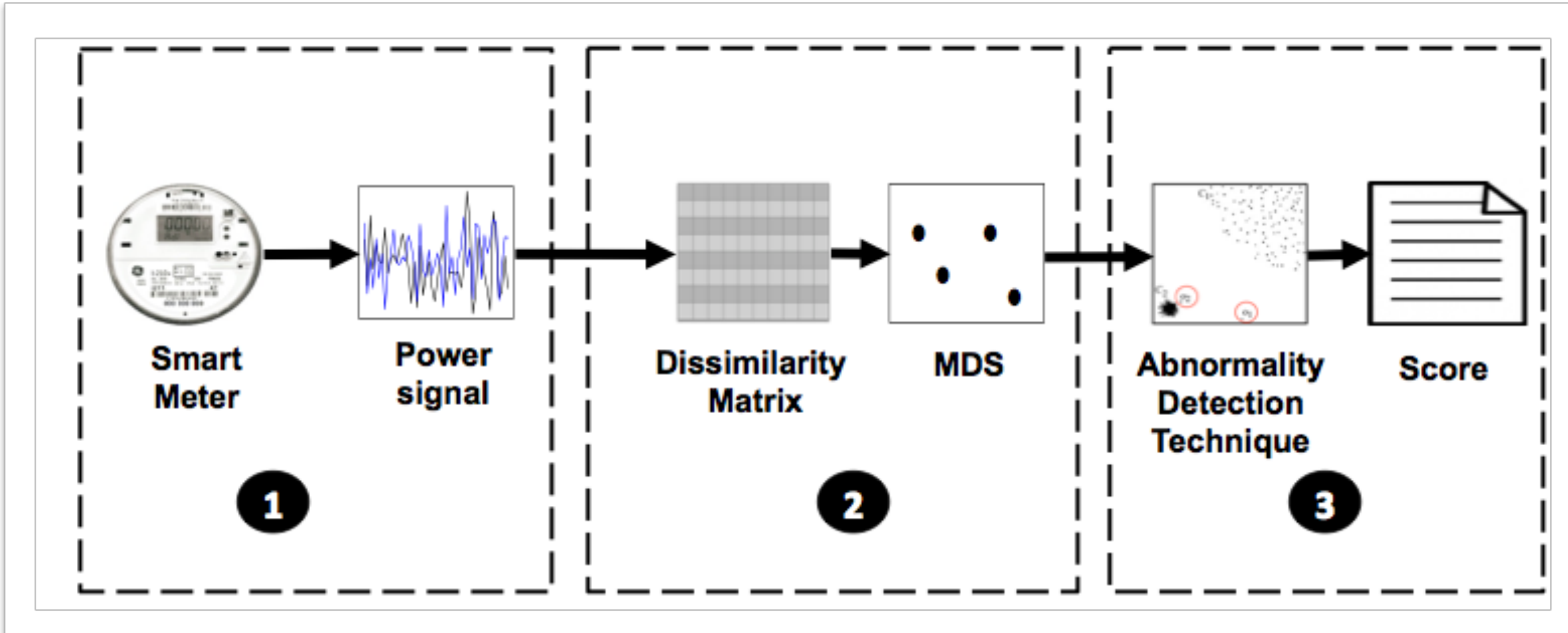
Problem statement

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

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

Dimensionality reduction

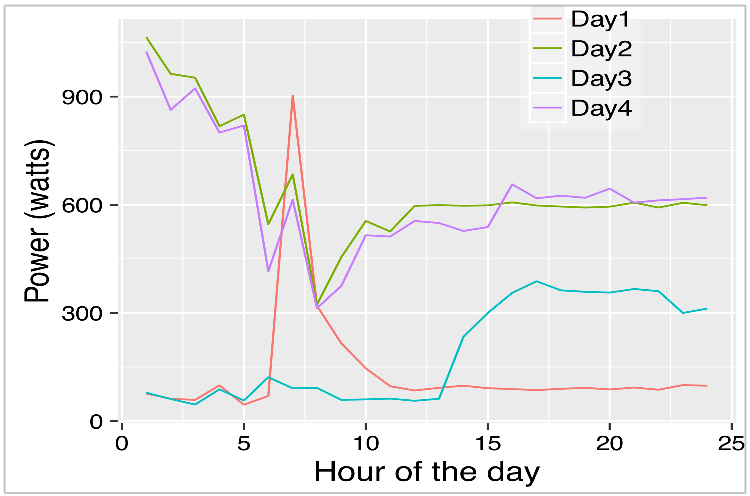


Fig: Hourly power consumption of four days

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

Dimensionality reduction

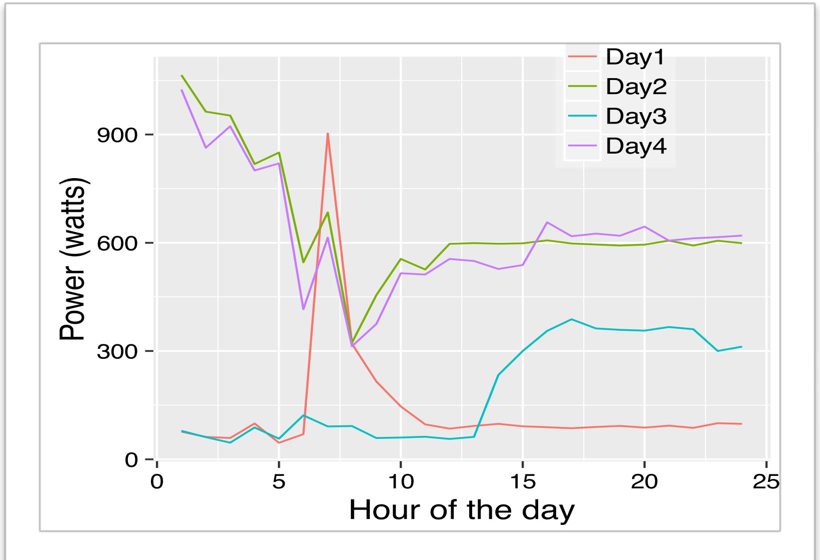


Fig: Hourly power consumption of four days

Multidimensional Scaling

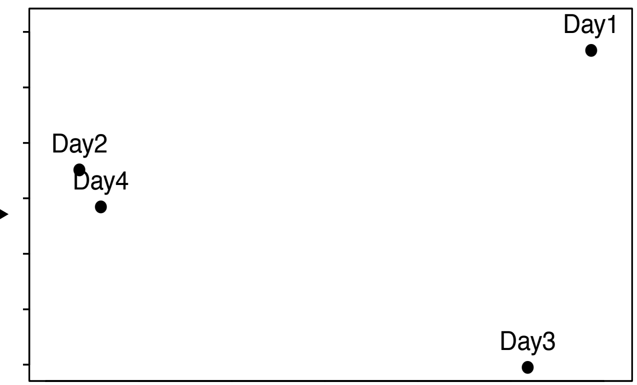


Fig: Lower dimensional representation

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.

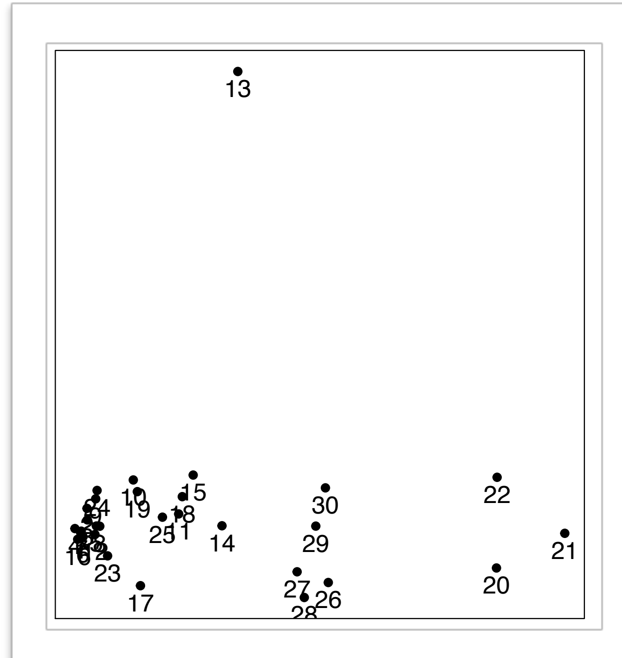


Fig: Lower dimensional representation

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

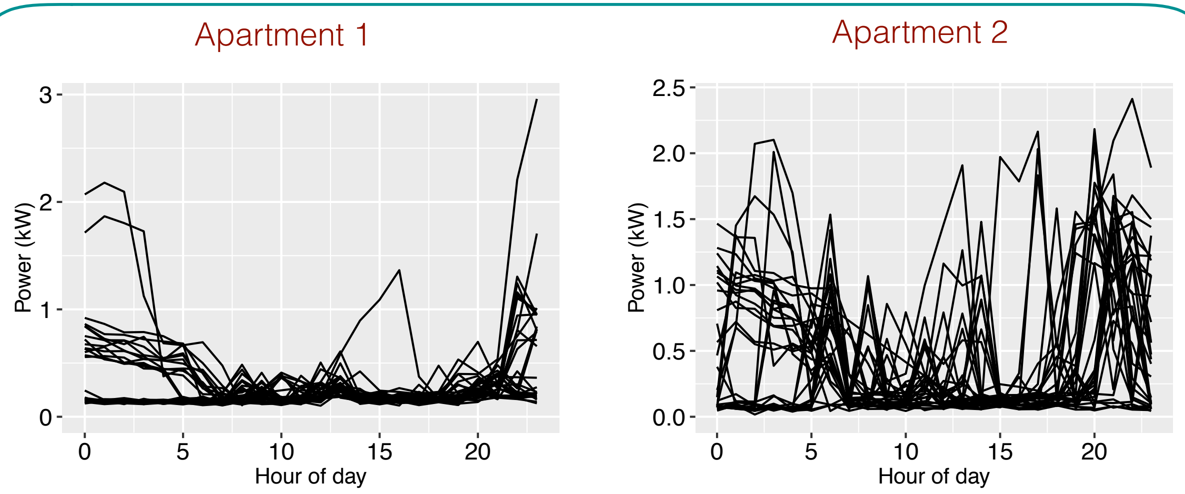
Two faculty apartments

- 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



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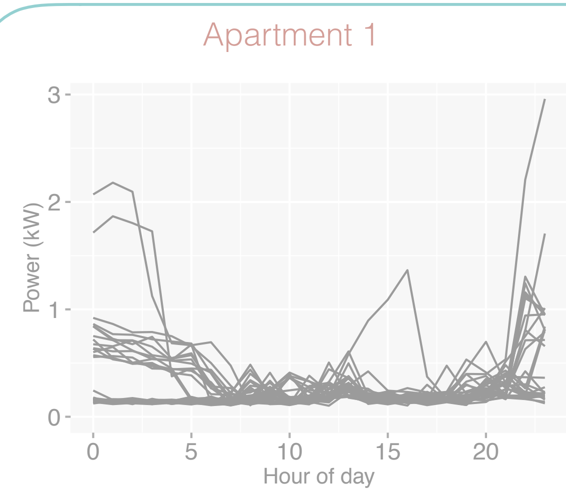
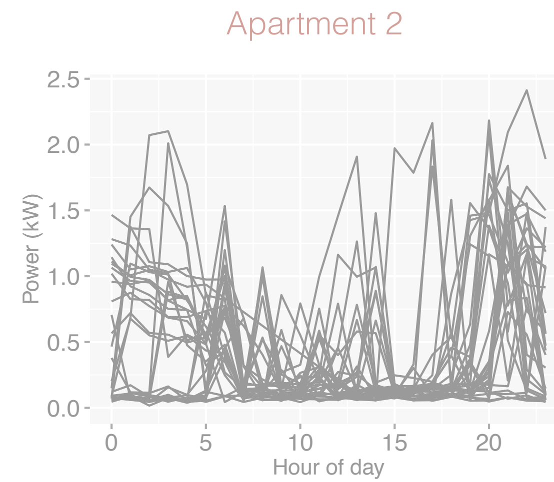
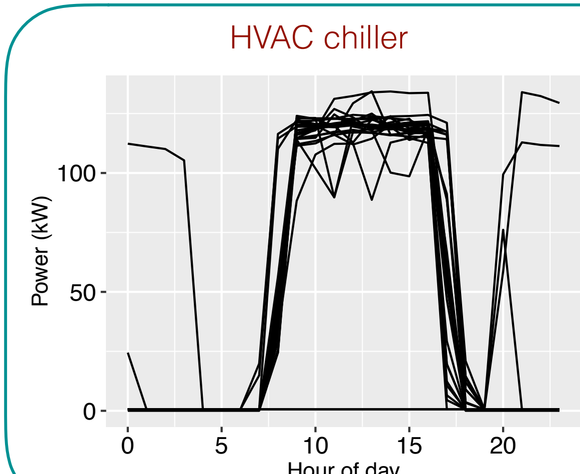
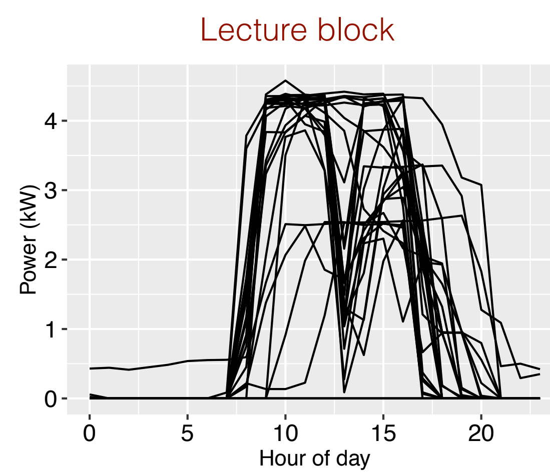




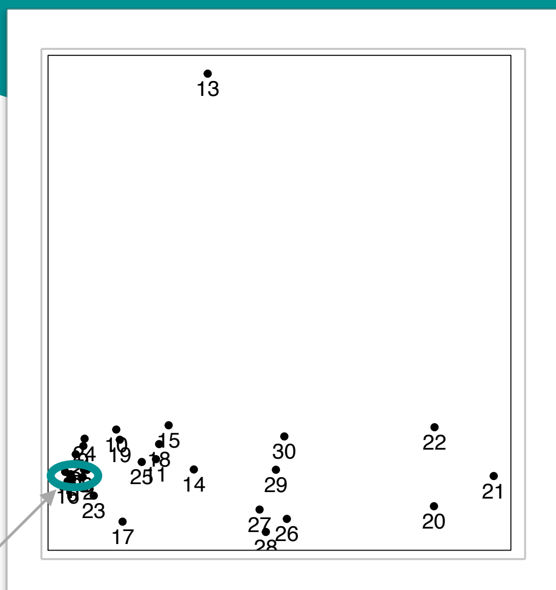




Baseline methods

- **ADM-I** [1]

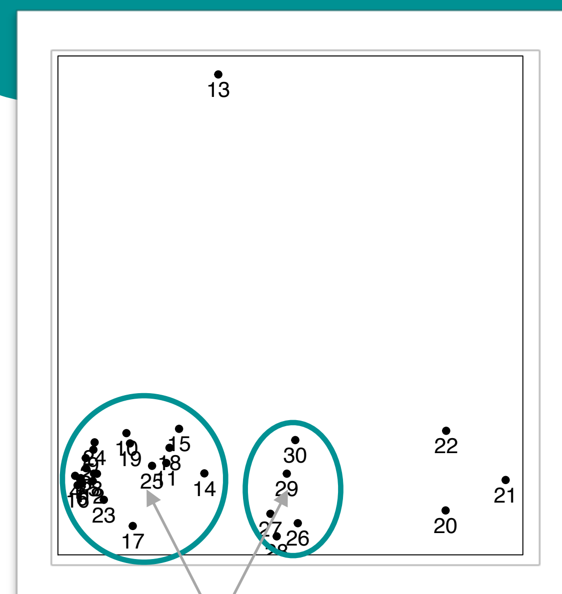
Computes abnormality score for all days with respect to one day having highest density



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

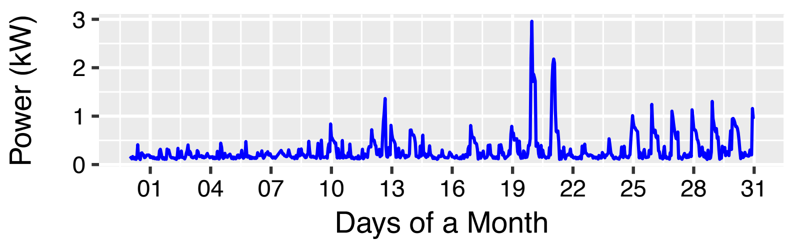


Fig: Power signature of an apartment for one month

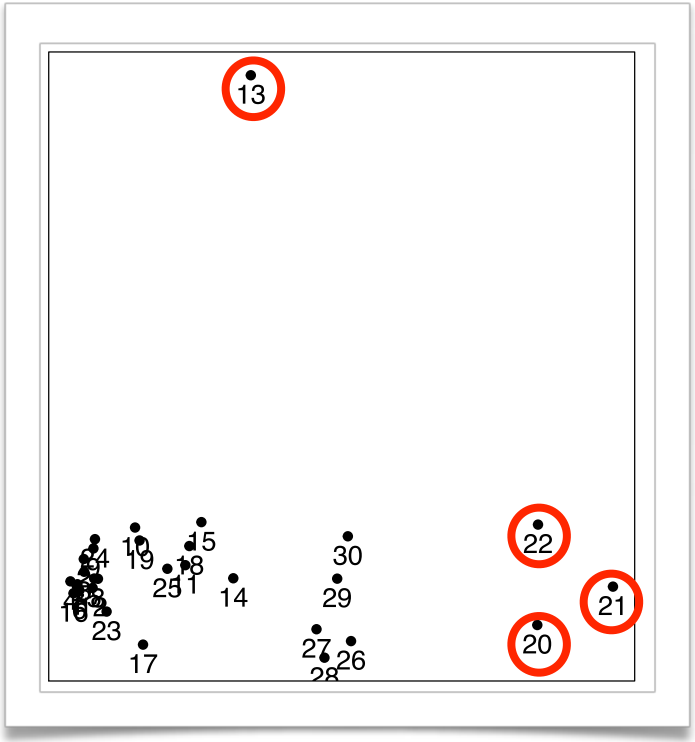
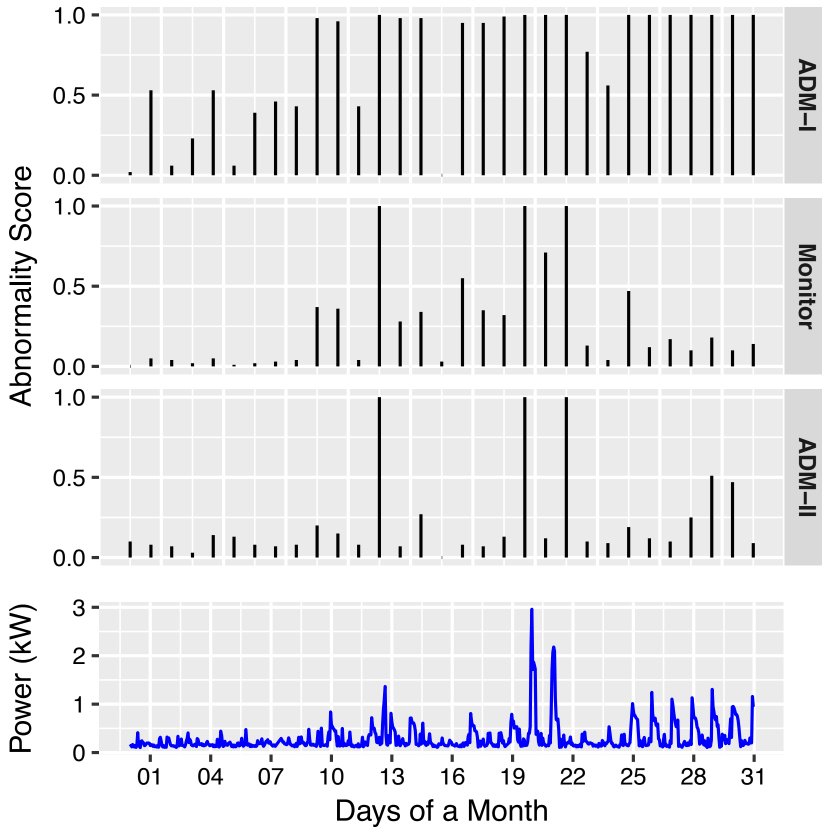


Fig: Lower dimensional representation of one month data

Results



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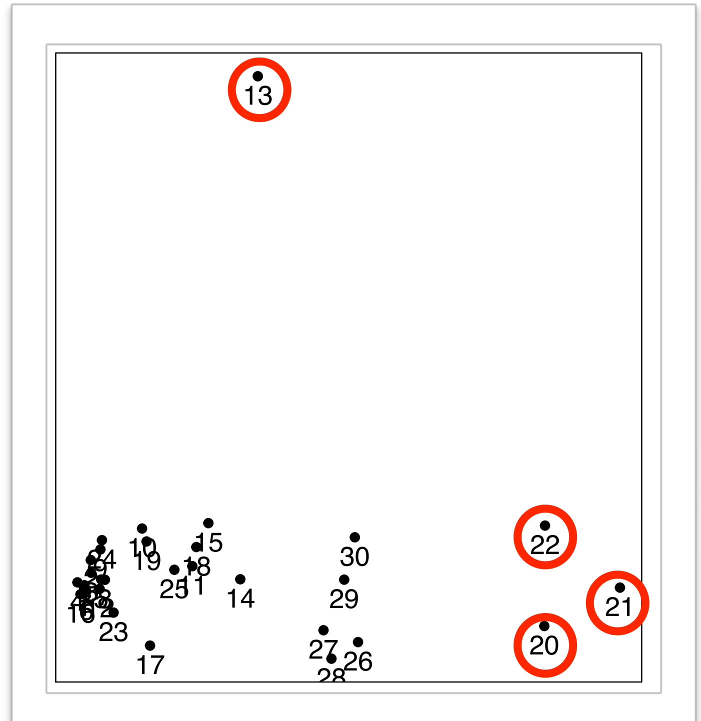

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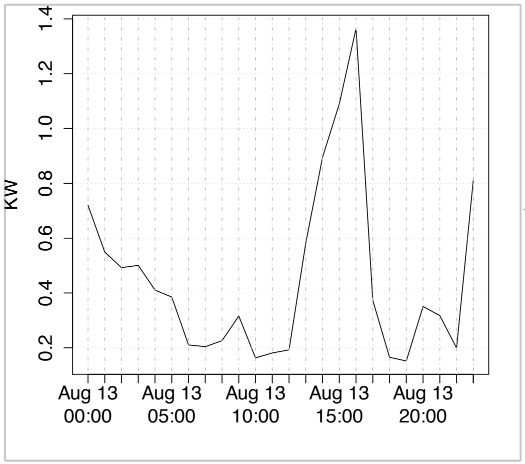
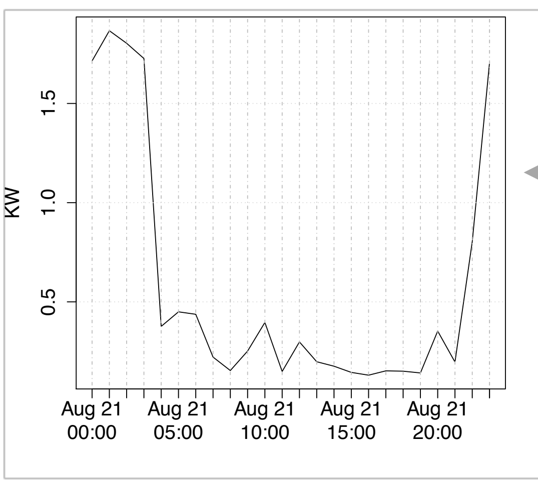




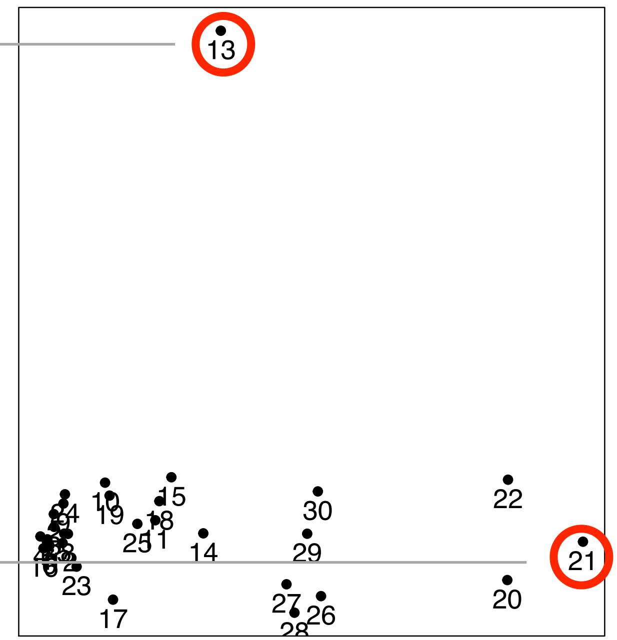
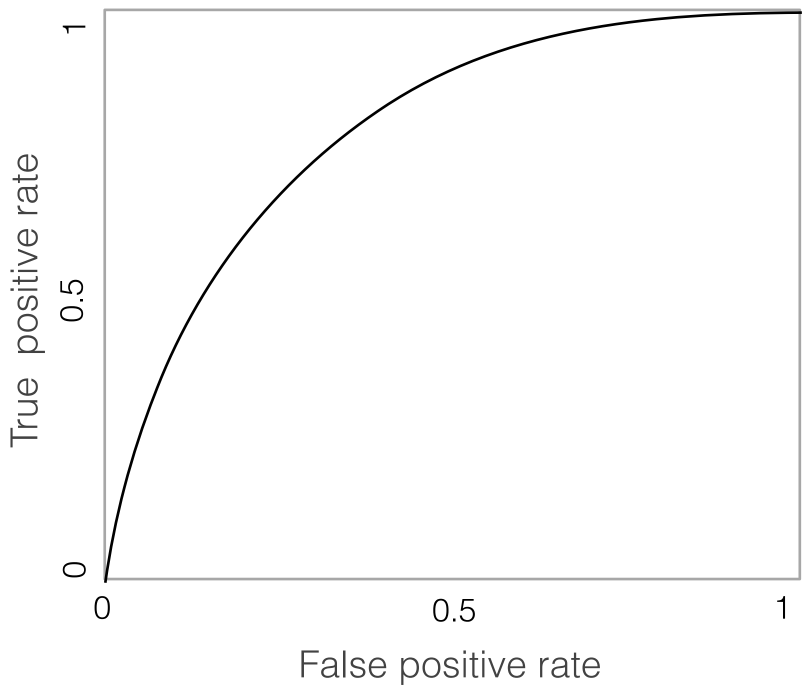


Fig: Lower dimensional representation of one month data

Accuracy metric: ROC curve ⟶ AUC

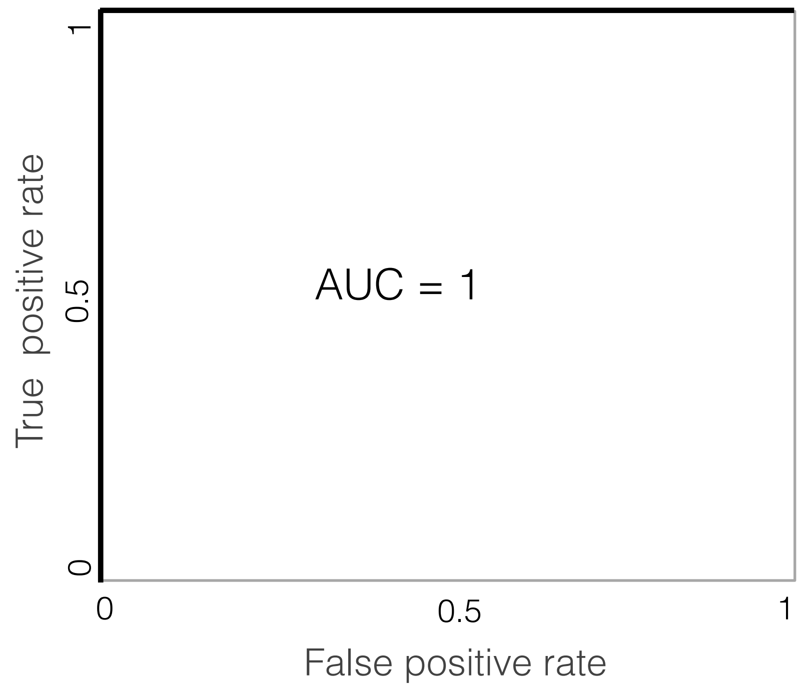


$$TPR = \frac{TP}{TP + FN}$$

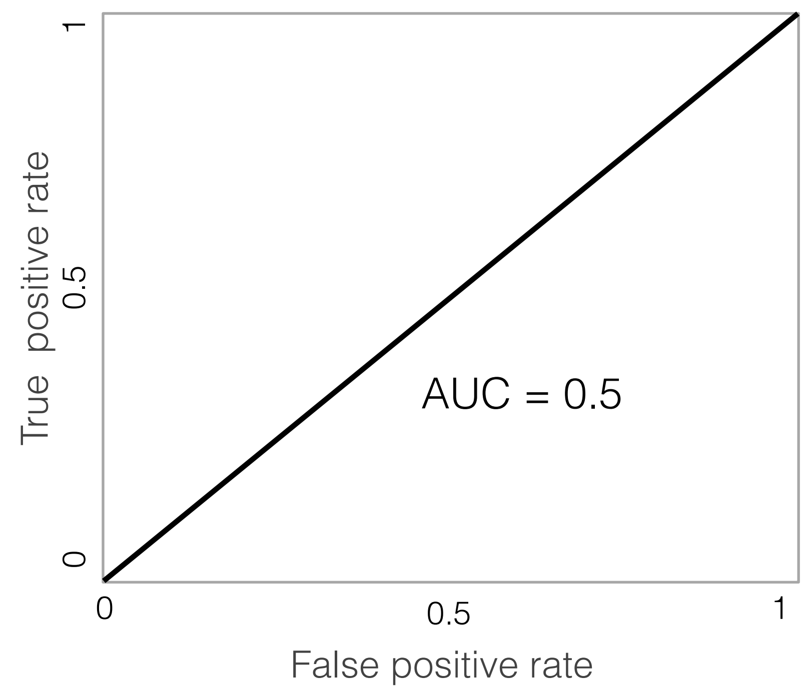
$$FPR = \frac{FP}{FP + TN}$$

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

Accuracy metric: ROC curve → AUC



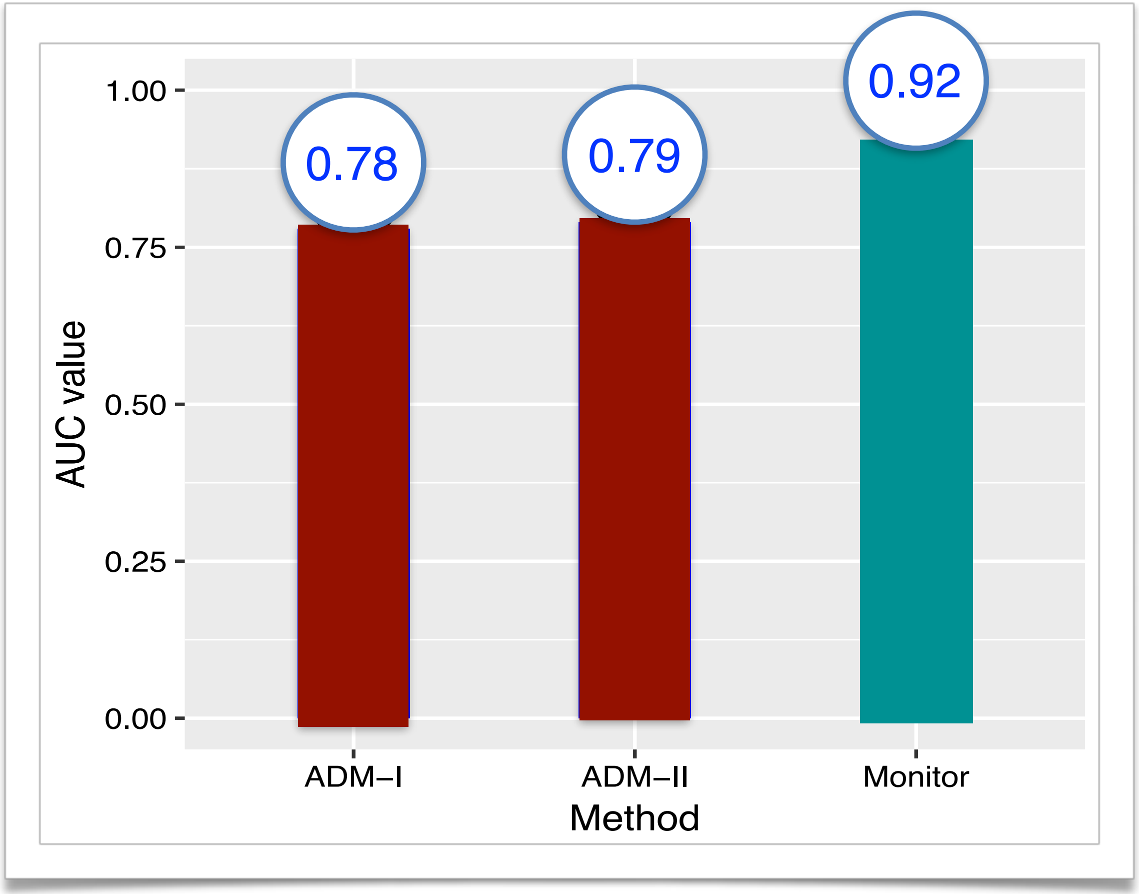
Best



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 (-)

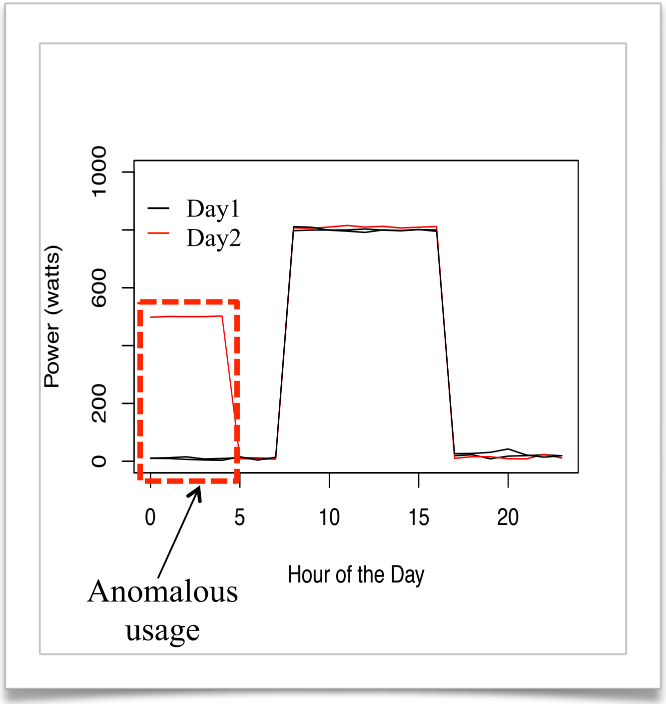
Method	A1	A2	Lecture block	Chiller
ADM-I	0	0	2	0
ADM-II	1	1	2	2
Monitor	1	1	3	1

Table: False negatives with different methods

Limitations

Limitations

- Anomaly detection not in real-time



Limitations

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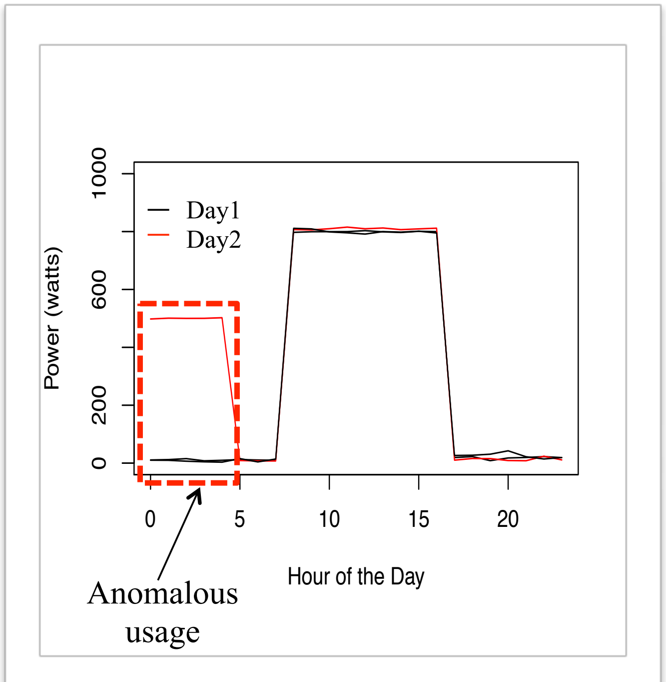

- Manual anomaly search

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!

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Looking for a Postdoc position :)

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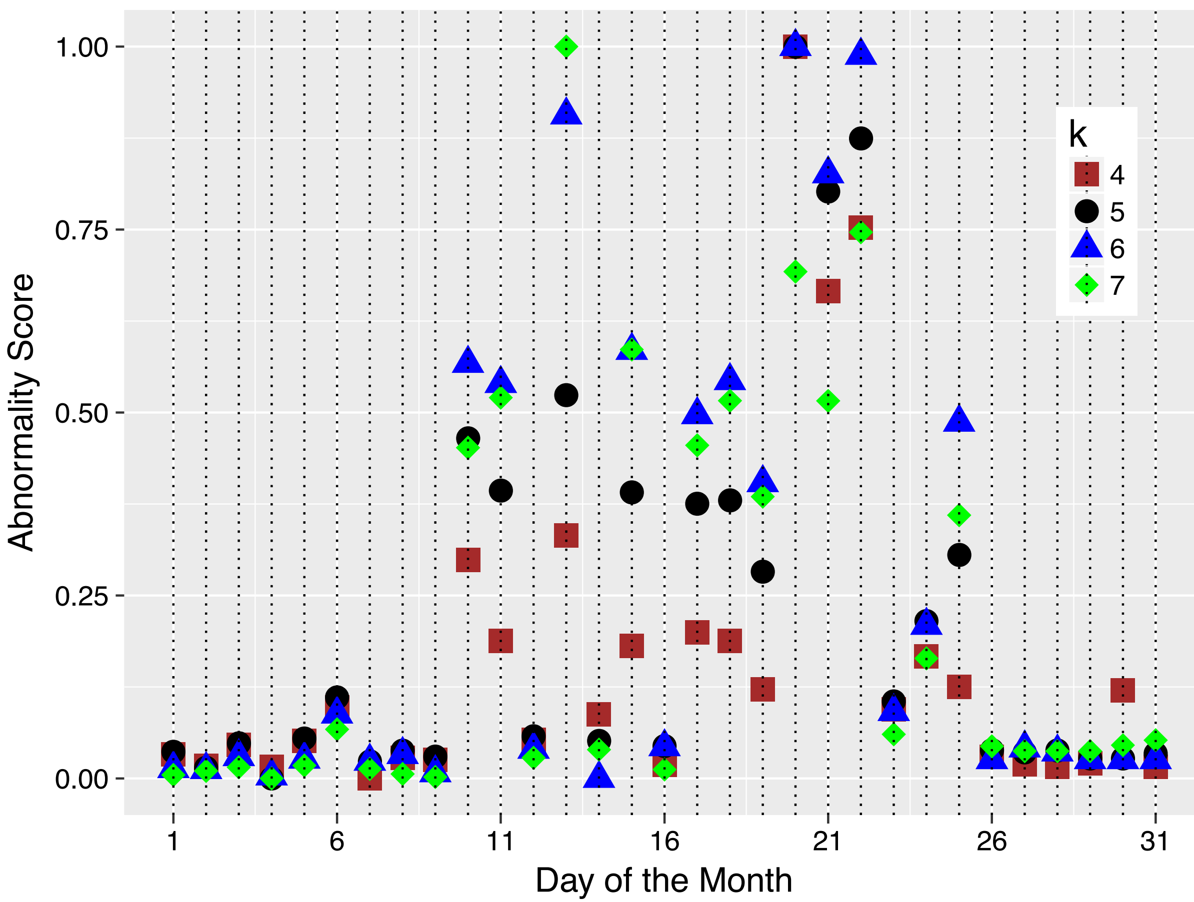
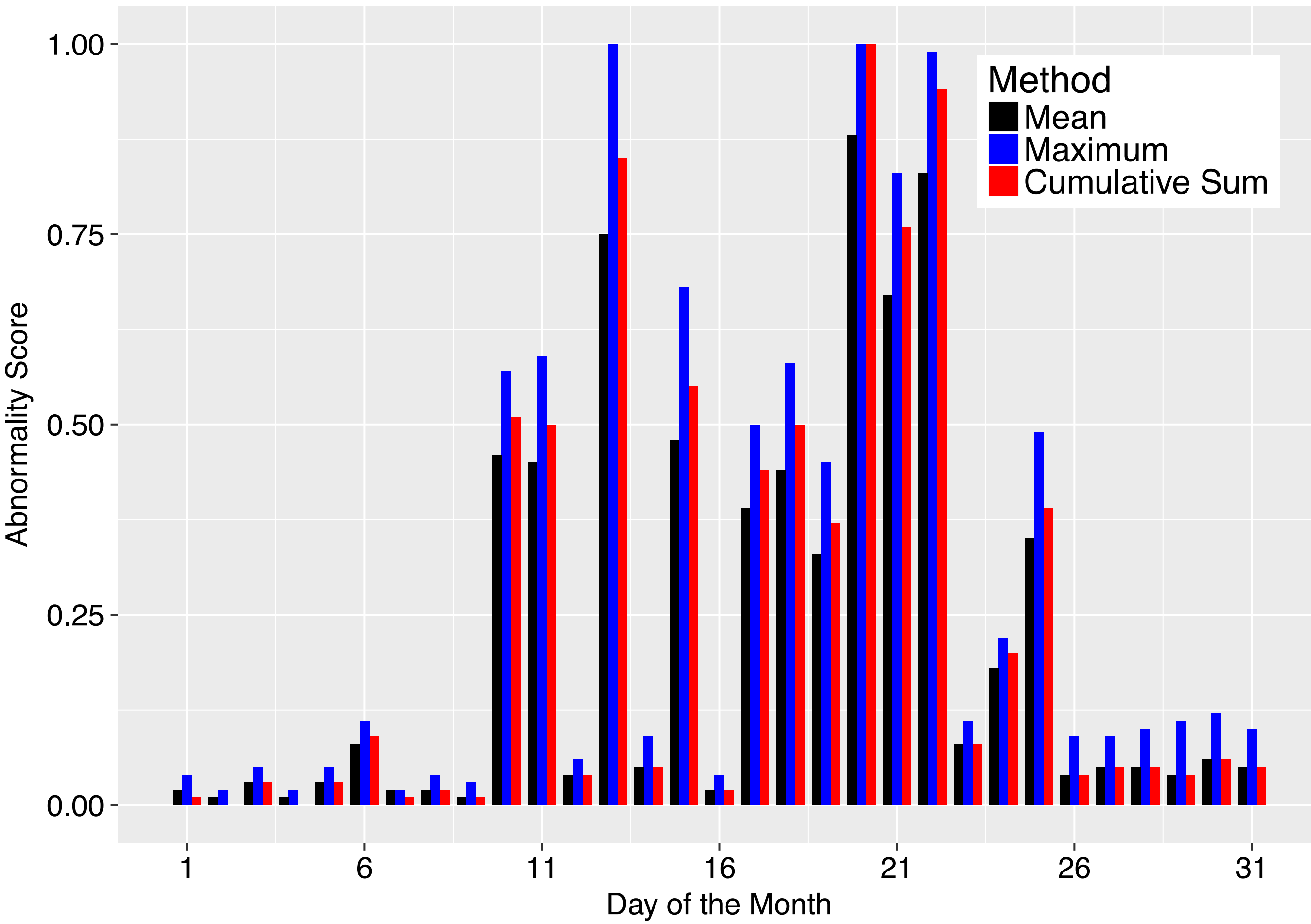
Annexure

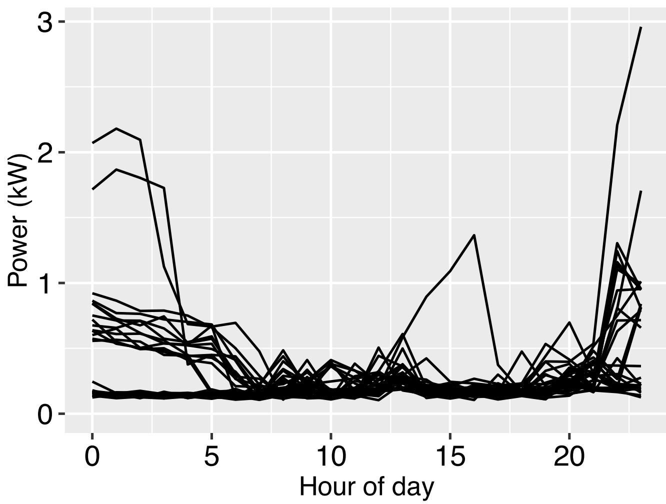
Effect of k on abnormality score



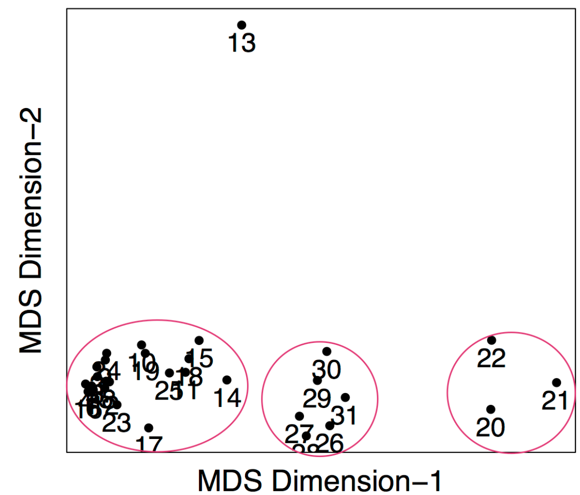
Effect of aggregation methods



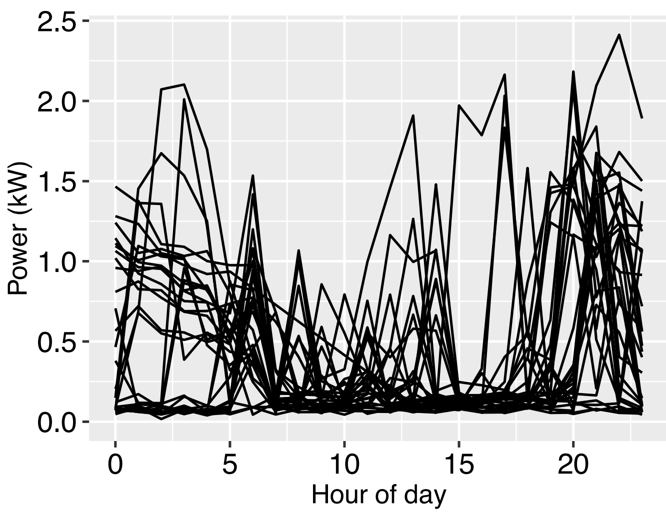
MDS: Example



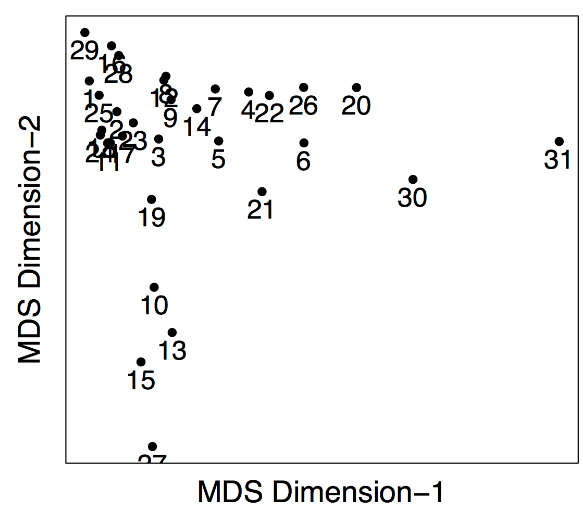
Power (kW)
Hour of day
0
1
2
3
5
10
15
20



MDS Dimension−2
MDS Dimension−1
13
22
21
20
30
29
31
26
14
15



Power (kW)
Hour of day
0.0
0.5
1.0
1.5
2.0
2.5
0
5
10
15
20



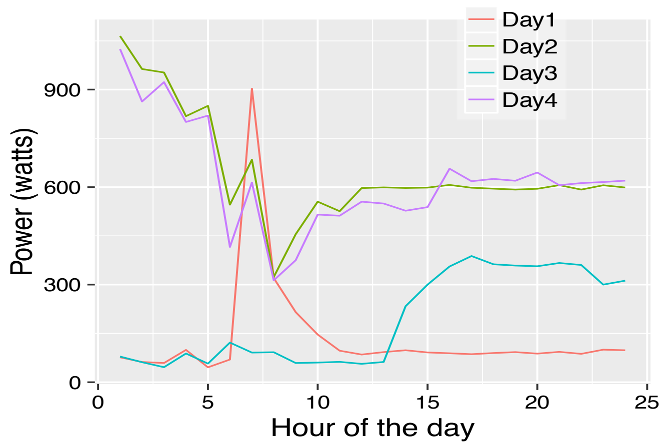
MDS Dimension−2
MDS Dimension−1
29
20
26
31
30
21
19
10
13
15
6
5
3
14
7

Dimensionality reduction

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

Dimensionality reduction

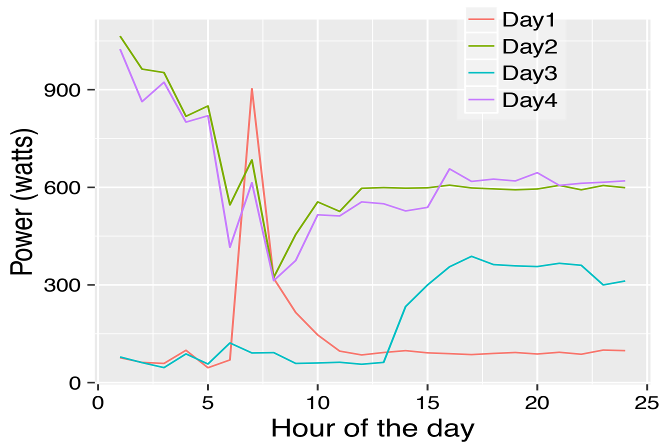
Power consumption



Data Input → Dimensionality reduction → Abnormality flagging

Dimensionality reduction

Power consumption



→

Dissimilarity matrix

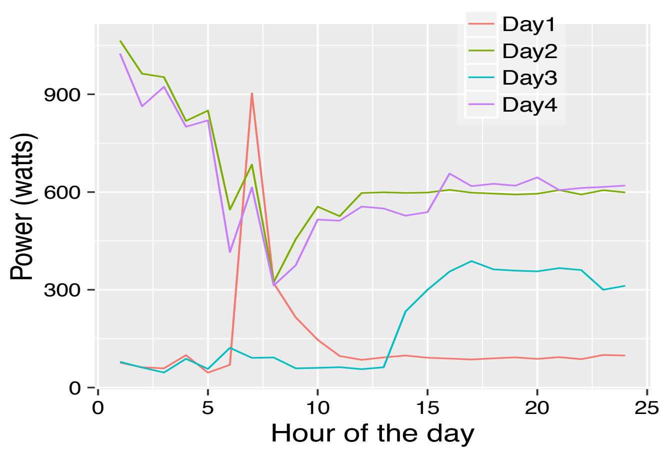
	Day1	Day2	Day3	Day4
Day1	0	2789	1194	2699
Day2	2789	0	2516	254
Day3	1194	2516	0	2371
Day4	2699	254	2371	0

$$dist(day_x, day_y) = \sqrt{\sum_{i=1}^{n=24} (day_x^i - day_y^i)^2}$$

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

Dimensionality reduction

Power consumption



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Dissimilarity matrix

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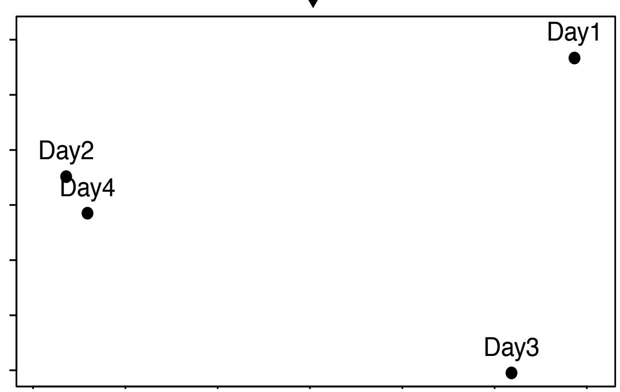
MDS



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