Machine learning algorithms for modelling consumption in district heating systems

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Motivation & Background

- DH systems introduced mandatory individual metering in accordance with EU EED Art 14 resulting in significant dissatisfaction with a large share of final consumers
- Stipulations of the Law on Heat Market were halted from 2016 (!?) – still 30% of final consumers have not introduced individual metering (!?!?)
- Doubt that individual metering results in savings (apartment, building, network, national) – let’s evaluate with AI
- Twofold application – prediction and evaluation of energy efficiency measures
Heat Consumption (in DH)

- Depends on a number of parameters of which some measurable and predictable, while other are hard to predict

  - Measurable/predictable:
    - building envelope characteristics
    - heating degree days (climatology)
    - number of occupants
    - schedule of space usage
    - energy source
    - building heat installation losses (including heating substation)
    - position of the apartment in the building
    - formula for calculating consumption in case of HCA
    - existence of individual metering

  - Hard to predict:
    - heat gains/losses form adjacent apartments
    - heat comfort level in the apartment
    - mode of space usage (opening windows)
    - income level of the owner, readiness to pay
Data?

• Most accessible and reliable = billing data
• Time series: from 2010 to Dec 2018 (individual metering introduced in 70% of buildings in 2015)
• Additionally – questionnaire with behavioral data
• Data frame matrix of ~5,000,000 observations in 50 predictors
• Statistical learning with machine learning algorithms:
  Linear Regression, Logistic Regression, Decision Trees, Random Forest, Support Vector Machines (for now)
Did we save? Yes...

Sample set of buildings
Heat Vs Heated Area

Source: dm

Sample set of buildings
Heat Vs Heated Area

Source: dm
...but... (on the apartment level):

Sample set of buildings
Heat Vs Heated Area

Heated Area
- 30
- 40
- 50
- 60
- 70
- 80

Year
- 2016
- 2017

Source: dm

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Building level?

Reduced, as well, but less steep...
Here come the outliers
Data distribution seems more “normal”
Network / Town Level

Specific Heat Consumption
Year 2013.

Specific Heat Consumption
Year 2014.

Specific Heat Consumption
Year 2016.

Specific Heat Consumption
Year 2017.

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Learning and predicting

1. Take a portion of the data set (60-80%) and learn on it.

2. Test what you have learned on the remaining portion (20-40%). If accuracy level is satisfactory:

3. Predict on the “new” data and use the model.
Foresting the District Heating

- Random Forest – best fit for (green) DH
  - Pros:
    - great prediction performance, robust, good variable importance estimate
  - Cons:
    - less interpretable, computationally intensive
Fitting of new data - prediction
Fitting accuracy is quite high

Type of random forest: regression
Number of trees: 500
No. of variables tried at each split: 8

Mean of squared residuals: 3075.775
(~55 kWh error)
% Var explained: 99.44
Importance plot
Predicting

Prediction of the forest for different values of ImpulsiKK and Povrsina
Conclusions & Further Steps

• Building energy consumption modelling and the usual methods used are traditional multiple regression models, simulation methods and methods of artificial neural networks
• In the last years machine learning has gain larger application in various fields – „chewing of data”
• Gives good results in cases where large amounts of data are to be processed with an aim to recognize a pattern and correlation of each of the relevant parameter as well as in the cases where the problem is too complex for a human intelligence to solve
• Testing the results on other data sets, networks, cities, climates
• Important variables crucial for determining policy in energy efficiency
• Deep learning
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QUESTIONS & THOUGHTS?