Application of Tree-based Machine Learning Models for Energy Performance Certificate Predictions of Dwellings in the Netherlands

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ENERGY EVALUATION

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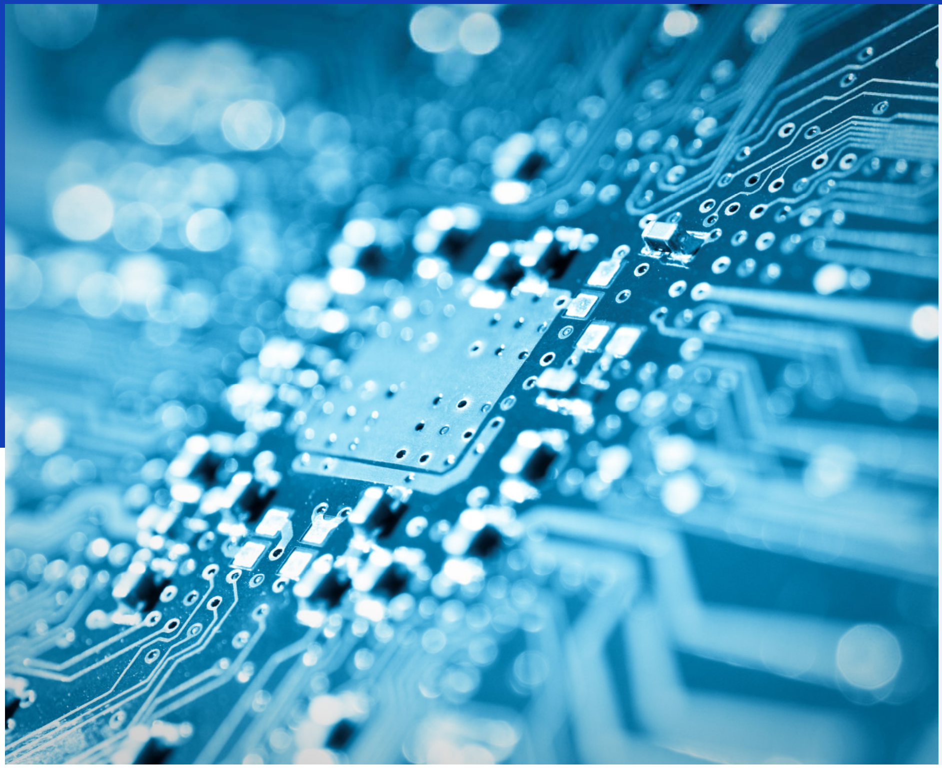
Agenda



1. Introduction
2. Methodology
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Introduction

- EU ambitions for increasing the energy performance of dwellings
  - EU Energy Performance of Buildings Directive (EU/2024/1275)
    - Fully decarbonize building stock by 2050
    - Reduce average primary energy consumption of dwellings with at least 16% by 2030 (RESCoop EU, 2024)

Figure 1: EU Directive (DR Deutsche Recycling Service GmbH, 2024)

- Energy Performance Certificate
  - Used as a metric to assess the energy efficiency of a household
  - Often represented in classes (A, B, C...)
    - Underlying classification expressed in some consumption metric such as $kWh/m^2/year$

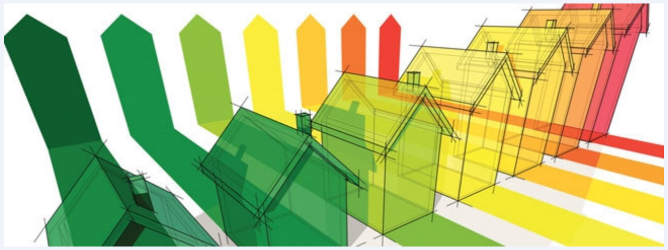

Figure 2: Dwelling classes (EPG, 2025)

Introduction

- Default methodology to assess energy performance of dwellings in the Netherlands – NTA 8800
  - Mandatory when a dwelling is constructed or sold
  - Not easily reproducible
  - Time consuming
  - Has not assigned energy labels to all dwellings yet (~40% missing as of 1st of January 2024)
  - Widely used by municipalities, architects, construction companies

- The aim of this study was to develop an alternative methodology
  - Tree-based machine learning
  - Assign labels and interpret the assignment

Figure 3: NTA 8800 (Duresta, 2019)

Methodology

- Tree-based machine learning model
  - Predicts using decision trees
  - Trees split data into smaller groups to make decisions
  - These decisions relate to classification

  - Random forest
    - Trees are developed in parallel
    - Combine many trees and average their predictions
  - Boosted trees (XGBoost)
    - Trees are developed sequentially
    - Each tree attempts to improve the performance of the former
    - Final tree is taken for prediction purposes

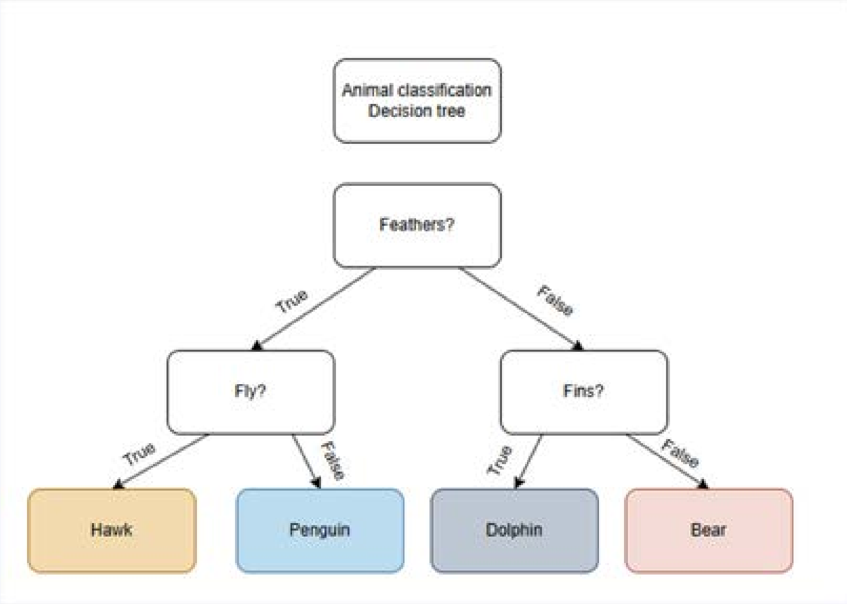

Figure 4: Example of a decision tree for animal multiclass classification

Methodology

- The machine learning models are trained on specific datasets that contain information on already labelled dwellings
  - Training set (~70%)
  - Stratified sampling

- These datasets contain the following dwelling-specific information:
  - Building year
  - Surface area
  - Compactness*
  - Ownership type
  - Ventilation type
  - Heating type
  - Surface and insulation quality of individual components
    - Roof, windows, doors, floors, walls, panels

Table 1: Example of dwelling-specific information in table format used for training the models

Parameter	Dwelling #1	Dwelling #2	Dwelling #3
Surface area	69	137	92
Area of heat loss	88.991	377.218	420.422
Compactness	1.29	2.753	4.57
Surface area of the walls	18.902	157.955	174.910
Surface area of the floor	0	87.15	67.813
Surface area of the roof	50.274	109.185	156.786
Surface area of the windows	17.116	16.699	15.787
Surface area of the doors	2.699	6.229	4.112
Surface area of the panels	0	0	1.012
Building year	2002	1900	1935
Building type	5	2	1
Ventilation type	Mechanical	Natural	Natural
Water heating type	HR	Other	HR
General heating type	HR	Other	Heat pump
Ownership type	2	0	0
Insulation quality of the walls	2	0	0
Insulation quality of the floors	Missing	1	0
Insulation quality of the roof	2	0	0
Insulation quality of the panels	Missing	Missing	0
Insulation quality of the windows	2	3	2
Insulation quality of the doors	1	1	1
Insulation quality of the sealing material	0	0	0

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*Measure of the ratio between area of potential heat loss and surface area

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Results

- Random forest model performs slightly better than boosted trees
    - Assessment of models is done through the *accuracy* metric (how often is the prediction correct?)
- Average accuracy of the model is around 80%
    - Randomly assigning labels would result in an accuracy of ~1/7 (14.3%)
- When inaccurate, model tends to predict a more efficient label

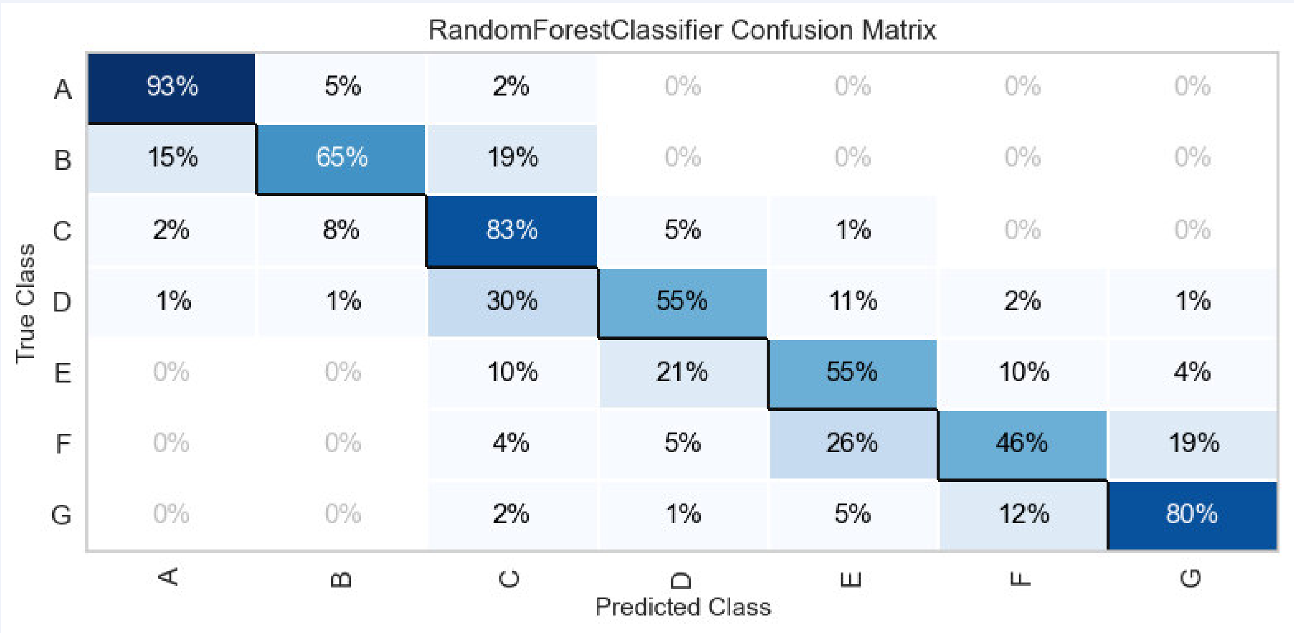

Figure 5: Confusion matrix result for the random forest classification model depicting predicted class against true class

Results

- Interpretability – influence of different individual building characteristics on EPC assignment
  - SHAP value indicates magnitude of impact (SHapley Additive exPlanations)
  - Results available per EPC assignment class – see below for 'label G' (worst performing dwellings)

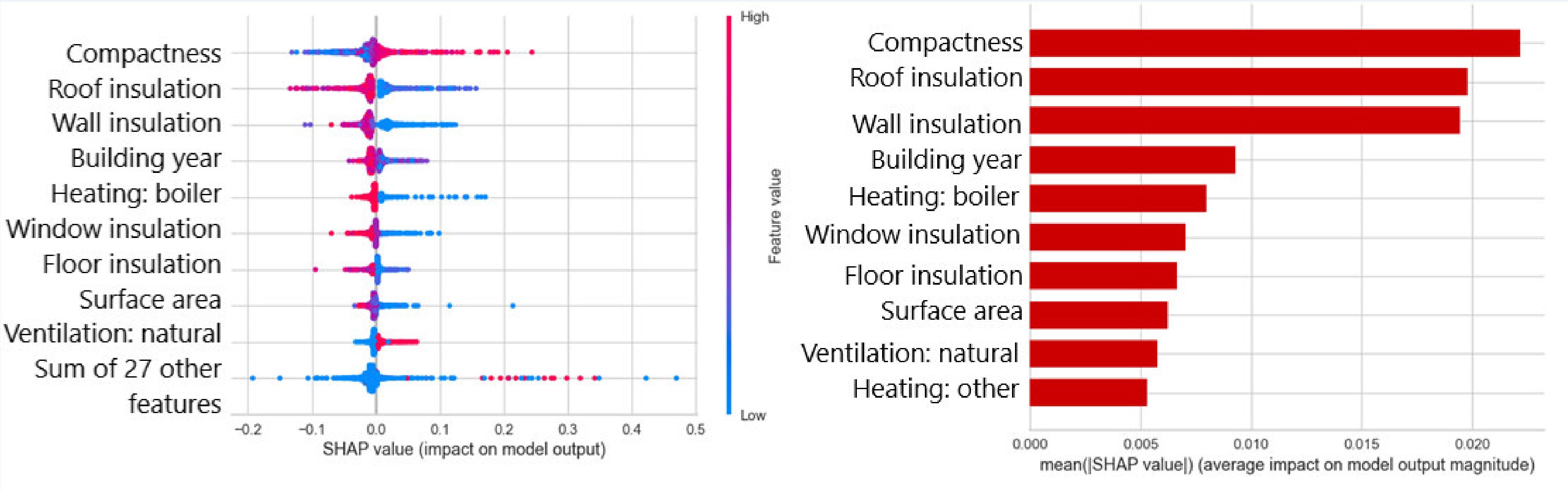

Figure 6: Interpretability plot of the impact of dwelling characteristics on the EPC assignment of the worst performing dwellings

Discussion

- Aim was to establish an alternative methodology
  - Machine learning model
  - However, subject to data quality
    - Skewed dataset
    - Limited number of parameters (including non-actionable such as building year)
    - Some impactful parameters excluded (solar PV, ventilation)

- Interpretability analysis
  - Provides insights on impact of specific characteristics on assignment
  - Can differentiate between different EPC classes (e.g. best- or worst-performing dwellings)
  - However, what are follow-up steps or research topics necessary for policy makers?
    - Non-actionable characteristics provide little to no available follow-up steps
    - Requires follow-up work to analyse improvement strategies of dwelling stock

Conclusion

- Alternative for the standard NTA 8800 procedure
  - Random forest classification model
  - Interpretability functionality
  - Not intended as a substitute, rather as a complimentary tool
  - Generalized enough to be applicable outside of the Netherlands

- We find that for the worst performing dwellings in the Netherlands are mostly impacted by:
  - The quality of the insulation of the roof and facades
  - The type of space heating
- Ongoing effort to train similar models on additional dwelling-specific criteria
  - Instead of multi-class classification, another option is to estimate energy efficiency directly (regression)
- Follow-up work necessary to translate into effective measures for improving energy efficiency metrics in dwellings

Questions

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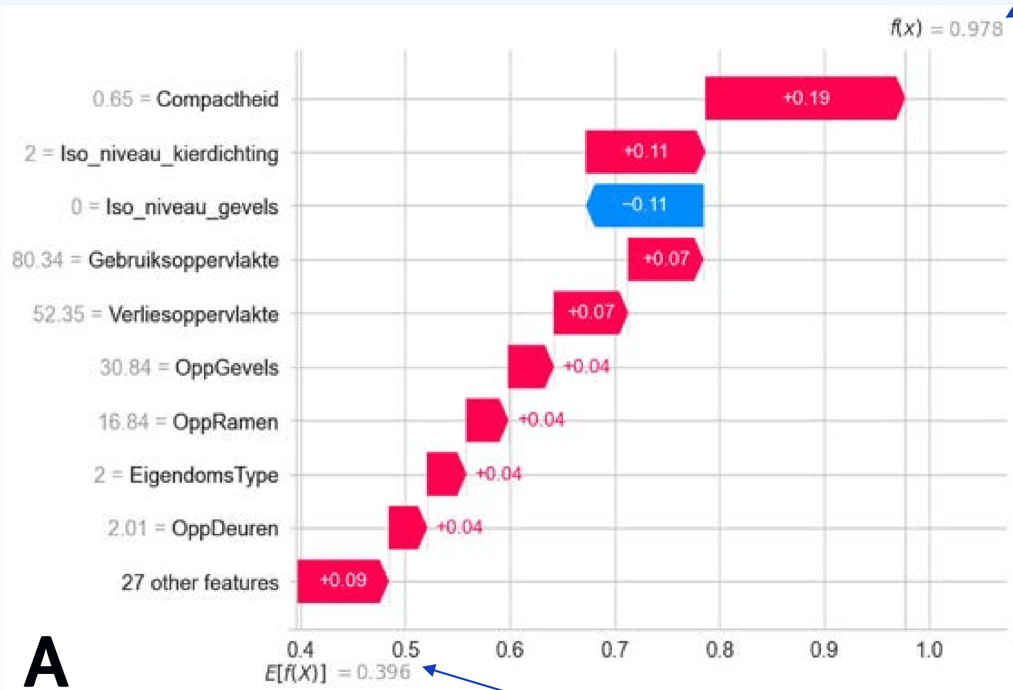
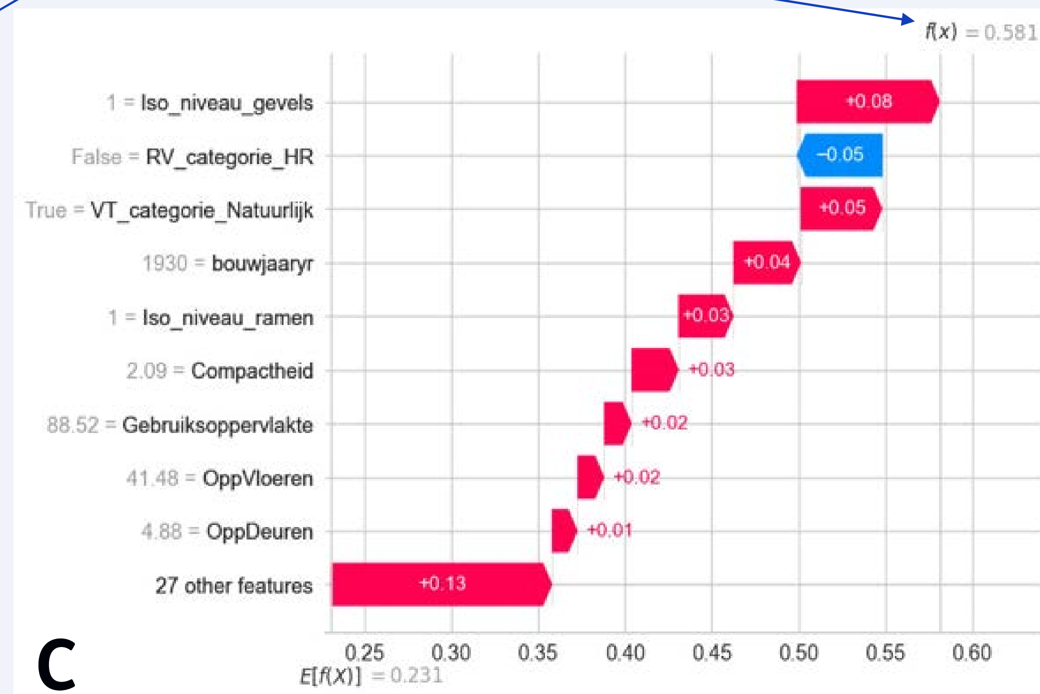
Appendix 1 – Interpretability of the Model

- Example of two dwellings with energy labels A and C.

Probability of the energy label

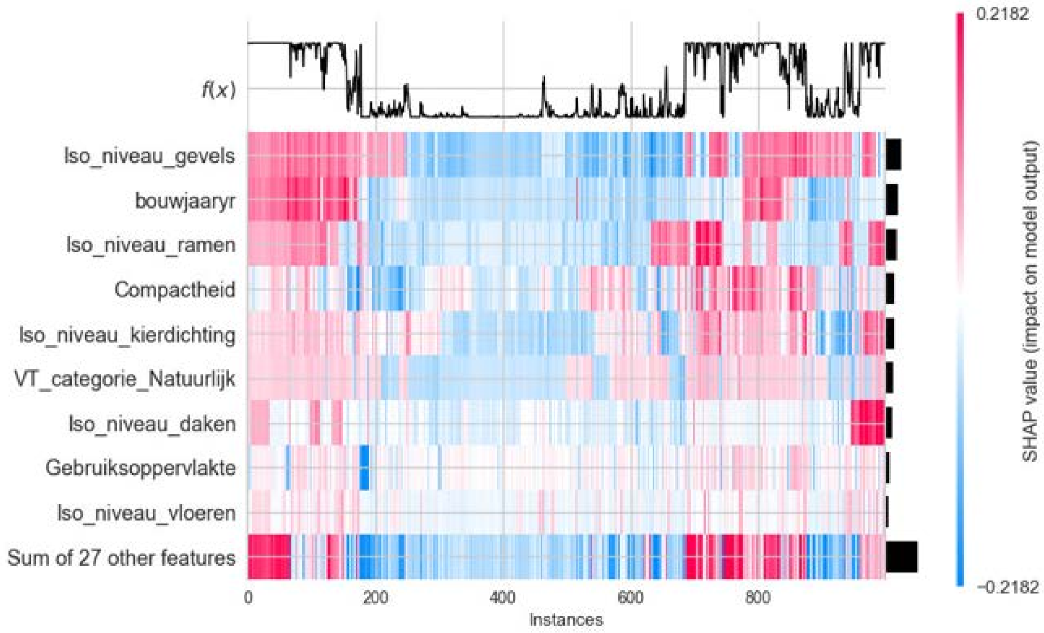




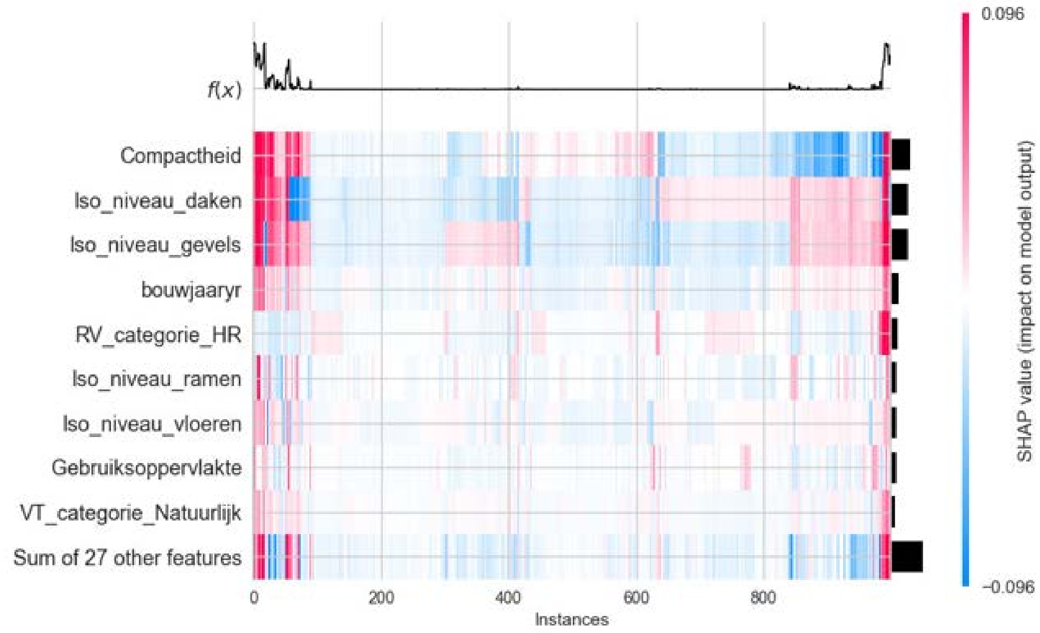
Expected probability of the energy label

Appendix 2 - Interpretability of Label A and G in 1000 dwellings

A



G



Appendix 3 – example decision tree