



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



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Heat Consumption (in DH)

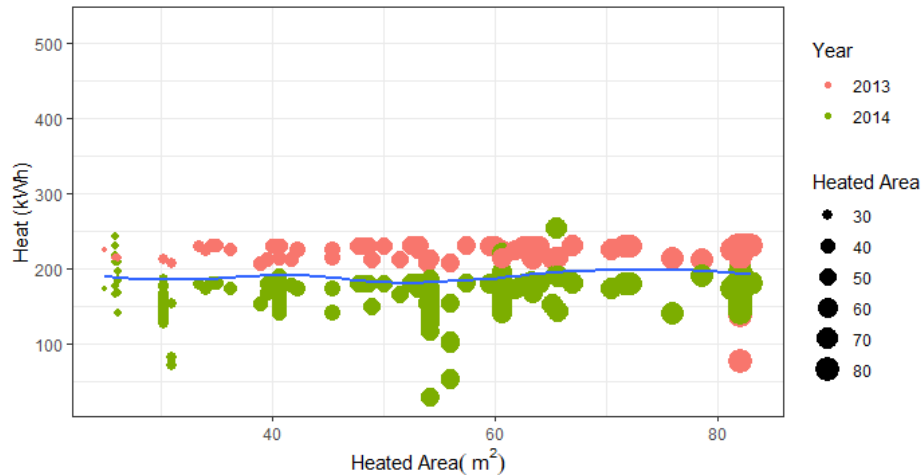
- Depends on a number of parameters of which some measurable and predictable, while other are hard to predict
- Measurable/predictable:
 - building envelope characteristics
 - heating degree days (climatology)
 - number of occupants
 - schedule of space usage
 - energy source
 - building heat installation 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 from adjacent apartments
 - heat comfort level in the apartment
 - mode of space usage (opening windows)
 - income level of the owner, readiness to pay

Data ?

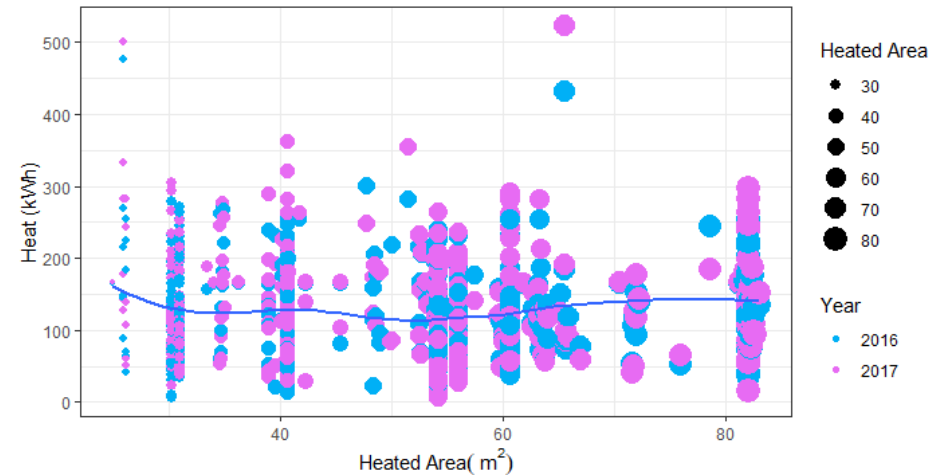
- Most accessible and reliable = billing data
- Time series: from 2010 to Dec 2018 (individual metering introduced in 70% of buildings in 2015)
- Additionally – questionnaire with behavioral data
- Data frame matrix of ~5,000,000 observations in 50 predictors
- Statistical learning with machine learning 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

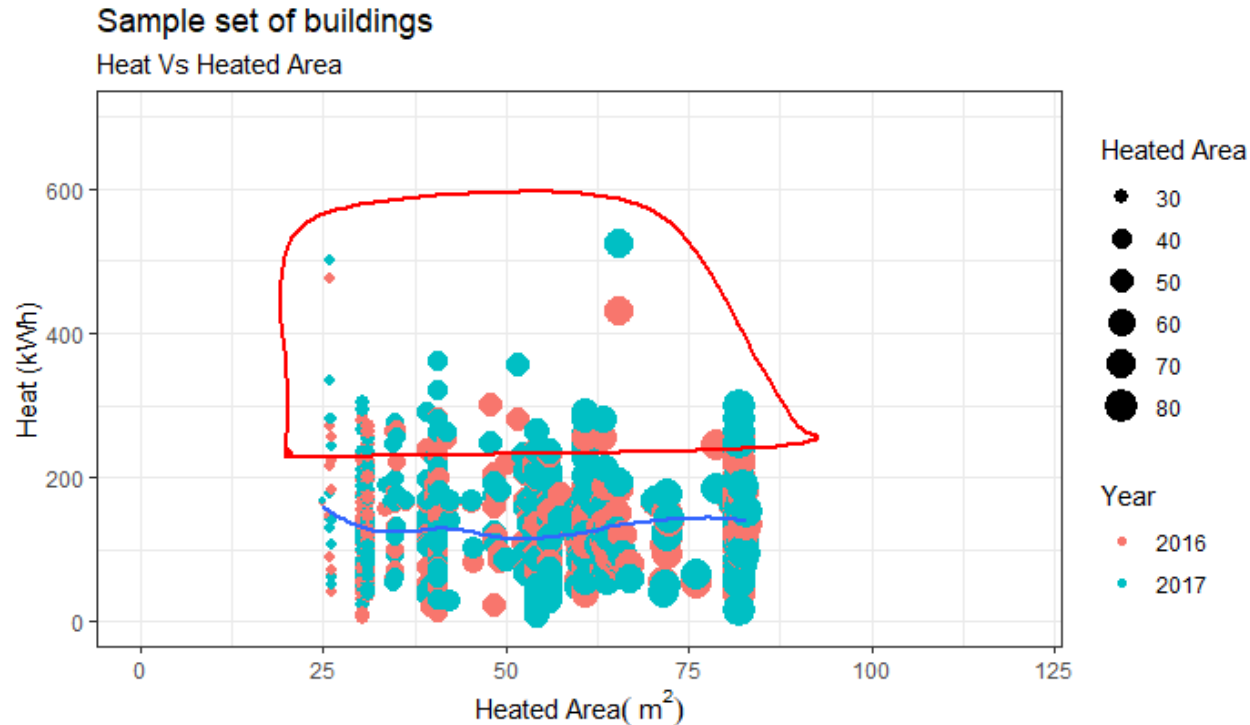


Sample set of buildings
Heat Vs Heated Area



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



Source: dm

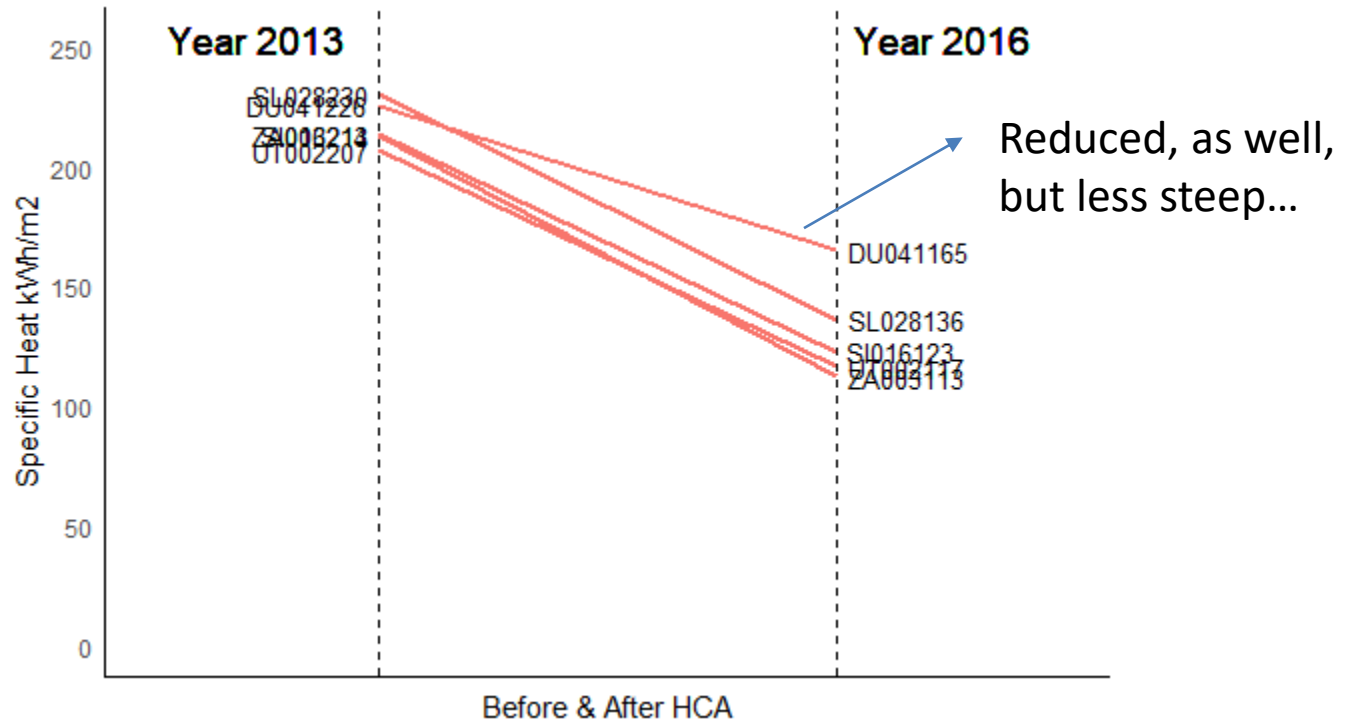
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Building level?



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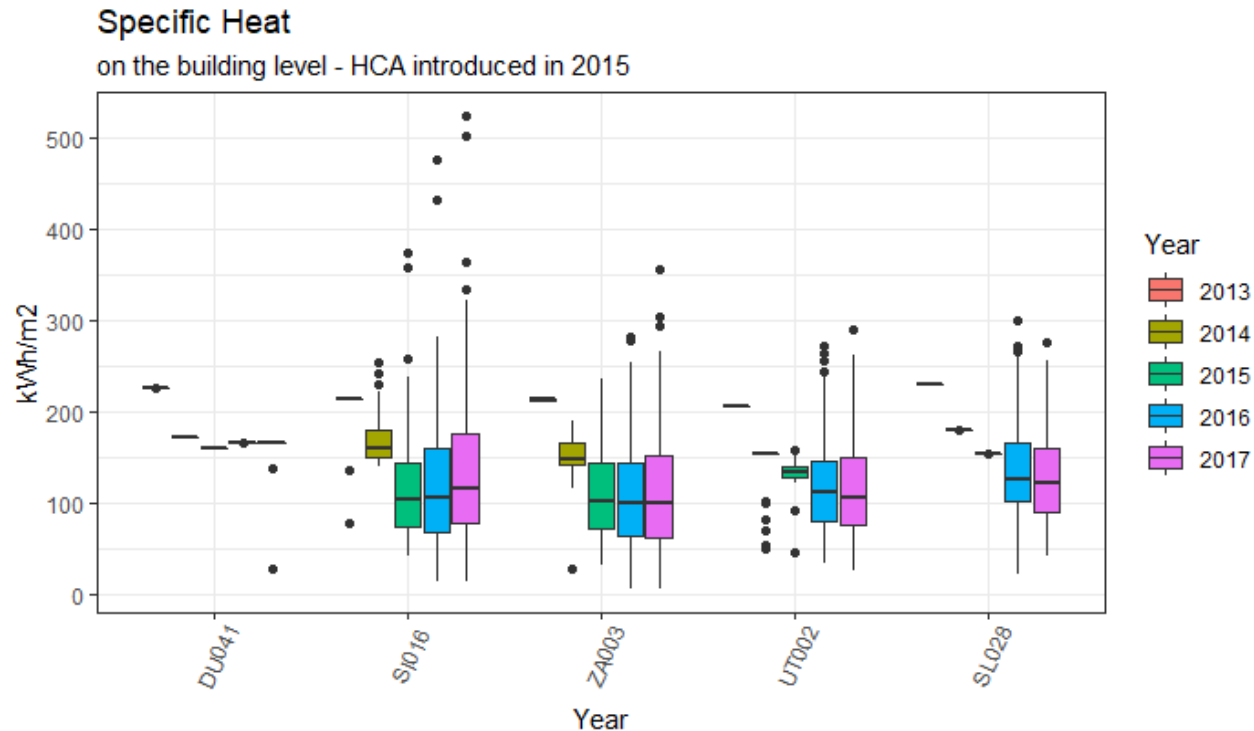


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Here come the outliers



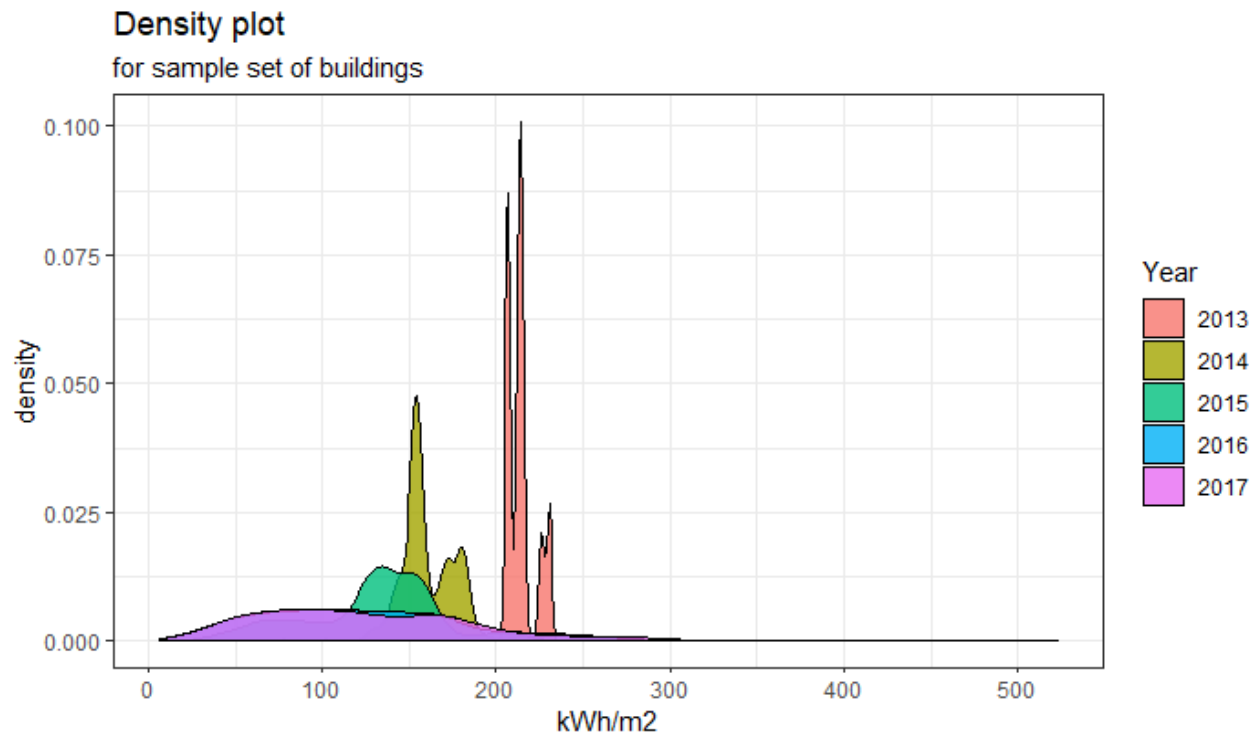
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Data distribution seems more “normal”



Source: dm

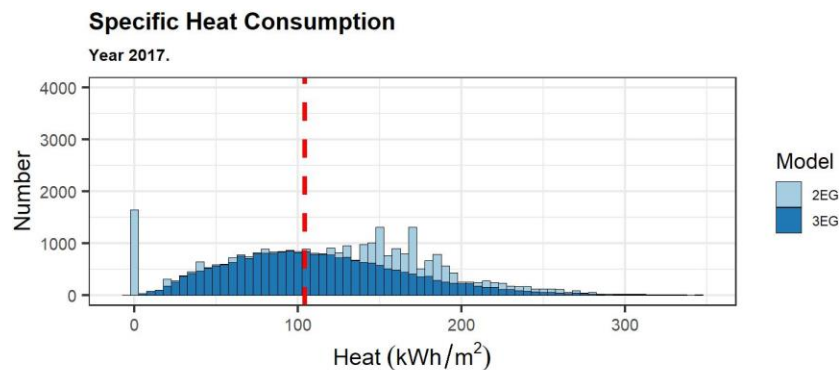
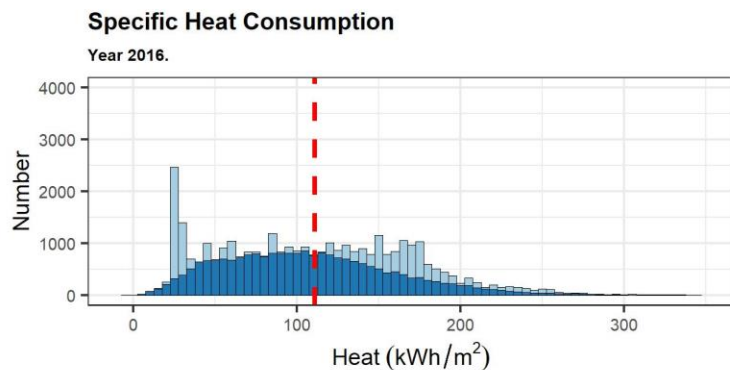
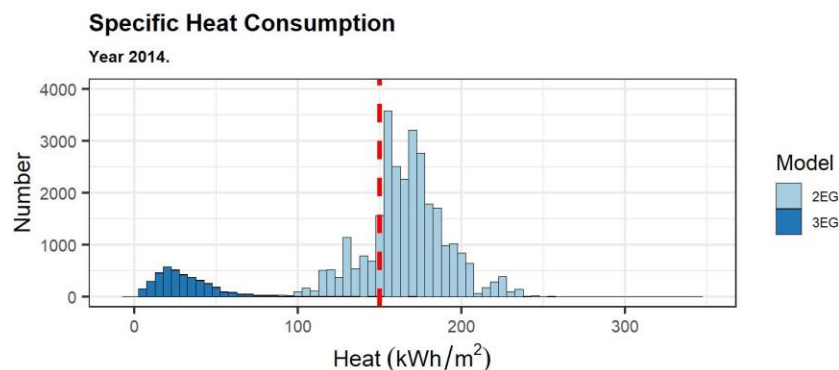
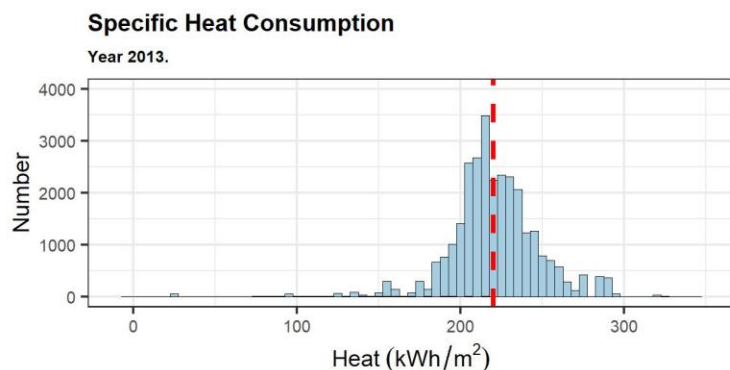
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Network / Town Level



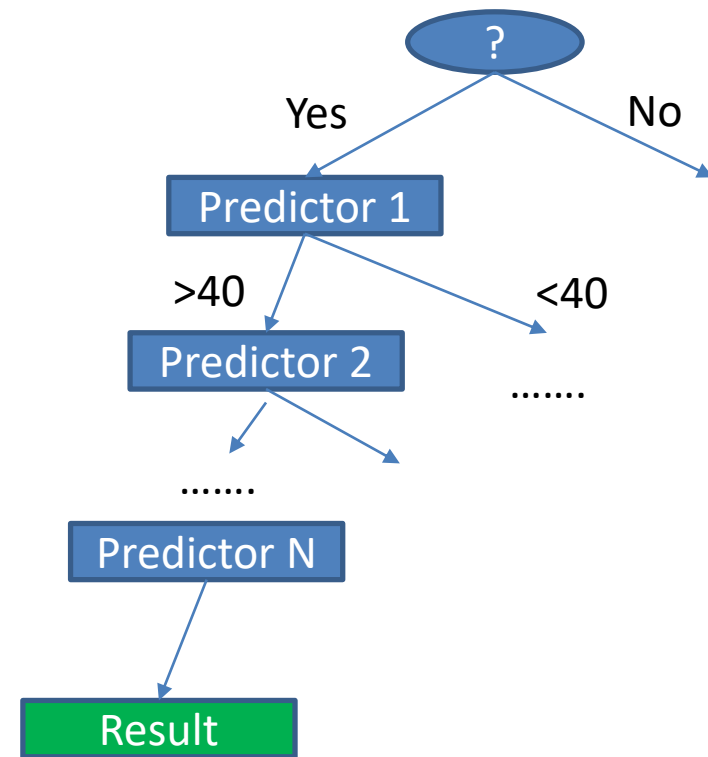
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Learning and predicting

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.

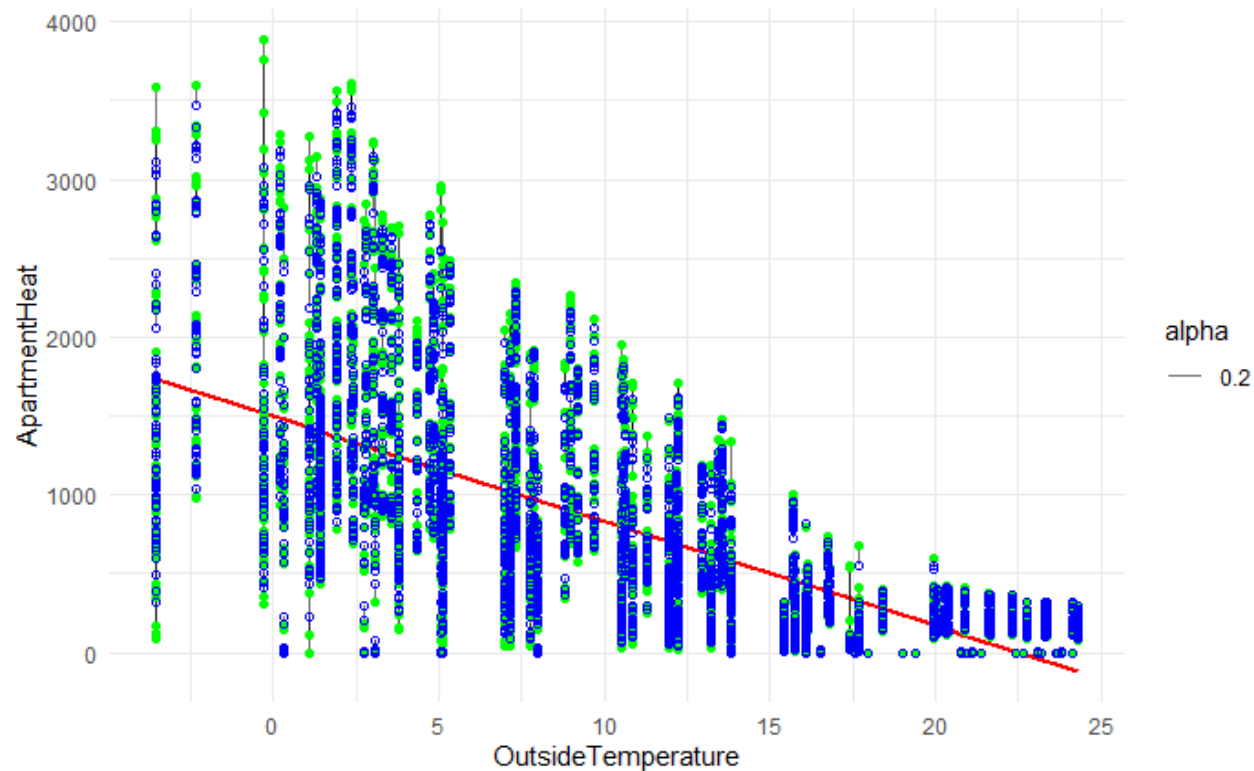
Forecasting the District Heating

- Random Forest – best fit for (green) DH
- Pros:
 - great prediction performance, robust, good variable importance estimate
- Cons:
 - less interpretable, computationally intensive



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Fitting of new data - prediction



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Fitting accuracy is quite high

Type of random forest: regression

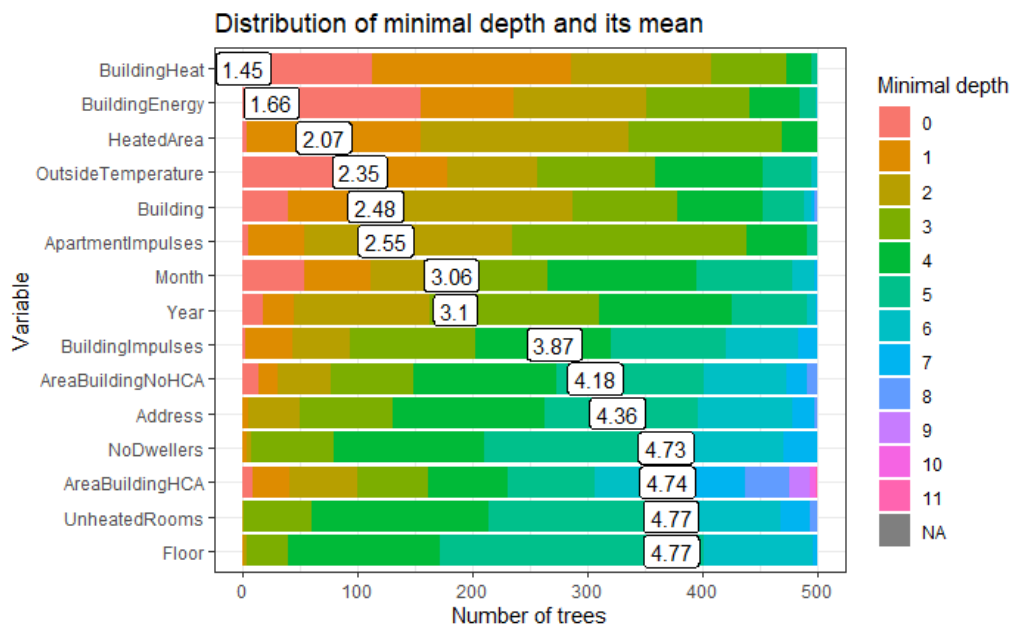
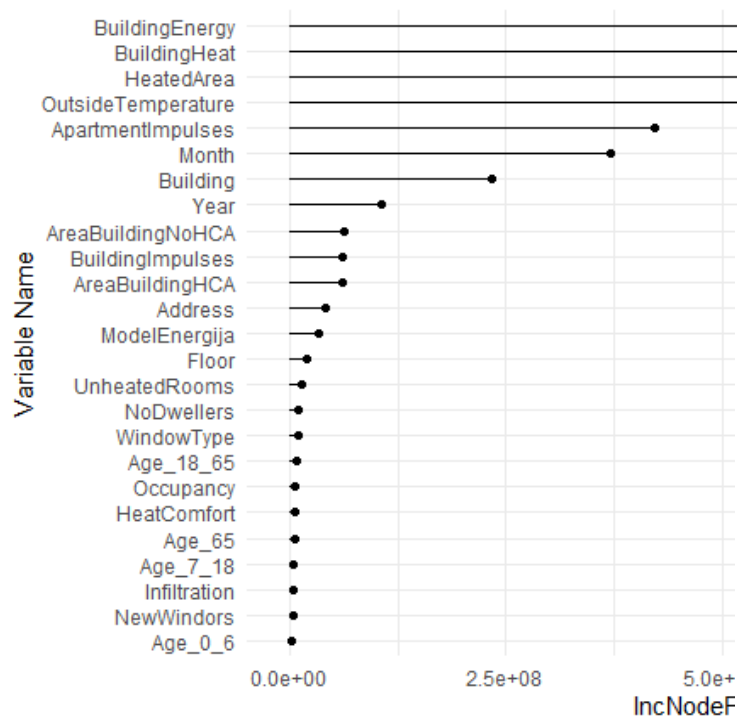
Number of trees: 500

No. of variables tried at each split: 8

Mean of squared residuals: 3075.775
(~55 kWh error)

% Var explained: 99.44

Importance plot



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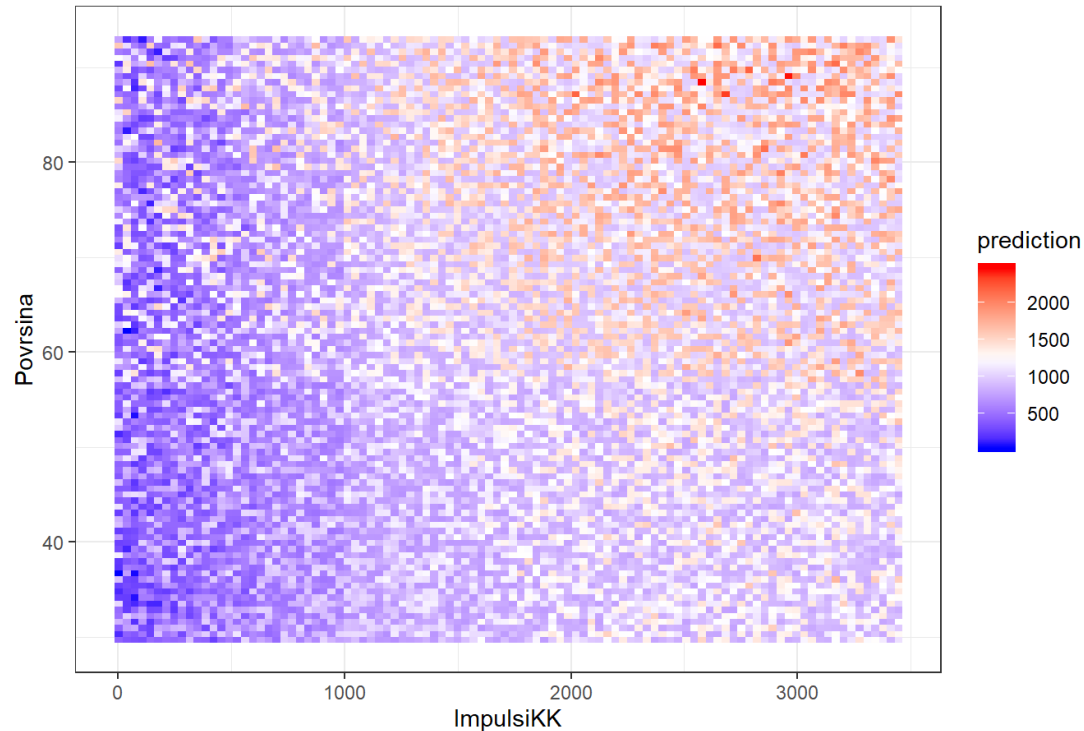
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Predicting

Prediction of the forest for different values of ImpulsiKK and Povrsina



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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 determing policy in energy efficiency
- Deep learning

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QUESTIONS & THOUGHTS?