

DAD

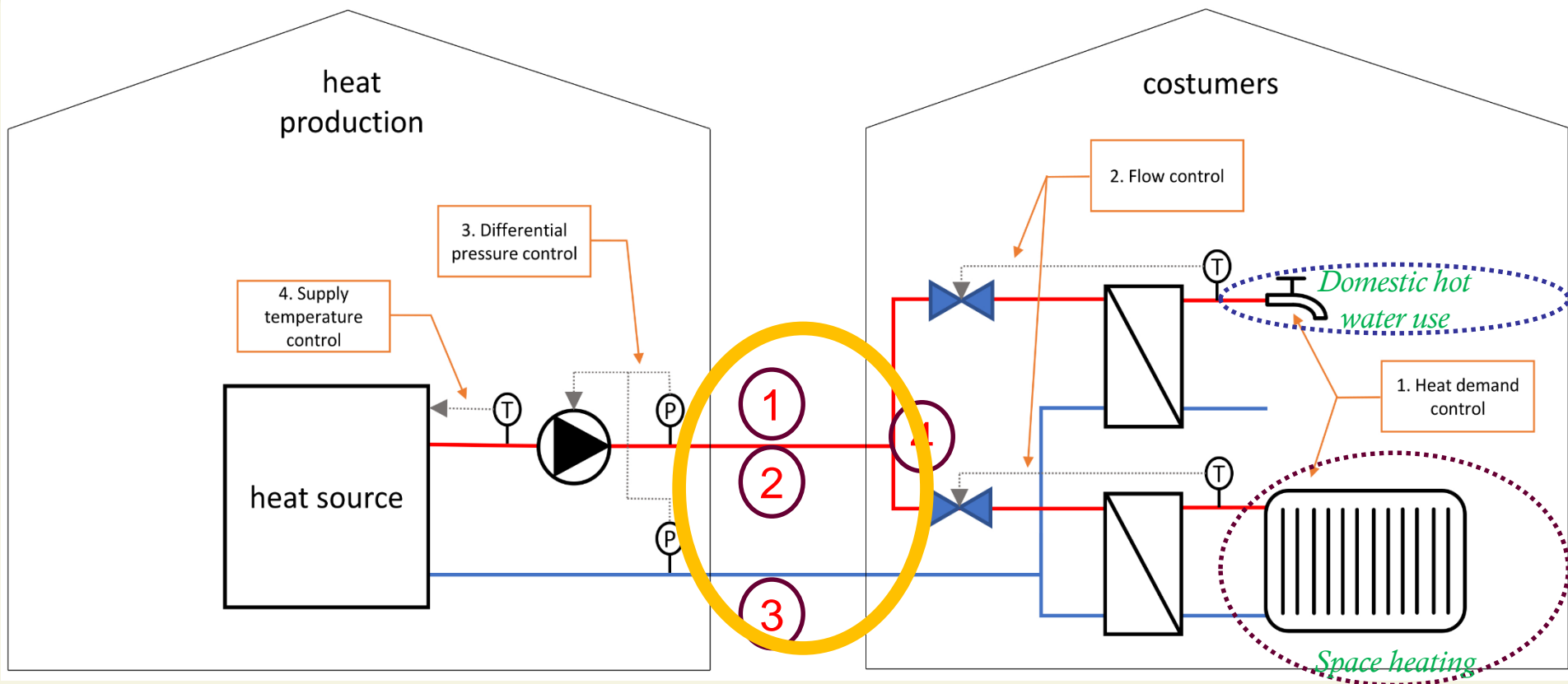
Data Analytics for fault Detection
in district heating systems



*How can analytics models be
used to detect defects in DH
substations?*

District Heating Substation

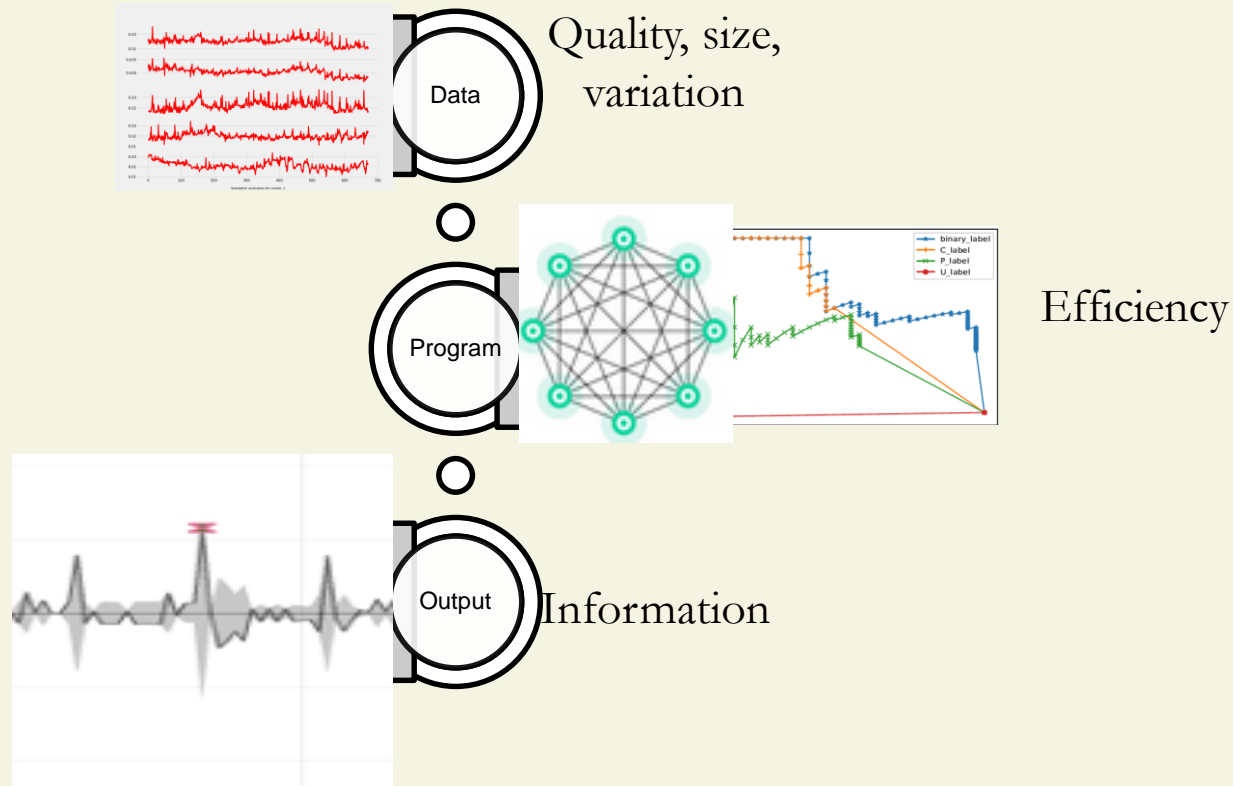
① Supply hot water temp in °C



② Hot water volume on arrival in m³ ③ Return hot water temp in °C ④ Energy in MWh

Data Analytics

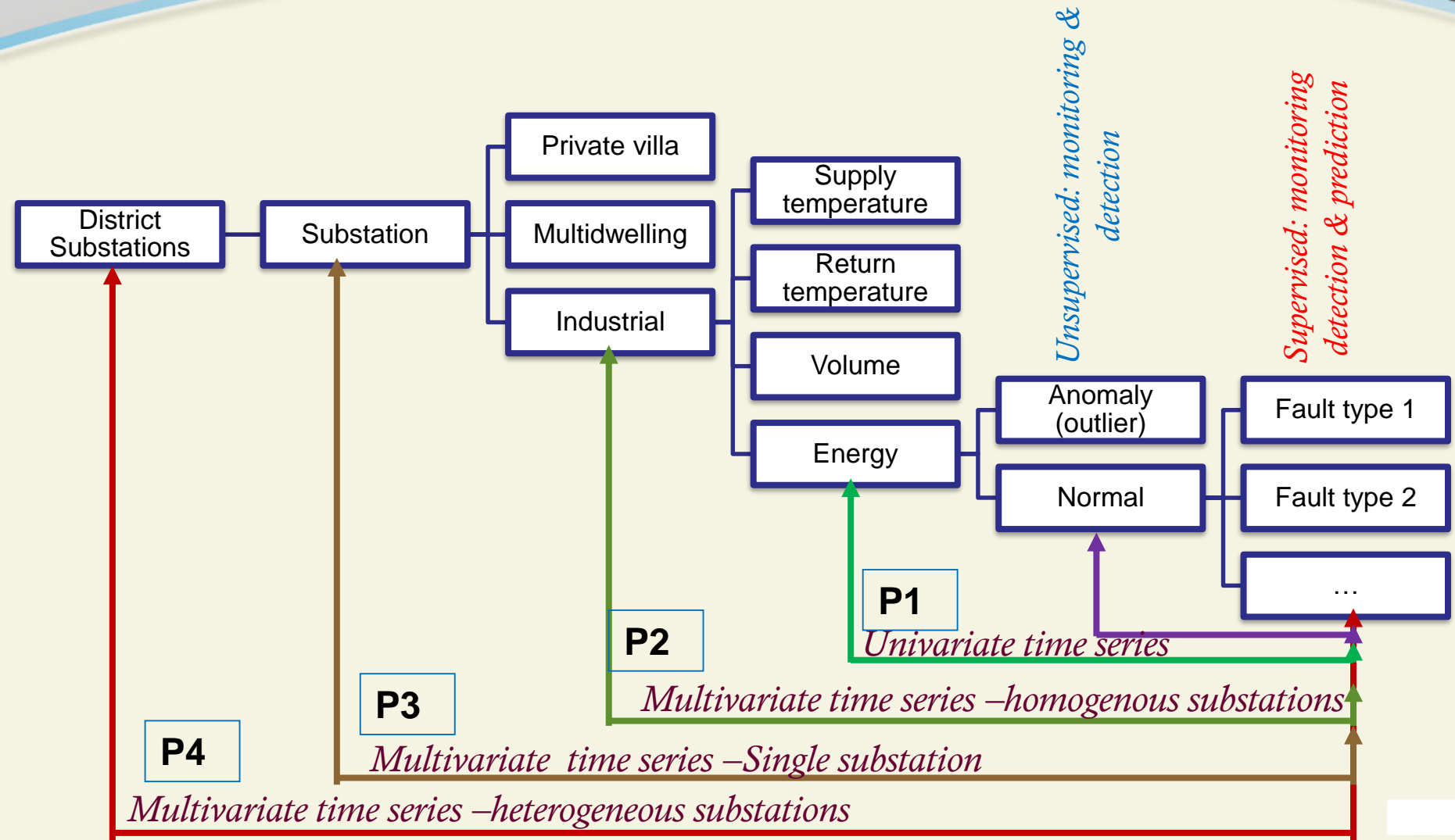
- Machine Learning (ML)



DAD Challenge

*Develop ML models to monitor, detect
and predict faults in DH substations*

Problem context

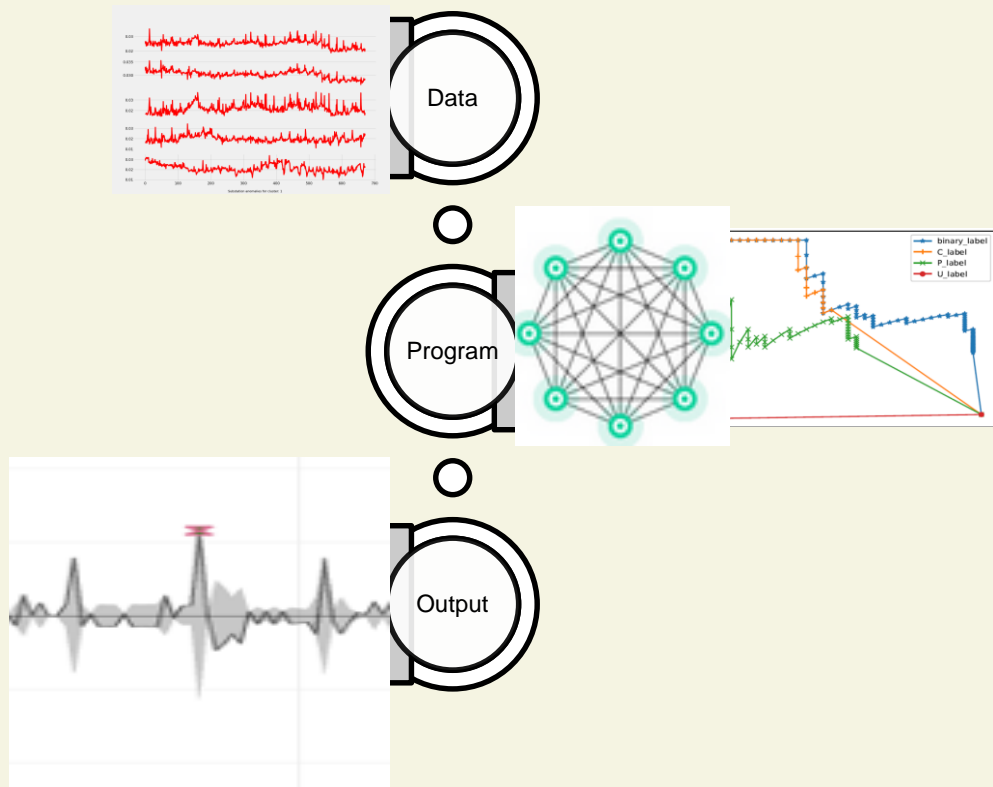


Objectives

- Algorithms:
 - learning deep representations from time series
 - fault detection and prediction with confidence in time series
 - knowledge representation to support real time decision making
- Reduce instability during model learning

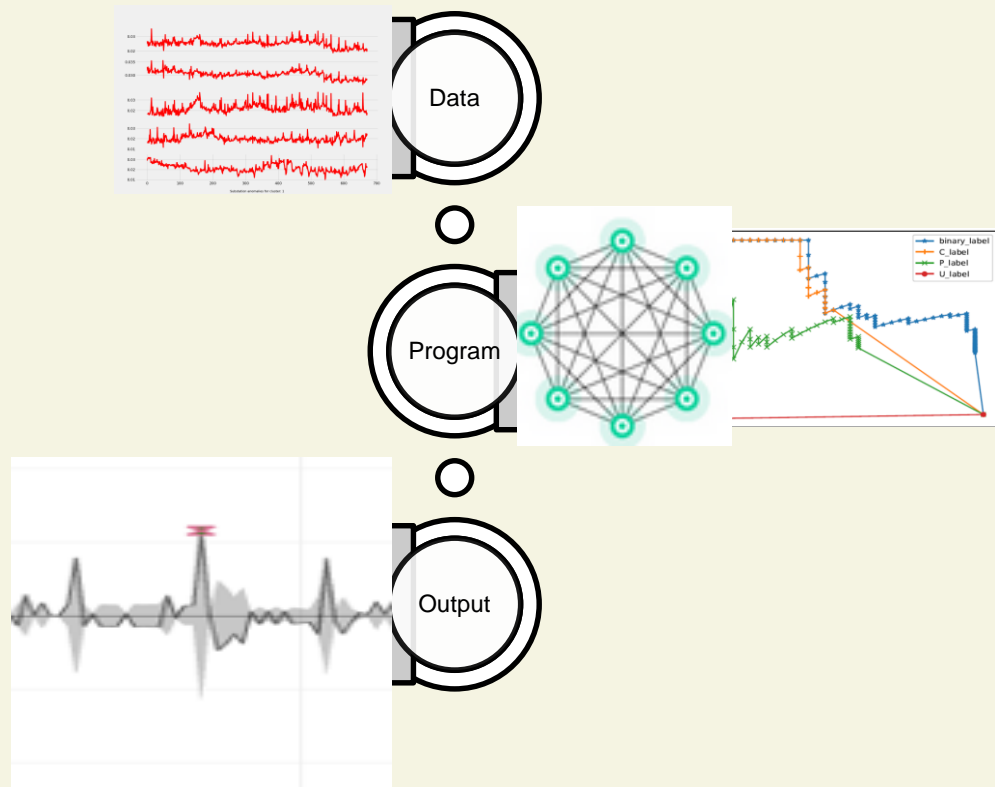
HDLS dataset anomaly detection

- Dataset 2:
 - [2017-01-01 2021-05-18]
 - [4766 rows x 38376 columns]
- Dataset 1:
 - [2017-01-01 2021-03-31]
 - [4766 rows x 10824 columns]



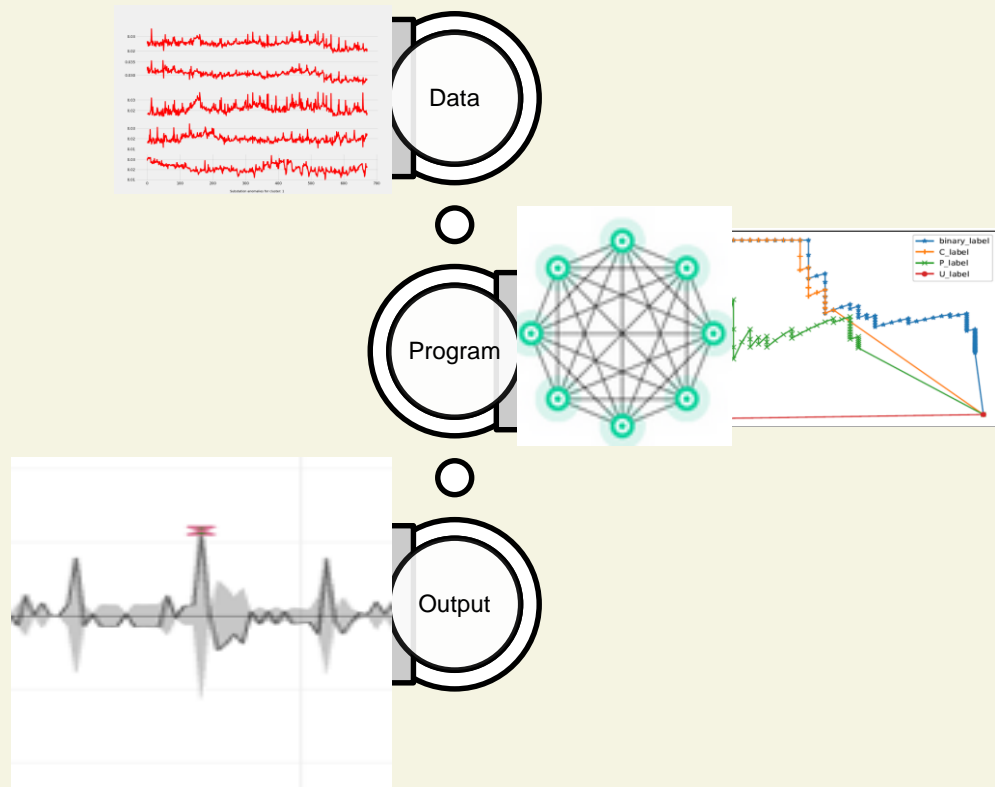
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- IQR/MAD
- PCA
- Spectral clustering
- OPTICS-Ordering points to identify the clustering structure
- LSTM Autoencoding
- Rule-based validation model



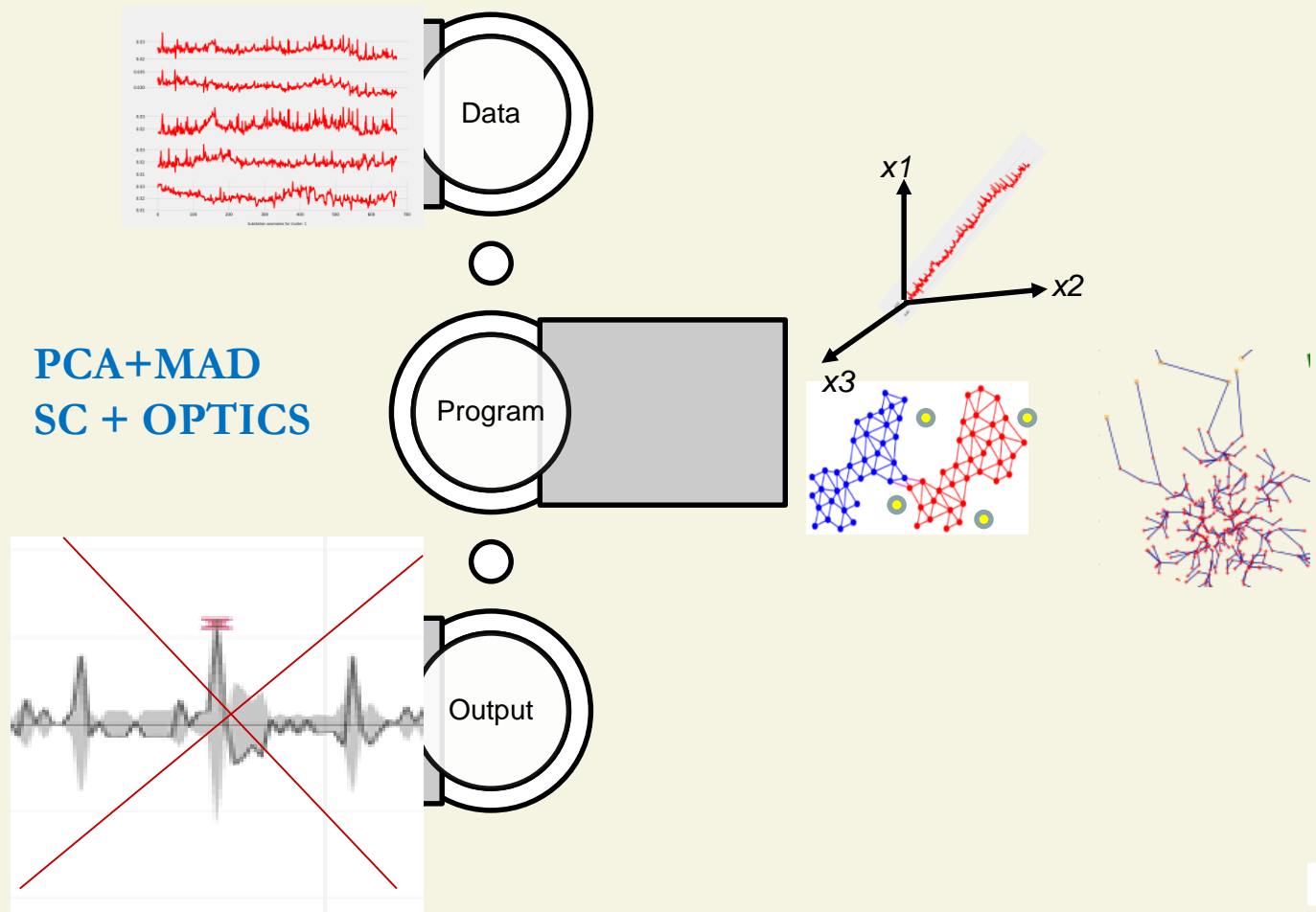
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- **IQR/MAD**
- **PCA**
- **Spectral clustering (SC)**
- **OPTICS-Ordering points to identify the clustering structure**
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PCA, SC, OPTICS

- Find k groups of most similar substations

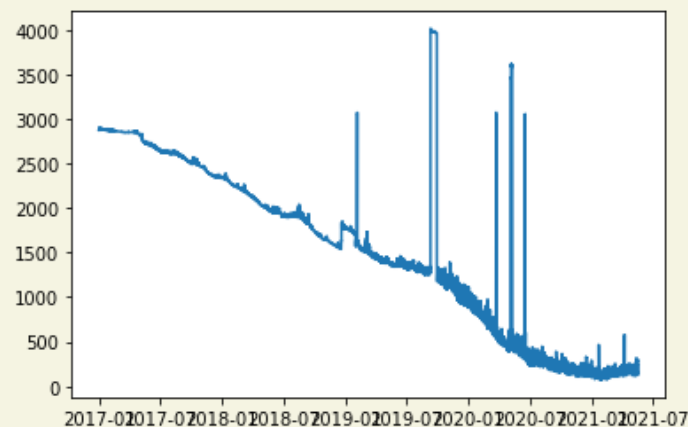
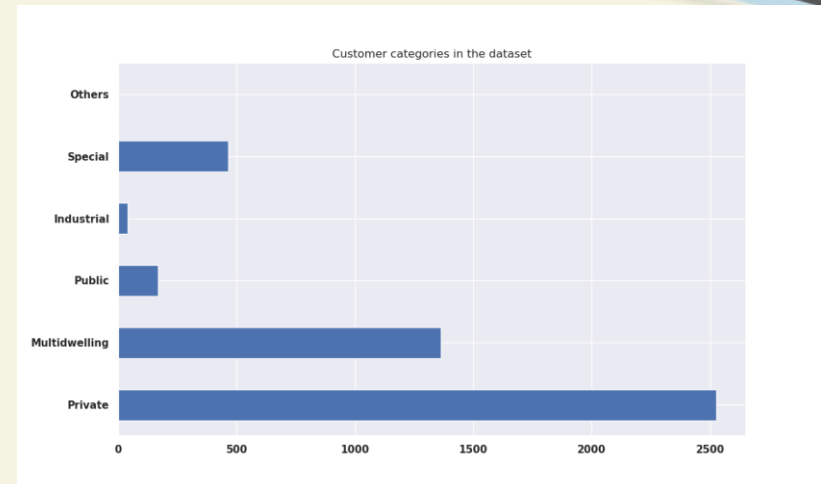


Why do this?

- The nature of the data:
 - Highly dimensional dataset
 - Large number of substations
 - No labels
 - Low quality
 - Claim: If an energy profile is too different from hundreds or thousands of energy profiles in the same DH network, it probably has an issue!
- Claim:
 - If a substation energy profile is **uniquely different** from hundreds or thousands of energy profiles in the same DH network, then it **probably** has an issue that deserve attention!
- Counter claim:
 - If a substation energy profile is **uniquely different** from hundreds or thousands of energy profiles in the same DH network, then there is no issue that deserve attention if we can **satisfactorily explain** it uniqueness.

Limitations

- PCA – how many factors to consider
- SC - which value of k ?
- OPTICS – how should density points be connected
- Stable results
- Variations in distributions of the data
- What can we learn from an anomaly?



Experiment

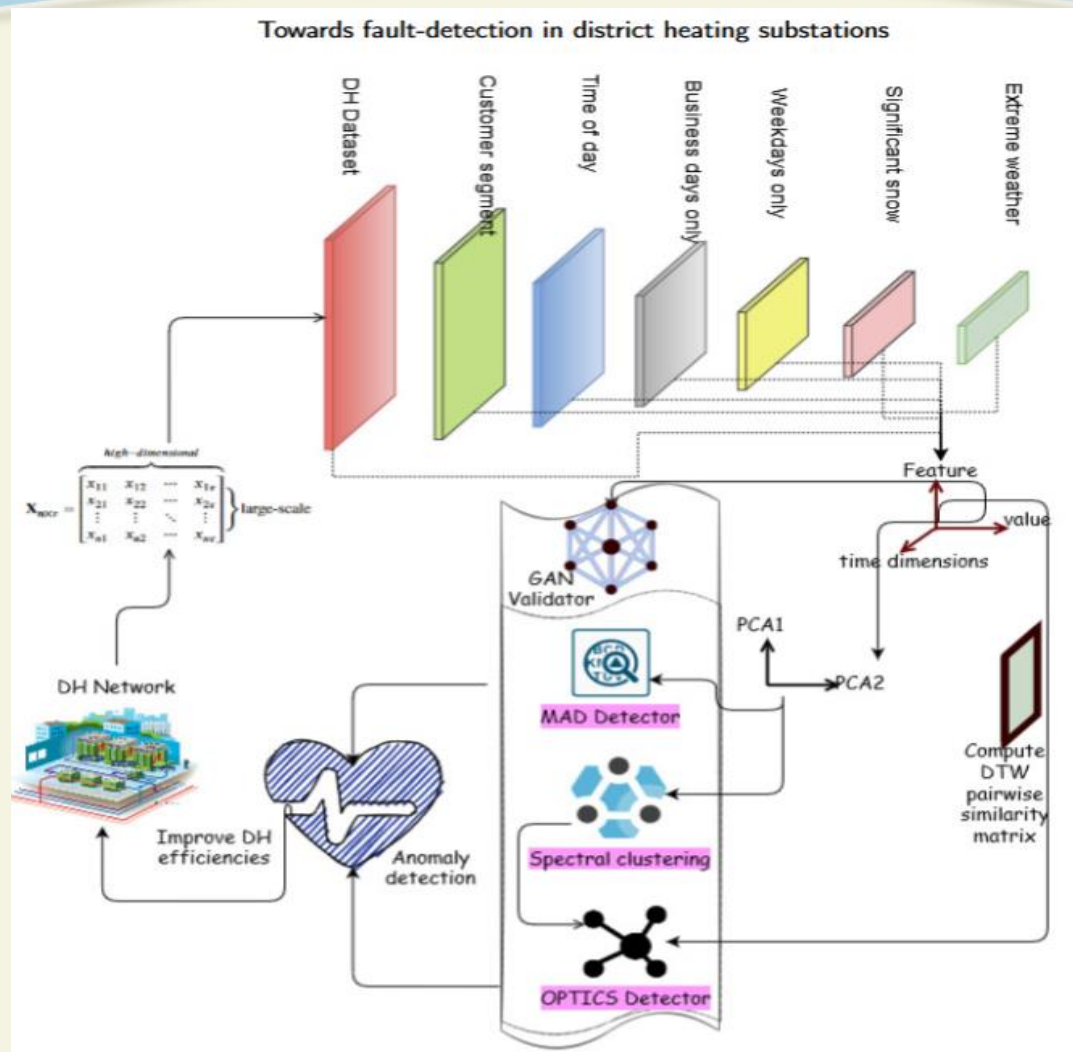
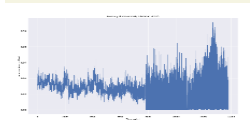
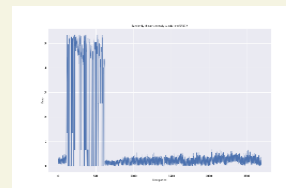
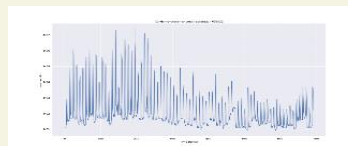
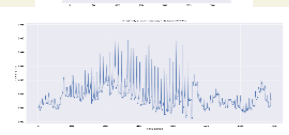
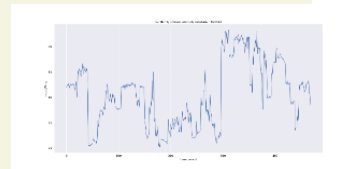
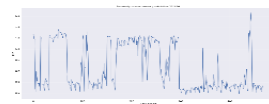
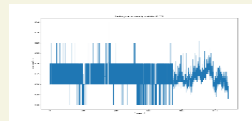
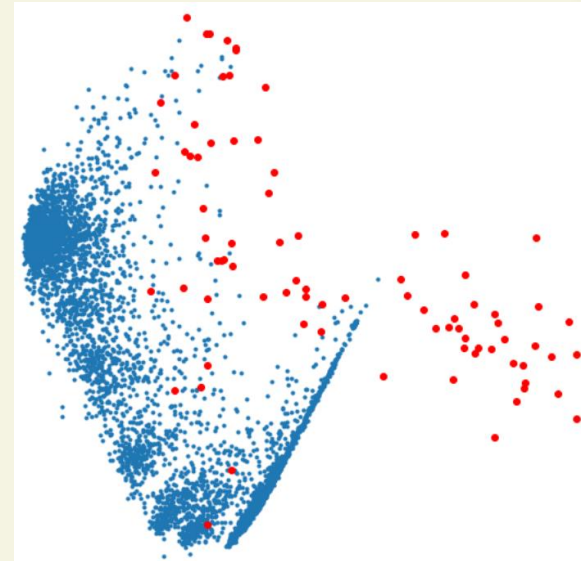
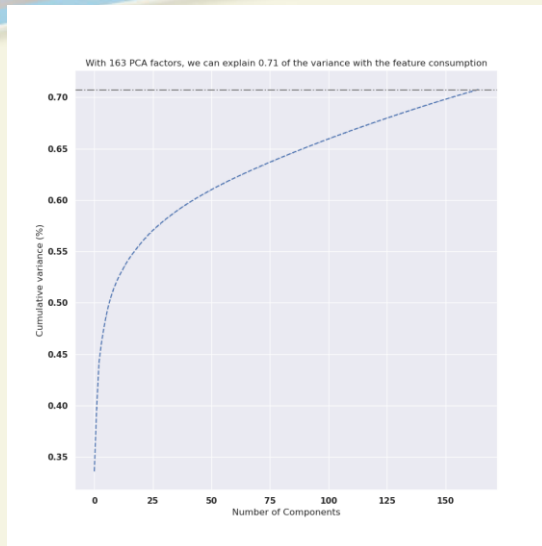
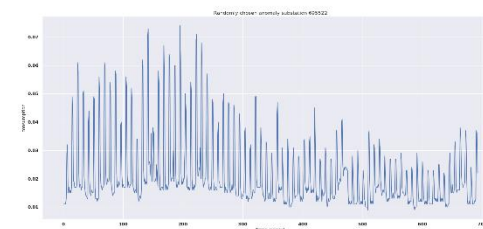
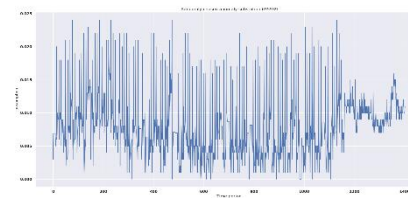
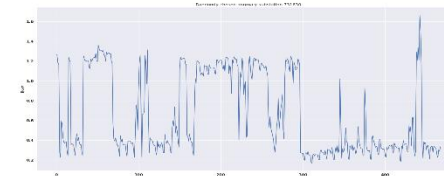
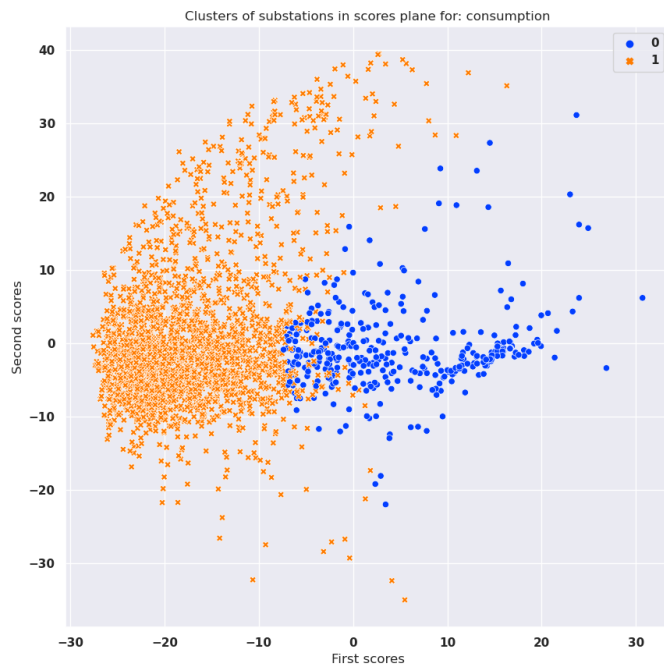


Figure 1: Method overview.

PCA+MAD



SC+OPTICS

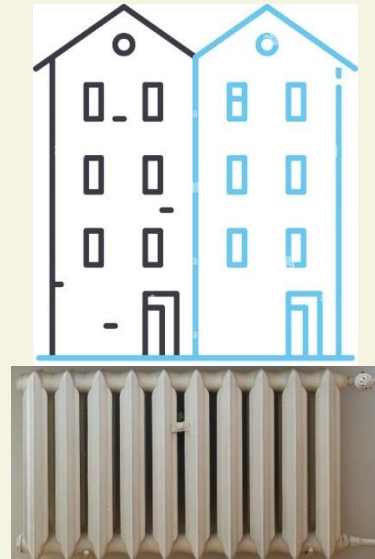


Data Driven Insights

- How does the system behavior changes in varying operational conditions?
 - Scenario 1-**space heating** [22:00 – 05:00] energy consumption in **multidwelling** customer facilities
 - Scenario 2 -**space heating and domestic hot water** use [05:00 – 22:00] in **multidwelling** customer facilities
 - Scenario 3 -Scenario 3, **space heating** and **domestic hot water** use in **all types of customer facilities**
 - Scenario 4 -**space heating** and **domestic hot water** use in **all types of customer facilities** for all sensor features

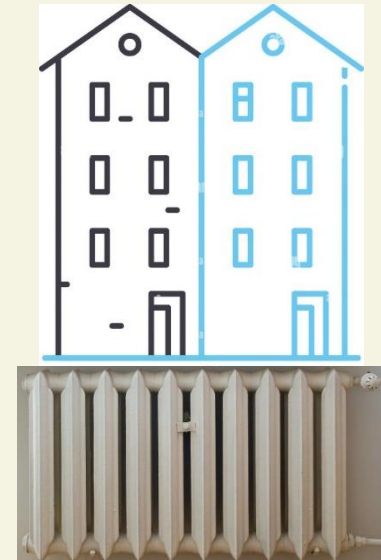
Scenario 1

- Target space heating in multidwelling customer facilities alone
 - $\ll 1\%$ anomaly rate across all features
- Open Question: Is the noise in substation data unrelated to space heating itself?



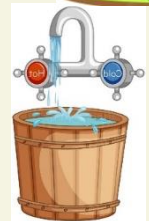
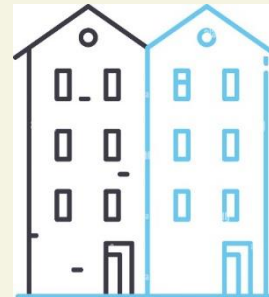
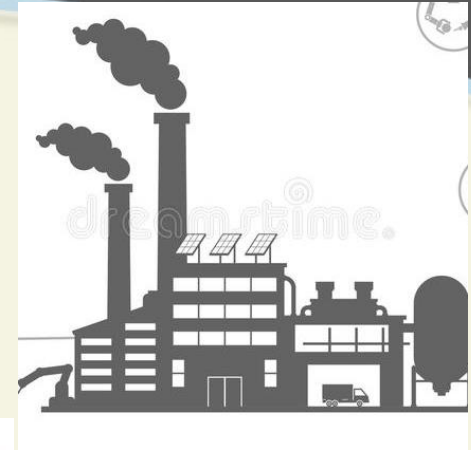
Scenario 2

- Target domestic hot water and space heating in multidwelling customer facilities
 - ~4% anomaly rate
 - Between 4 to 8% for all features
- Open Question: Is hot water use the source of unusual behavior in multidwelling customer facilities?
- Unaccounted heat activities: ventilation, use of doors and windows as well as micro heat sources including cooking, electronic appliances and air pumps



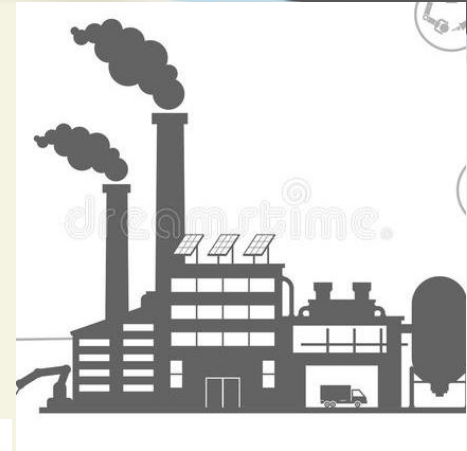
Scenario 3

- Target domestic hot water and space heating in all types of customer facilities (consumption in MWh alone)
 - ~12% anomaly rate (combining rate from each type of customer facility)
 - ~23% anomaly rate (all facilities together)
- Expected: increase data variability → increase of possibility of abnormal energy signatures
- Open Question: Is it a good idea to combine customer facilities when performing anomaly detection on a DH network level?



Scenario 4

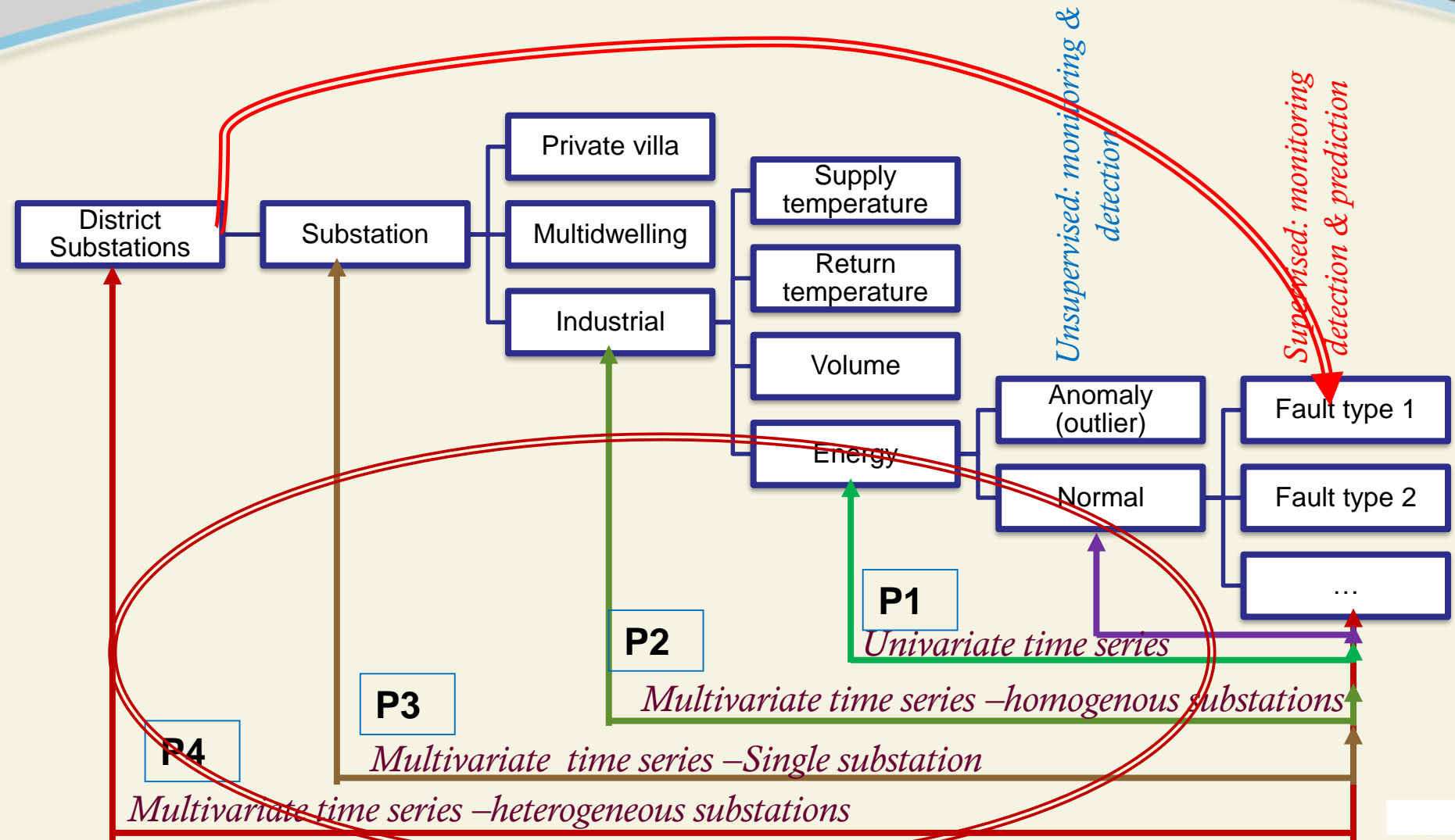
- Target domestic hot water and space heating in all types of customer facilities for all types of sensor features
 - ~43% anomaly rate (combining rate from each feature)
- Comments → Results aligning with values from literature
- Open Question: which sensor characteristics are most effective for anomaly detection in substations and why?



Scenario 5

- How does weekends and holidays affect abnormal energy signals?
 - Without weekends and holidays:
 - ~34% anomaly rate
 - With weekends and holidays:
 - ~28% anomaly rate
 - With snow and extreme weather:
 - ~39% anomaly rate
- Open Question: how should we handle weekends and holidays when training models to be deployed in monitoring networks?

Key message



DAD Partners

KK-stiftelsen



DAD is a KK-HÖG 2017 initiative
Funding: 50% ca 3.8 MKr
Duration: 2018-01-01 to 2020-12-31.

Project home page:

<https://www.hb.se/en/Research/Research-Portal/Projects/Data-Analytics-for-Fault-Detection-in-District-Heating-DAD/>



DAD Team

KK-stiftelsen



patrick.gabrielson@hb.se



gideon.mbiydzenyuy@hb.se



anders.gidenstamm@hb.se



henrik.linusson@hb.se



cj@noda.se



Andreas.Carlsson



josefine.norresjo@bo

Unsupervised detection of anomalies in high-dimensional large-scale data using Clustering[★]

Gideon Mbiyzenyuy^{a,*,1}, Federico Benzi^b, Anders Gidenstam^c, Jens Brage^d, Håkan Sundell^e
and Ulf Johansson^f

^a*University of Borås, Allégatan 1, Borås, SE-501 90, Sweden*

^a*SOLITA, Tulegatan 11, Stockholm, SE-113 53, Sweden*

^a*University of Borås, Allégatan 1, Borås, SE-501 90, Sweden*

^a*NODA, Biblioteksgatan 4, Karlshamn, SE-374 35, Sweden*

^a*University of Borås, Allégatan 1, Borås, SE-501 90, Sweden*

CSL@BS



Forskningsinriktningar är maskininlärning, data mining, high performance computing och distributed computing.

<https://www.hb.se/forskning/forskningsportal/forskargrupper/cslbs---computer-science-lab-at-boras-sweden/>

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