IDEAL 2019

Detection of Abnormal Load Consumption in the Power Grid Using Clustering and Statistical Analysis

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14.11.2019, Manchester UK

Problem statement

- Identification of abnormal behavior
  - data evolution, unlabeled dataset, noise, anomaly definition etc.
  - classification, clustering, statistical methods etc.
  - local and global anomalies
- Prevention of illegal consumption, identification of malfunctioning devices, optimization of energy distribution
- Behavior that differs from behavior of neighboring instances

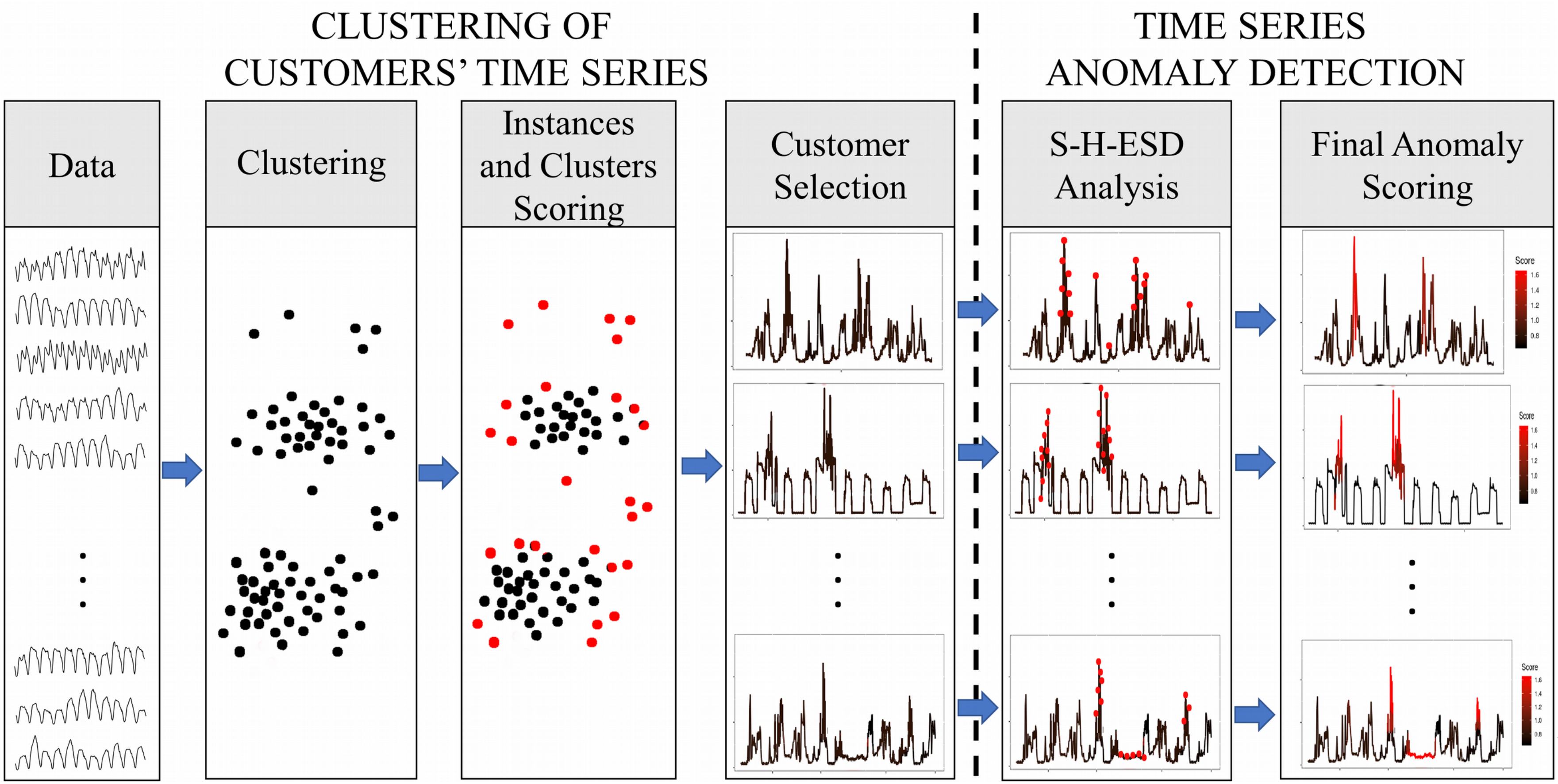
Existing solutions

- Clustering based
  - sliding windows to keep relevant information
  - suitable for quasi-periodic time series
- Statistical based
  - robust to anomalous fluctuations
  - reduction of false-alarms
- Other
  - distance based
  - density based

Proposed method

1. Clustering of time series
2. Scoring of instances and clusters
3. Customer selection
4. S-H-ESD analysis
5. Combining of computed scores

Proposed method



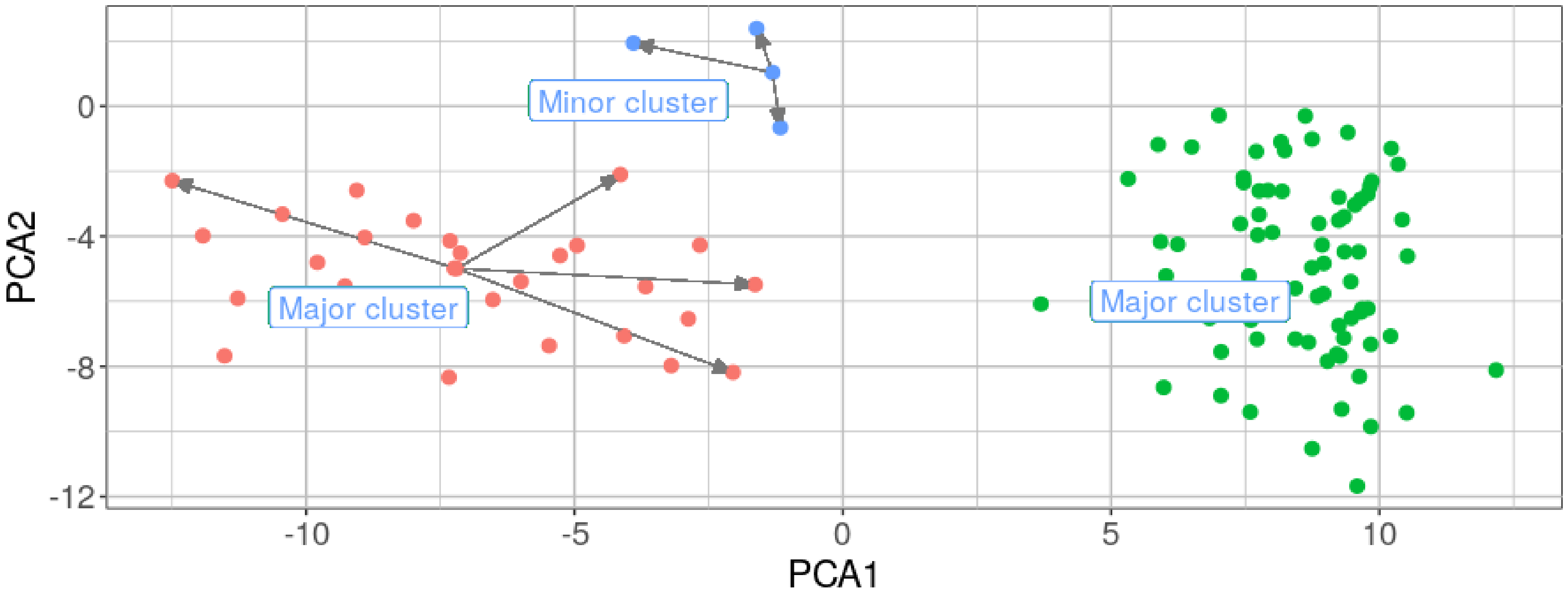
1. Clustering of time series

- Data preprocessing
  - normalization (z-score)
  - window alignment
  - division (workdays and non-workdays)
- Dataset aggregation by sliding windows
  - windows size (2 weeks)
  - window shift (1 week)
- Clustering using k-medoids
  - distance metric (GAK)

2. Scoring of instances and clusters

- Instance scoring
  - different values for different instances
  - relative distance of instance within given cluster
- Cluster scoring
  - different values for different clusters
  - small cluster penalization

2. Scoring of instances and clusters



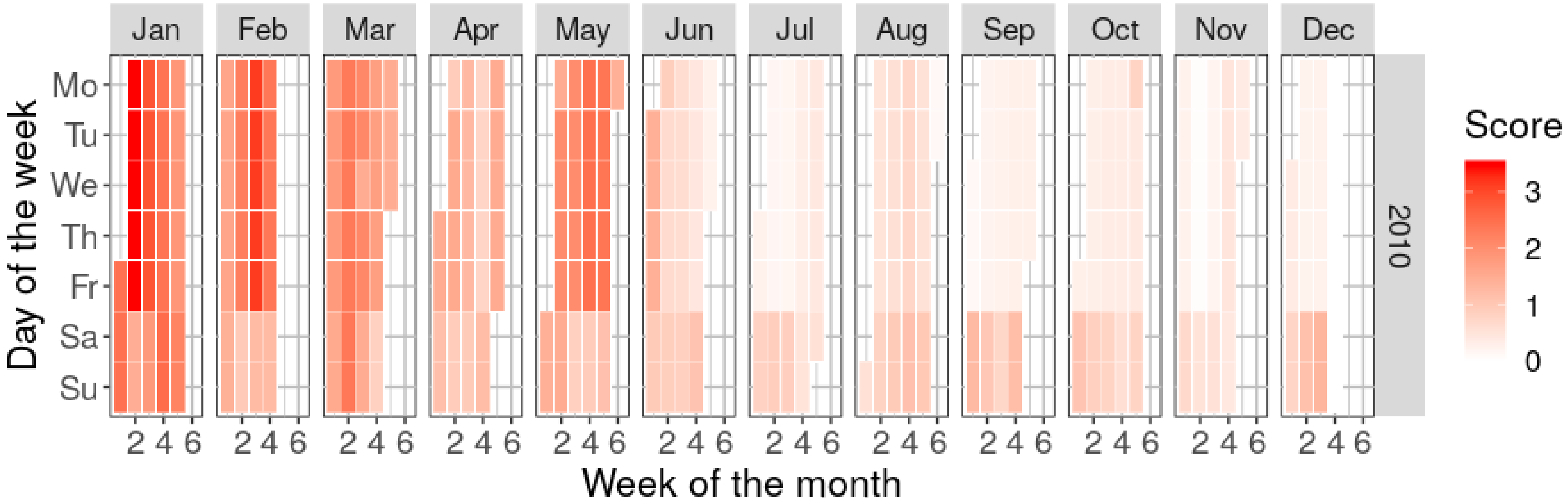
3. Customer selection

- Interval of interquartile rule for anomaly detection

<Q1 – 1.5*IQR, Q3 + 1.5*IQR>

- FeaClip method
- Based on suspicion
- Visualization

3. Customer selection



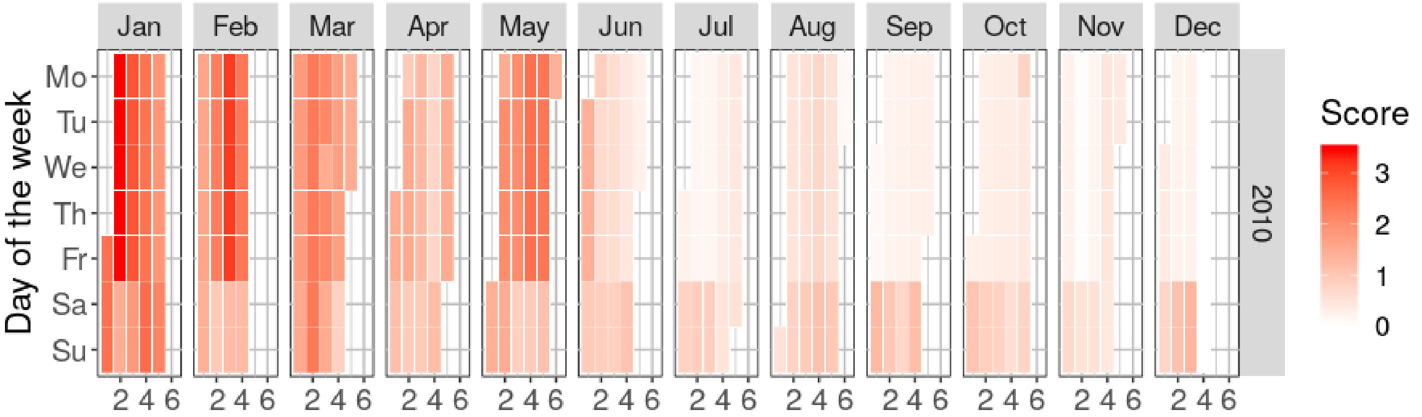
4. S-H-ESD analysis

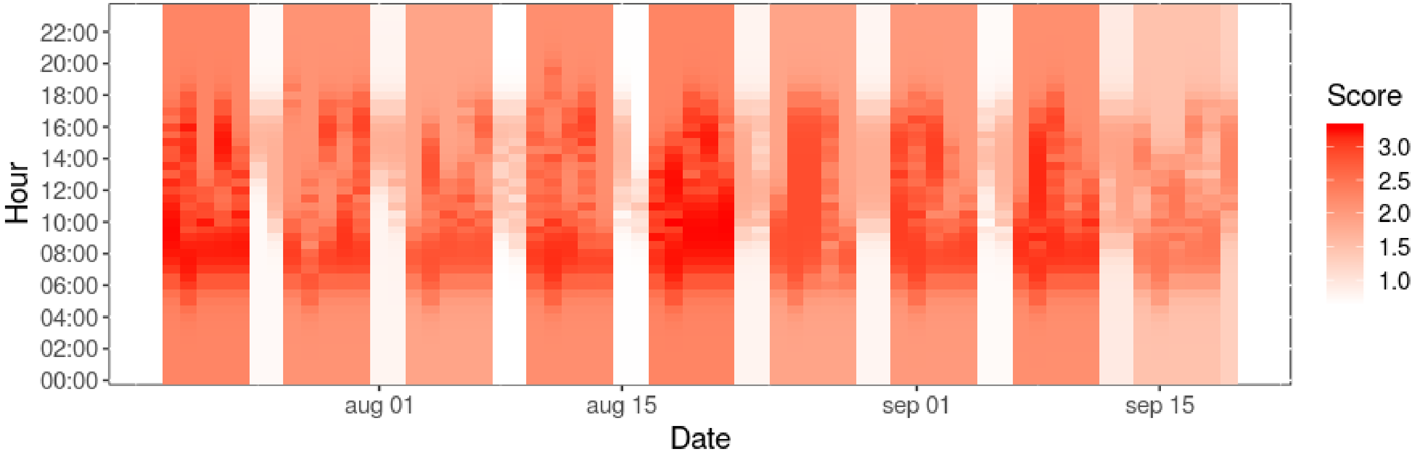
- Smoothing in order to eliminate numerous local anomalies
- S-H-ESD analysis
  - based on Grubb’s test
  - using median absolute deviation
  - capable of identifying up to 50% anomalies
- Output of S-H-ESD analysis is a flag
  - Intervals with dense occurrence of flags are grouped
  - Intervals with sparse occurrence of flags are smoothed

5. Combining of computed scores

- Combining of smoothed flags from S-H-ESD analysis and computed score from k-medoids
- Lower granularity
- Result is not flag indicating anomalousness, but number representing degree of anomalousness of given measurement

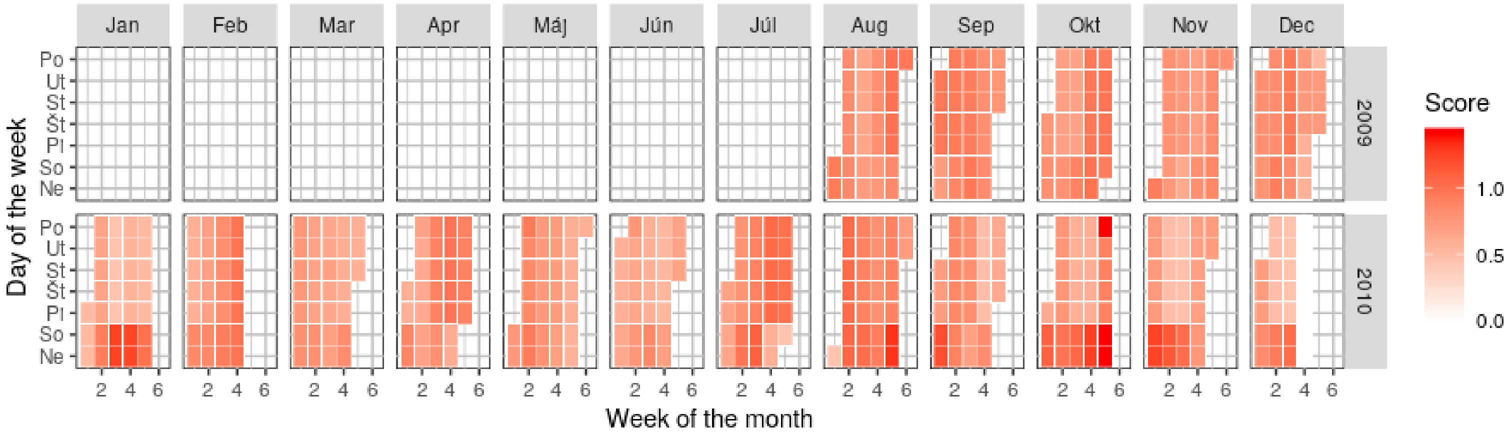
5. Combining of computed scores

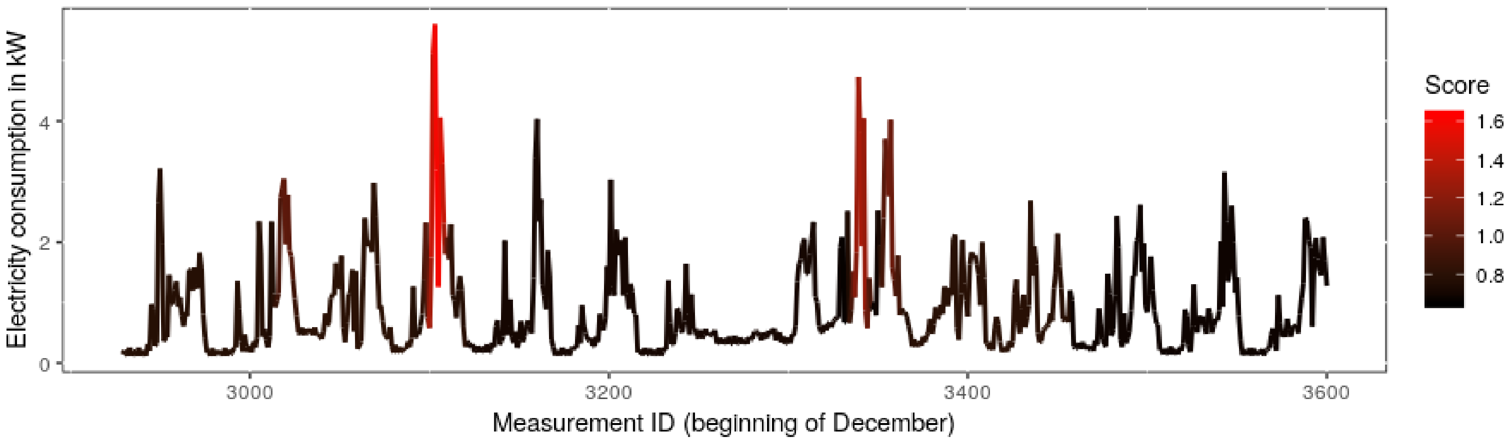




Anomaly score =
Consumer score + S-H-ESD score

5. Combining of computed scores



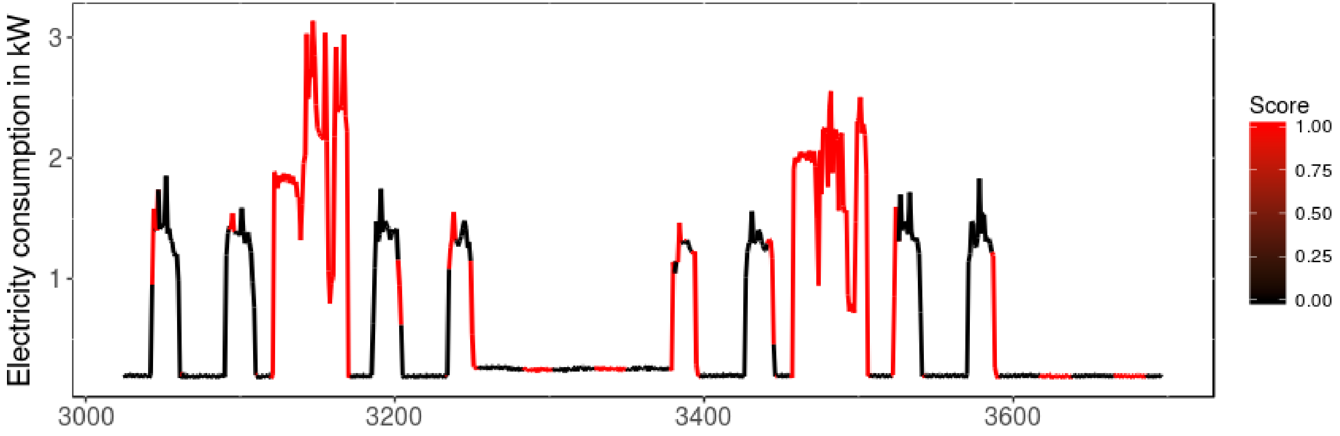


Evaluation

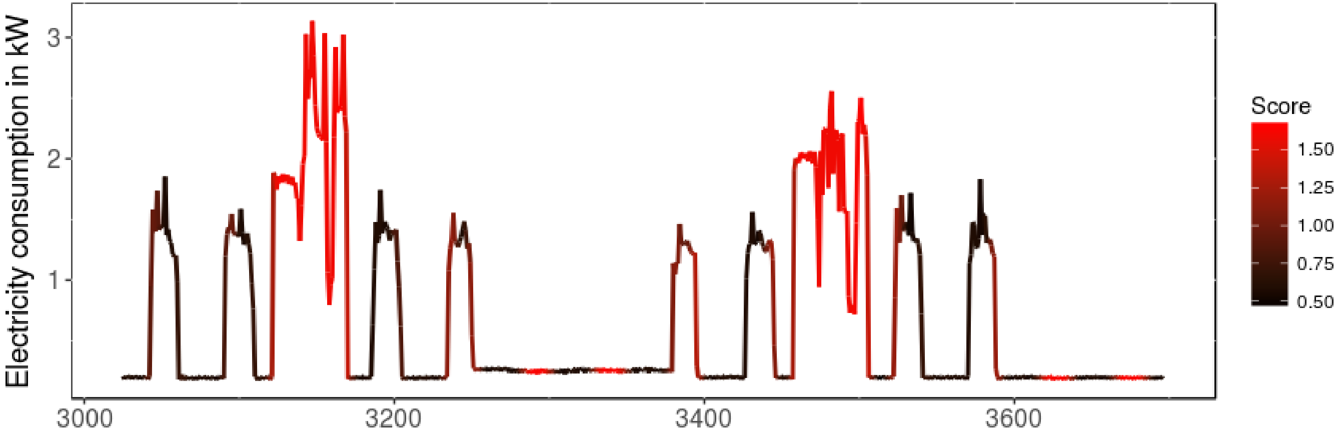
- Dataset from Irish CER Smart Metering Project
- Clustering
  - experiments
  - cluster validation indexes
- Proposed method compared to
  - PEWMA
  - SD-EWMA
  - KNN-LDCD
  - S-H-ESD

Evaluation

S-H-ESD



Proposed Method



Evaluation

Method Name	TP	TN	FP	FN	Precision	Recall	F1 score
PEWMA	0.6 %	82.5 %	3.3 %	13.6 %	17.67 %	4.90 %	7.67 %
SD-EWMA	0.7 %	83.1 %	2.6%	13.6 %	20.36 %	4.69 %	7.62 %
KNN-LDCD	0.04 %	85.6 %	0.03 %	14.2 %	60.00 %	0.31 %	0.62 %
S-H-ESD	6.4 %	58.1 %	27.6 %	7.9 %	18.82 %	44.90 %	26.52 %
Proposed Method	**4.4 %**	**80.6 %**	**5.1 %**	**9.9 %**	**42.84 %**	**39.27 %**	**40.98 %**
Reality	14.3 %	85.7 %	-	-	-	-	-

Summary

- Only consumers with high score are analyzed
- Flag replaced by degree of anomalousness
- Possible online processing

Thank you for your attention