City of Seattle

# *Energy consumption*
# and
# *Greenhouse gases emission*
# predictions

for the non-residential properties of Seattle.

Julien Le Boucher

03 - 31 - 2023

# Plan

- Context / motivation of this mission.
- Work on the dataset and modelling approach
- The best model and its performance.

# Seattle's Climate plan Objectives

The city objectives :

- zero net core greenhouse gas emission by 2050.
- Sector-specific emissions reduction goals of 39% from building energy by 2030 comparing to 2008.

My missions :

- Predict :
  - Energy Consumption
  - GHG emissions

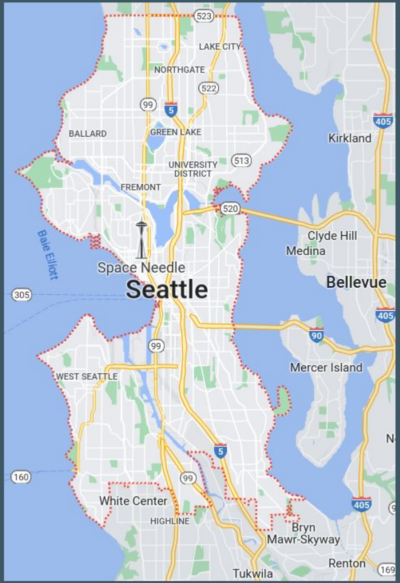
  of Non-residential Buildings from its structural attributes.
- Evaluate the impact of the Energy Star Score when used as an input in the models.

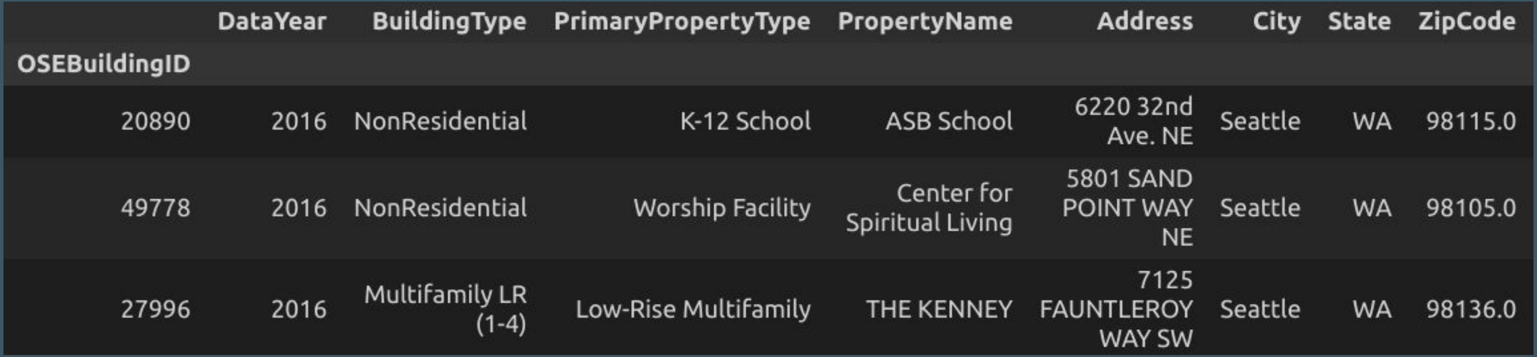
# Dataset Overview

# The dataset

- information gathered in 2016. Mandatory for all Seattle's properties with a GFA >  20 000 feet square.

- 3376 properties of Seattle (rows).
- 45 features (columns).

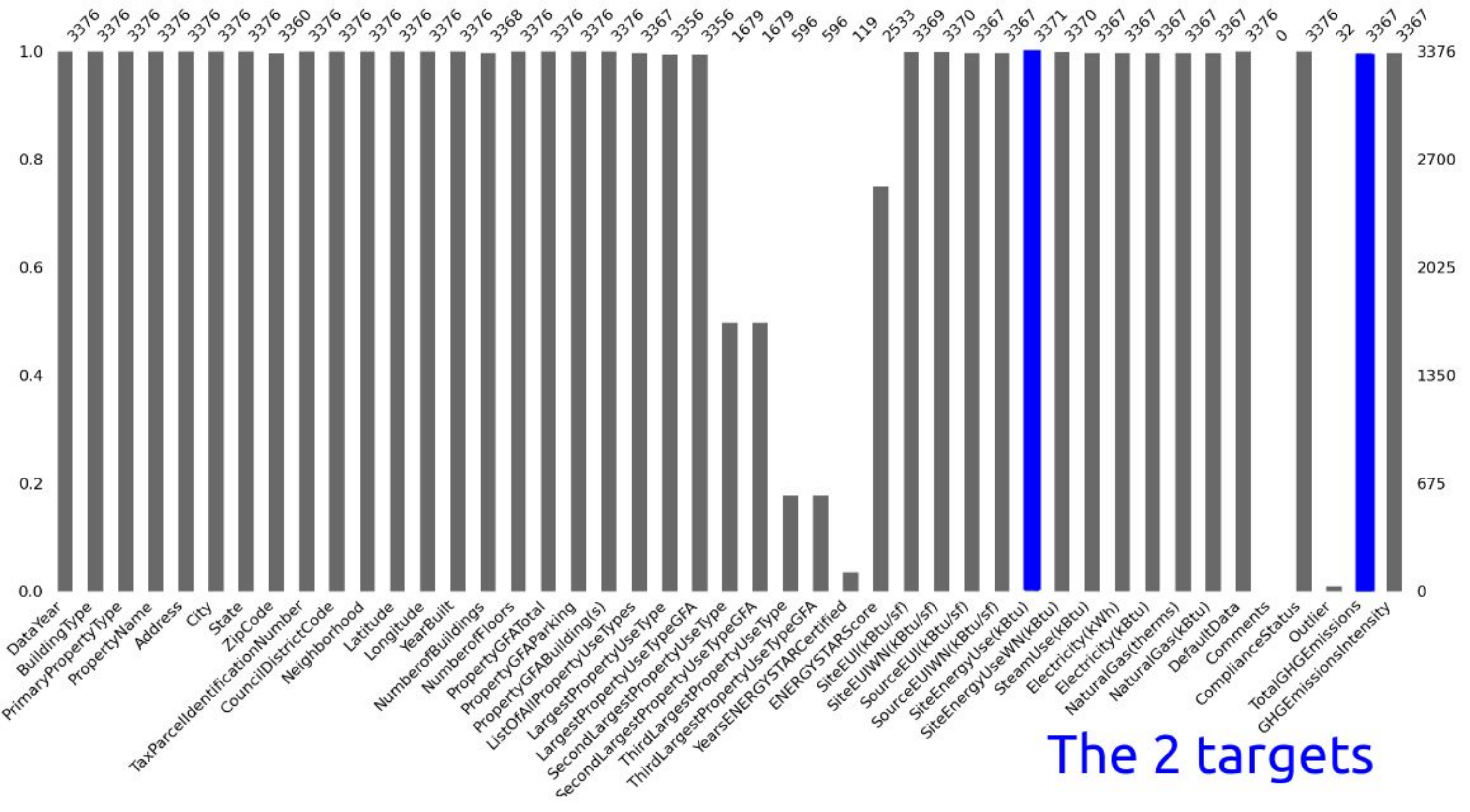




| OSEBuildingID | DataYear | BuildingType | PrimaryPropertyType | PropertyName | Address | City | State | ZipCode |
|---|---|---|---|---|---|---|---|---|
| 20890 | 2016 | NonResidential | K-12 School | ASB School | 6220 32nd Ave. NE | Seattle | WA | 98115.0 |
| 49778 | 2016 | NonResidential | Worship Facility | Center for Spiritual Living | 5801 SAND POINT WAY NE | Seattle | WA | 98105.0 |
| 27996 | 2016 | Multifamily LR (1-4) | Low-Rise Multifamily | THE KENNEY | 7125 FAUNTLEROY WAY SW | Seattle | WA | 98136.0 |

A chunk of the dataset

# Missing values, Features groups and Targets.



1 - Type and primary use

2 - Name and localization.

3 - Buildings' attributes.

4 - ENERGY STAR Score.

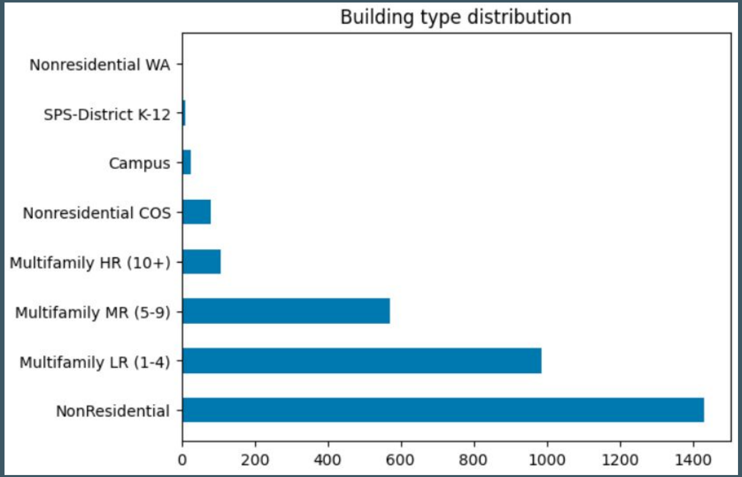
5 - Energy Consumption.

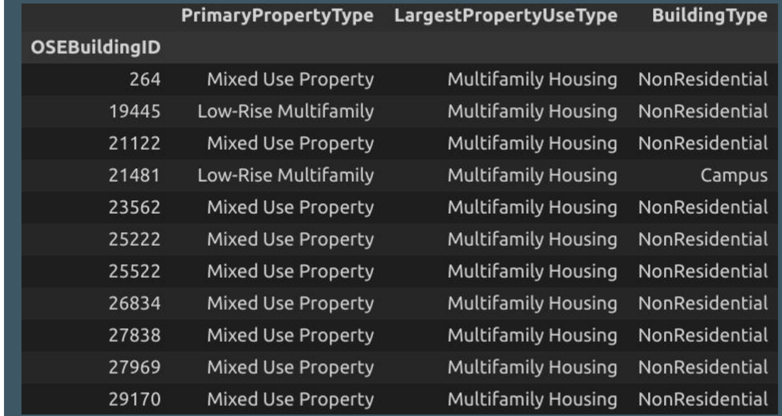
6 - Data Status.

7 - GHG Emissions.

# Filtering non-residential properties

- Compliant Status → 165 properties discarded (missing or default data)
- Filtered on a triplet of features to ensure only Non-Residential properties remained in the data.





| | PrimaryPropertyType | LargestPropertyUseType | BuildingType |
|---|---|---|---|
| OSEBuildingID | | | |
| 264 | Mixed Use Property | Multifamily Housing | NonResidential |
| 19445 | Low-Rise Multifamily | Multifamily Housing | NonResidential |
| 21122 | Mixed Use Property | Multifamily Housing | NonResidential |
| 21481 | Low-Rise Multifamily | Multifamily Housing | Campus |
| 23562 | Mixed Use Property | Multifamily Housing | NonResidential |
| 25222 | Mixed Use Property | Multifamily Housing | NonResidential |
| 25522 | Mixed Use Property | Multifamily Housing | NonResidential |
| 26834 | Mixed Use Property | Multifamily Housing | NonResidential |
| 27838 | Mixed Use Property | Multifamily Housing | NonResidential |
| 27969 | Mixed Use Property | Multifamily Housing | NonResidential |
| 29170 | Mixed Use Property | Multifamily Housing | NonResidential |

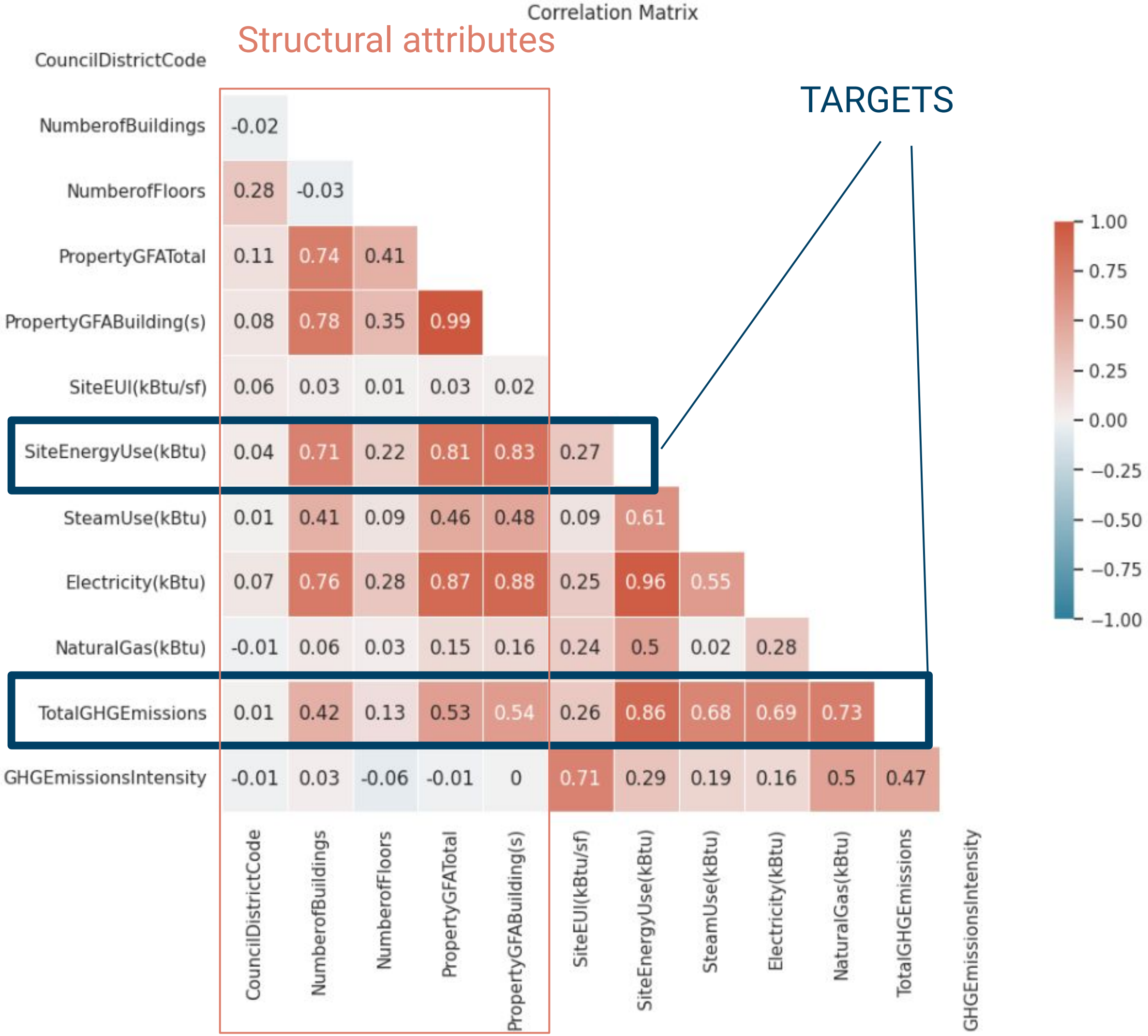
Example of inconsistencies found.

3376 properties

1487 properties

# EDA on non-residential properties

## Features selection motives



Correlation Matrix

Structural attributes

TARGETS

| | CouncilDistrictCode | NumberofBuildings | NumberofFloors | PropertyGFATotal | PropertyGFABuilding(s) | SiteEUI(kBtu/sf) | SiteEnergyUse(kBtu) | SteamUse(kBtu) | Electricity(kBtu) | NaturalGas(kBtu) | TotalGHGEmissions | GHGEmissionsIntensity |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CouncilDistrictCode | | | | | | | | | | | | |
| NumberofBuildings | -0.02 | | | | | | | | | | | |
| NumberofFloors | 0.28 | -0.03 | | | | | | | | | | |
| PropertyGFATotal | 0.11 | 0.74 | 0.41 | | | | | | | | | |
| PropertyGFABuilding(s) | 0.08 | 0.78 | 0.35 | 0.99 | | | | | | | | |
| SiteEUI(kBtu/sf) | 0.06 | 0.03 | 0.01 | 0.03 | 0.02 | | | | | | | |
| SiteEnergyUse(kBtu) | 0.04 | 0.71 | 0.22 | 0.81 | 0.83 | 0.27 | | | | | | |
| SteamUse(kBtu) | 0.01 | 0.41 | 0.09 | 0.46 | 0.48 | 0.09 | 0.61 | | | | | |
| Electricity(kBtu) | 0.07 | 0.76 | 0.28 | 0.87 | 0.88 | 0.25 | 0.96 | 0.55 | | | | |
| NaturalGas(kBtu) | -0.01 | 0.06 | 0.03 | 0.15 | 0.16 | 0.24 | 0.5 | 0.02 | 0.28 | | | |
| TotalGHGEmissions | 0.01 | 0.42 | 0.13 | 0.53 | 0.54 | 0.26 | 0.86 | 0.68 | 0.69 | 0.73 | | |
| GHGEmissionsIntensity | -0.01 | 0.03 | -0.06 | -0.01 | 0 | 0.71 | 0.29 | 0.19 | 0.16 | 0.5 | 0.47 | |

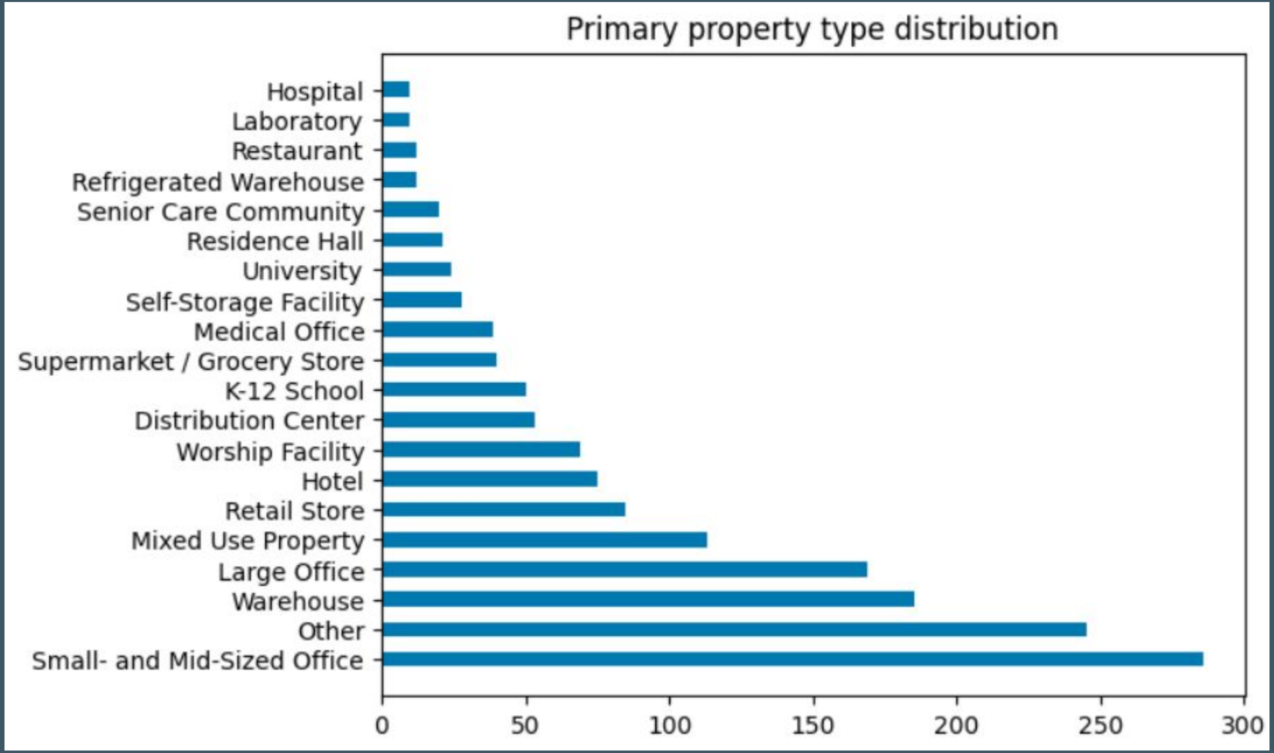
- 4 structural attributes out of 5 are correlated with the targets.
  Thus, should go in the inputs.

- Total GFA and buildings' GFA are highly correlated .
  → Choose only 1 as input to avoid multicollinearity.

Retained Structural Features as inputs :

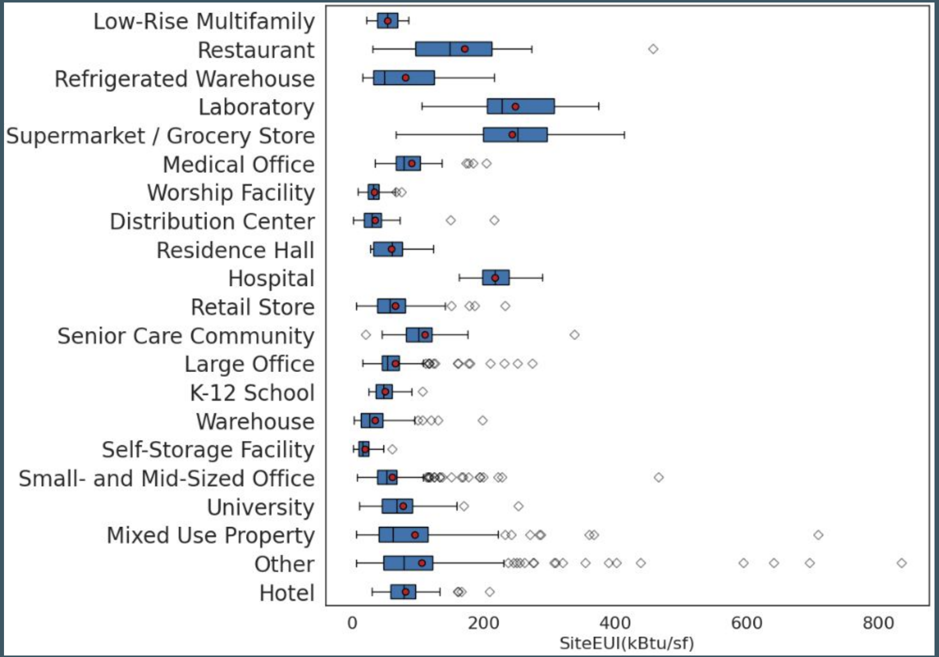
- 'PropertyGFABuilding(s)'
- 'NumberofFloors
- 'NumberofBuildings

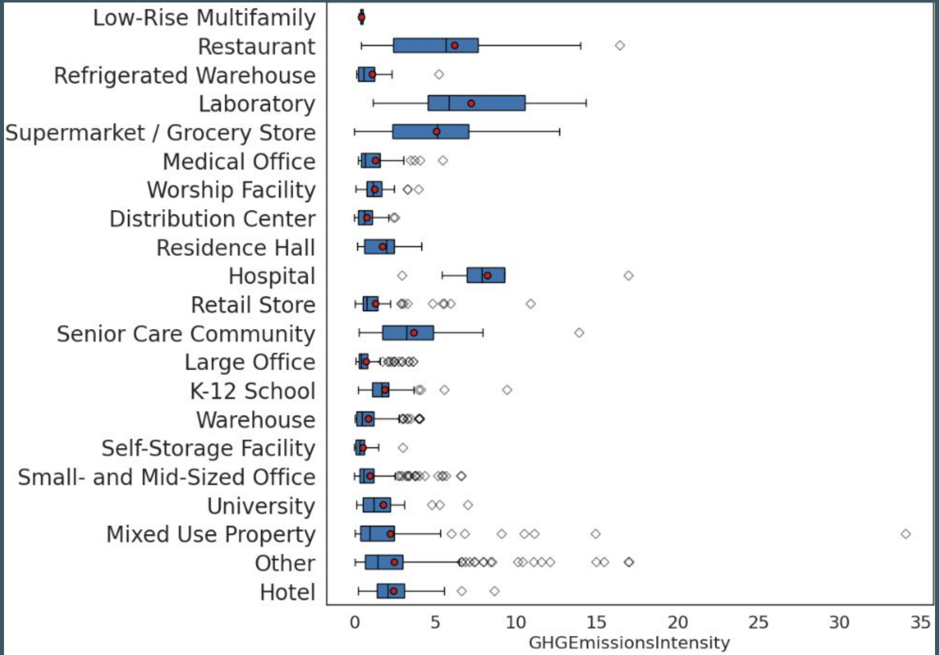
# Grouping thanks to 'PrimaryPropertyType'

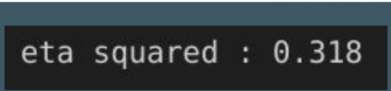


- Enables to split properties in several groups without being too specific (unlike 'LargestPropertyUseType').
- One-Hot Encoded dropping one column to avoid multicollinearity.
- Correlated with the targets.

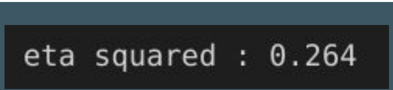
# 'PrimaryPropertyType' correlations with the targets' intensities







```
eta squared : 0.318
```



```
eta squared : 0.264
```

The category has an influence regardless of the surface of the property.
Must be feed in the model

# Features engineering

# 4 derived features.

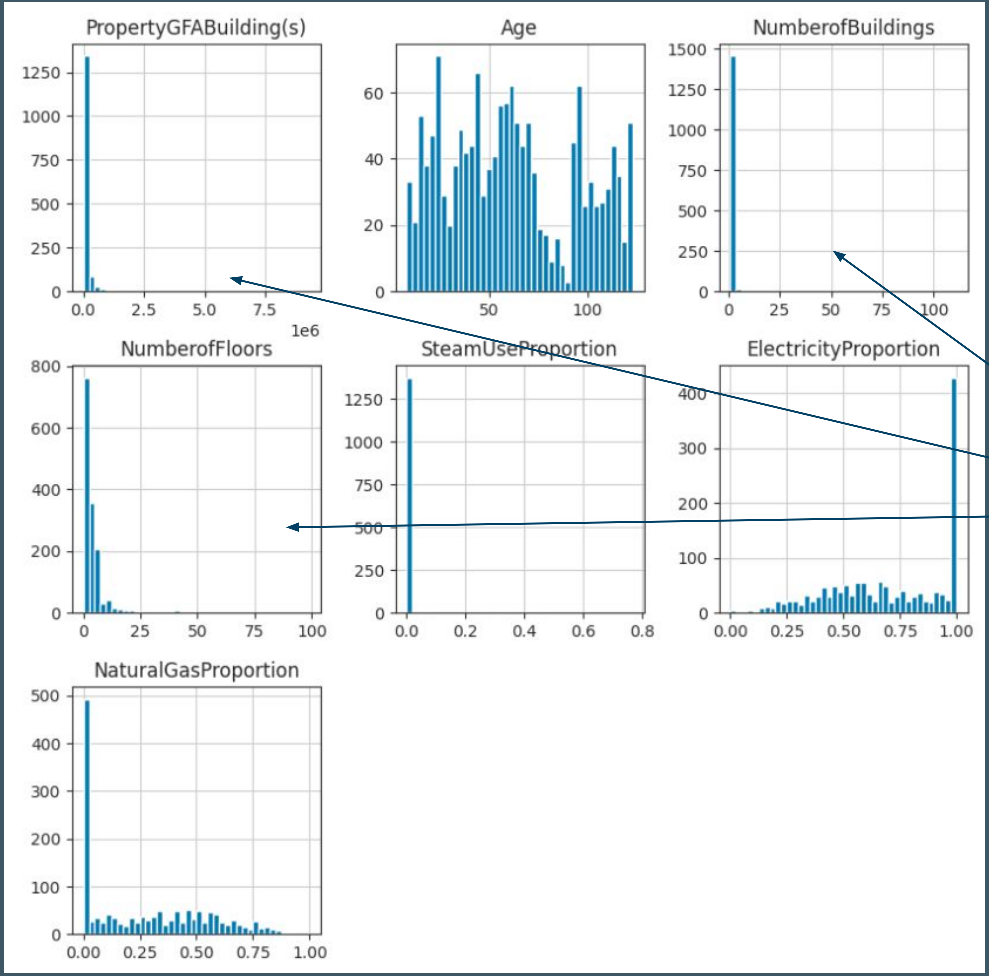
- From YearBuilt (date of construction or of a total renovation)
  → 2023 - YearBuilt = Age

- From SiteEnergyUse and the 3 features (Electricity, NaturalGas, SteamUse).
  → Proportions of energy used per source type which can be seen as structural and should be assessable when building a new structure or renovating.
  - SteamUseProportion
  - ElectricityProportion
  - NaturalGasProportion.

  Currently not 100% reliable : Outliers problem ?

# Models' inputs and targets

# 26 inputs



## 7 numericals inputs

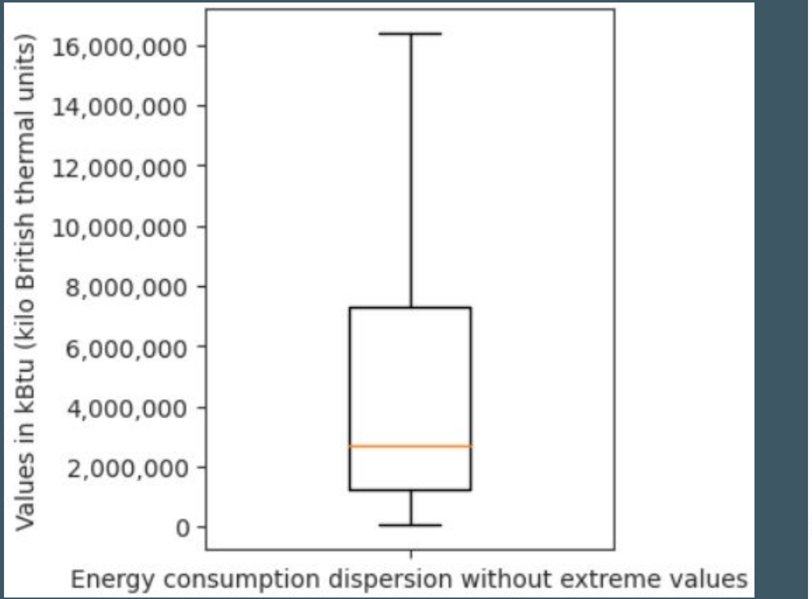
**Pre-processing possibilities**

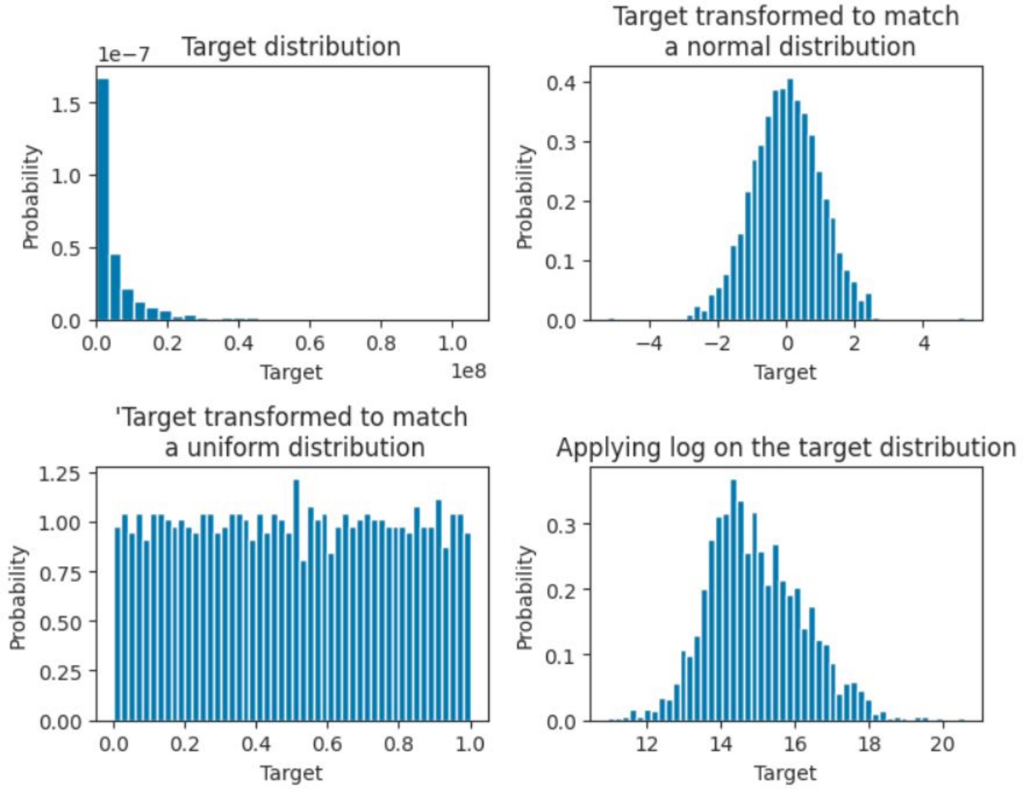
- The proportions are already scaled between 0 and 1.
- All the other features should be scaled? (MinMax, StandardScaler?)
- 3 skewed distributions. Transformation before going in the model? (log, quantile ?)

## + 19 binary inputs

Primary property type One-Hot encoded feature.

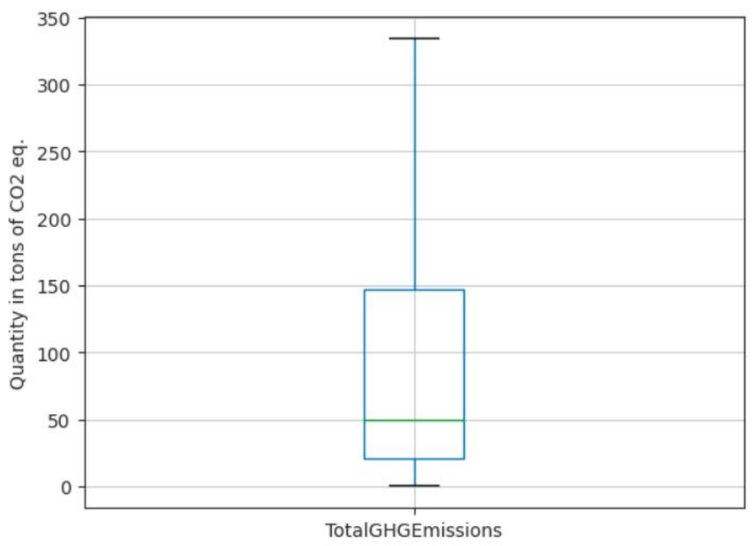
# 1st target : Total energy consumption (kBtu)



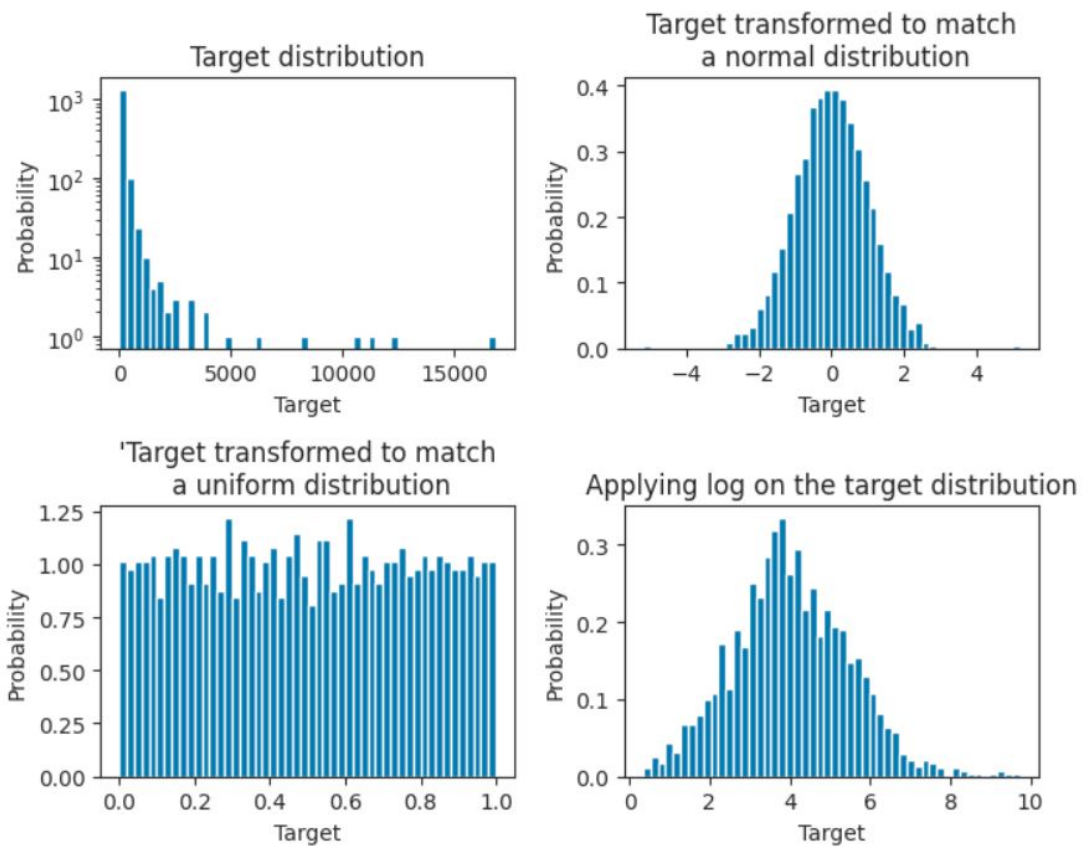


Min : 5 713 kBtu
Max :  874 000 000 kBtu

# 2nd target : Greenhouse gases emissions (in tons of CO2 eq)

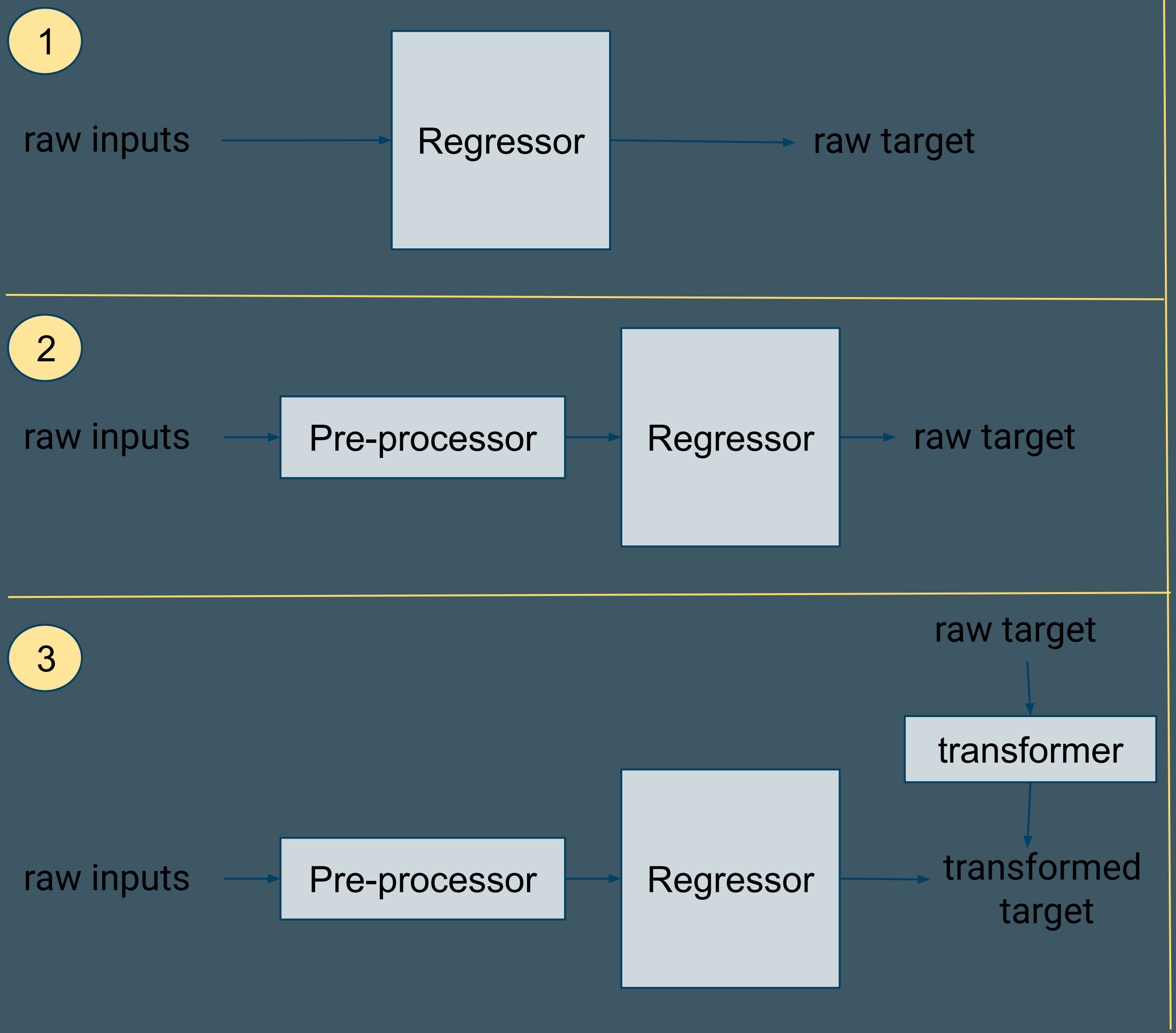


Min : 0.4 tons CO2 eq.
Max : 16 870 tons CO2 eq.



# Modelling approach

## Searching the best model



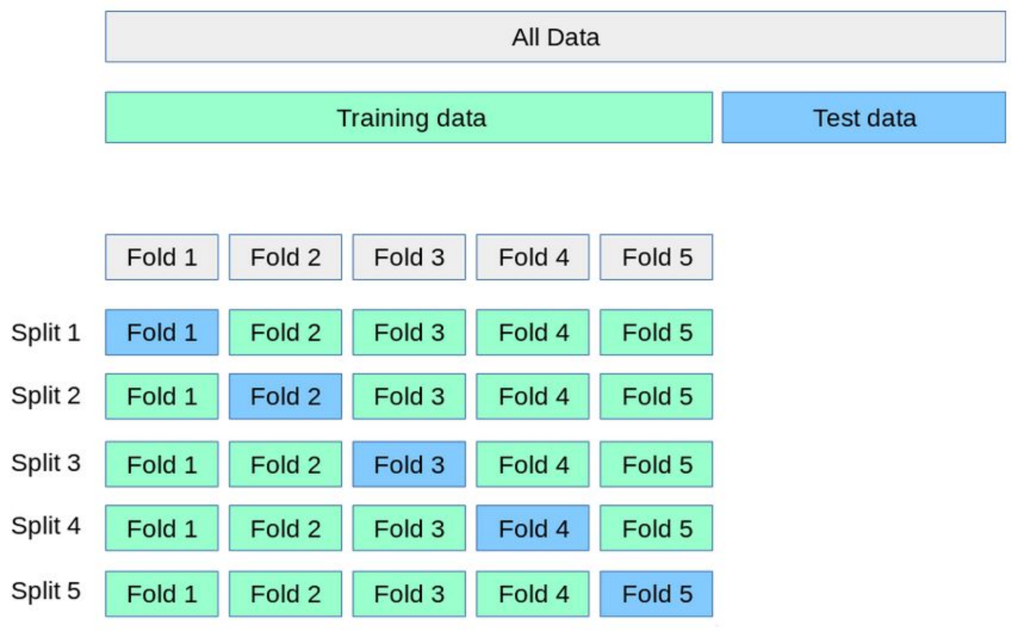
- Playing on the modelling steps complexity (1, 2, or 3) and permuting the following elements :

- REGRESSOR :
  - OLS regressor
  - Lasso
  - Ridge
  - ElasticNet
  - Knn
  - Random Forest
  - XGBoost (gbtree)

- PRE-PROCESSOR :
  - passthrough
  - MinMax
  - Standard
  - log transformer
  - log into the 2 firsts.
  - quantile transformer

- TRANSFORMER :
  - log transformer
  - quantile transformer fit on the train set.

# Hyperparameters tuning + evaluation of models' performances.



All Data

Training data | Test data

Fold 1 | Fold 2 | Fold 3 | Fold 4 | Fold 5

Split 1 | Fold 1 | Fold 2 | Fold 3 | Fold 4 | Fold 5

Split 2 | Fold 1 | Fold 2 | Fold 3 | Fold 4 | Fold 5

Split 3 | Fold 1 | Fold 2 | Fold 3 | Fold 4 | Fold 5

Split 4 | Fold 1 | Fold 2 | Fold 3 | Fold 4 | Fold 5

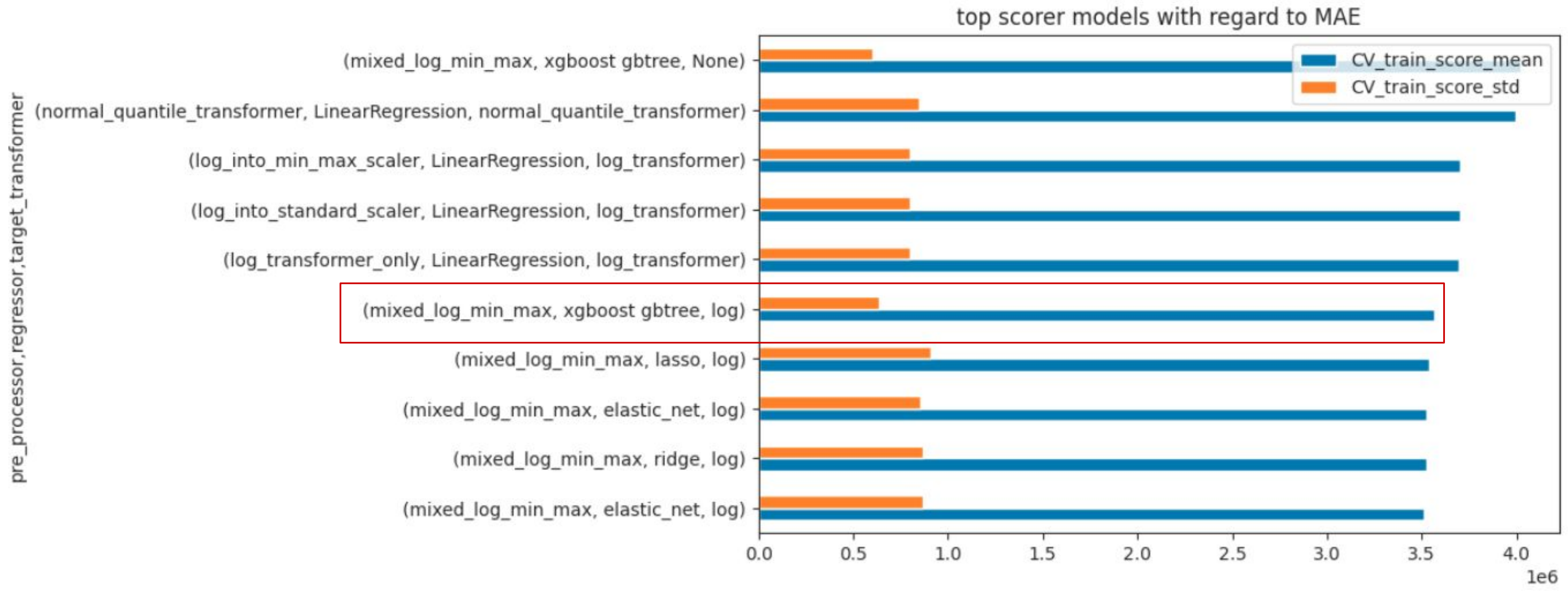
Split 5 | Fold 1 | Fold 2 | Fold 3 | Fold 4 | Fold 5

*sklearn's illustration of a 5-fold cross validation*

- Test data : 25 % of the data.
- Hyperparameters tuning :
  - Optimized sequentially thanks to grid searches.
  - Choices made with regard to 3 differents metrics : R2, MAE, RMSE.
    (can lead to model slightly different)
  - Optimized the mean score on 5 folds. Kept in mind that minimizing the variance was also important.
- Evaluation of the model :
  - Saved the mean score on folds and the variance.
  - Compared fitting time on the train set.
  - Plotted predictions against the real values of the target on the test data.

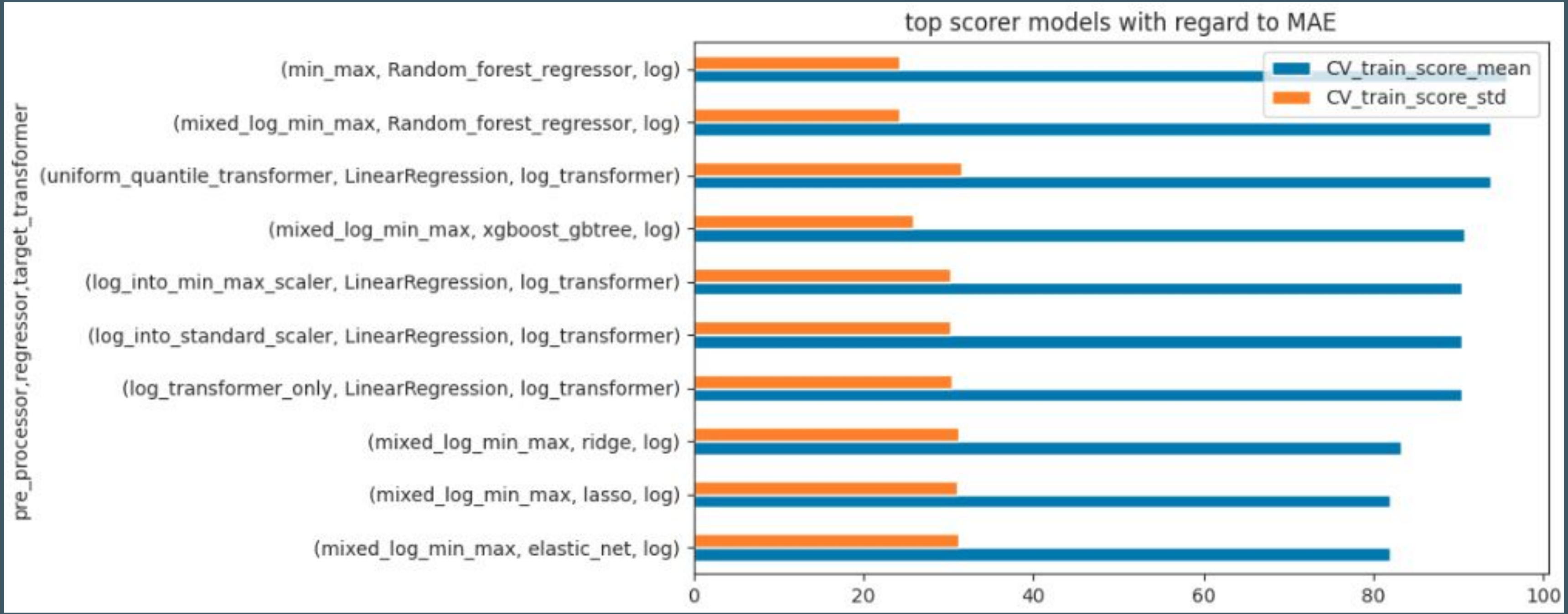
# Top scorers models

# Energy prediction (MAE)



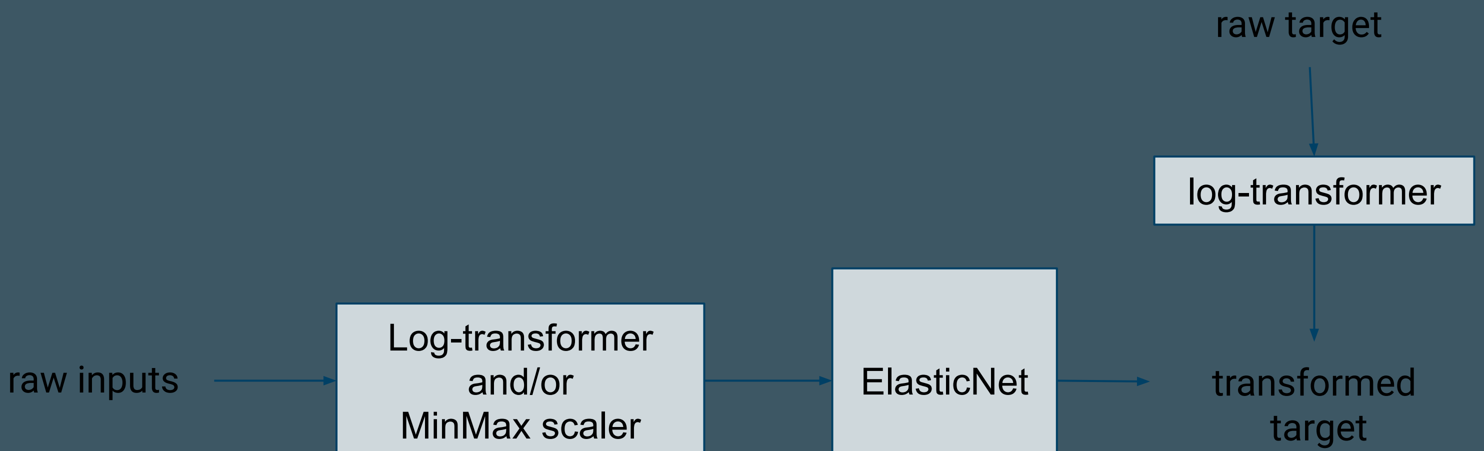
- Dummy regressor : MAE ~ 8e6 kBtu
- Regardless of the regressor, a log transformation on both skewed inputs and the target gave the best results.
- Linear regression models gave the best results.
- Interesting to note that the Xgboost model coming close after linear models has a lower variance

# GHG emissions (MAE)



- Dummy Regressor : MAE ~ 187 tons CO2 eq
- log transformation also very important (inputs and target)
- regularized version of linear models outperform the rest more significantly.

# Best model for both predictions

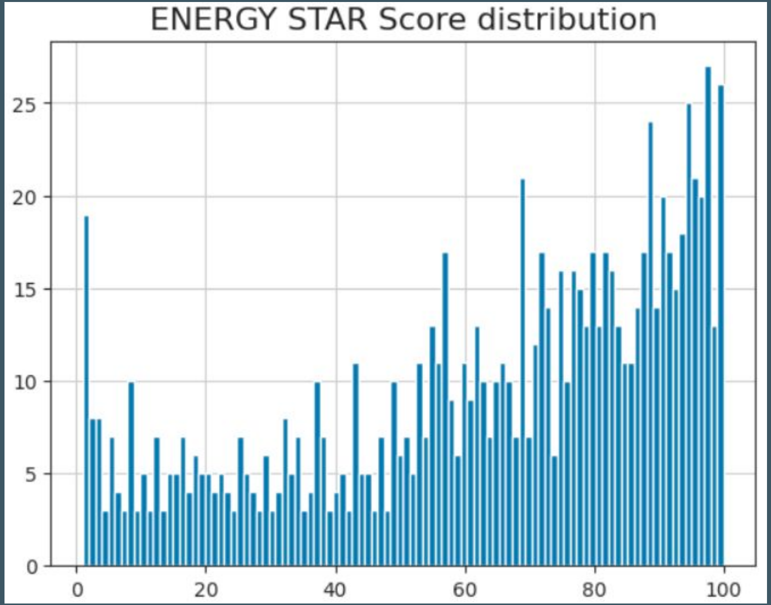


Note that results are fairly consistent when evaluating with the R2 , MAE and the RMSE metric.

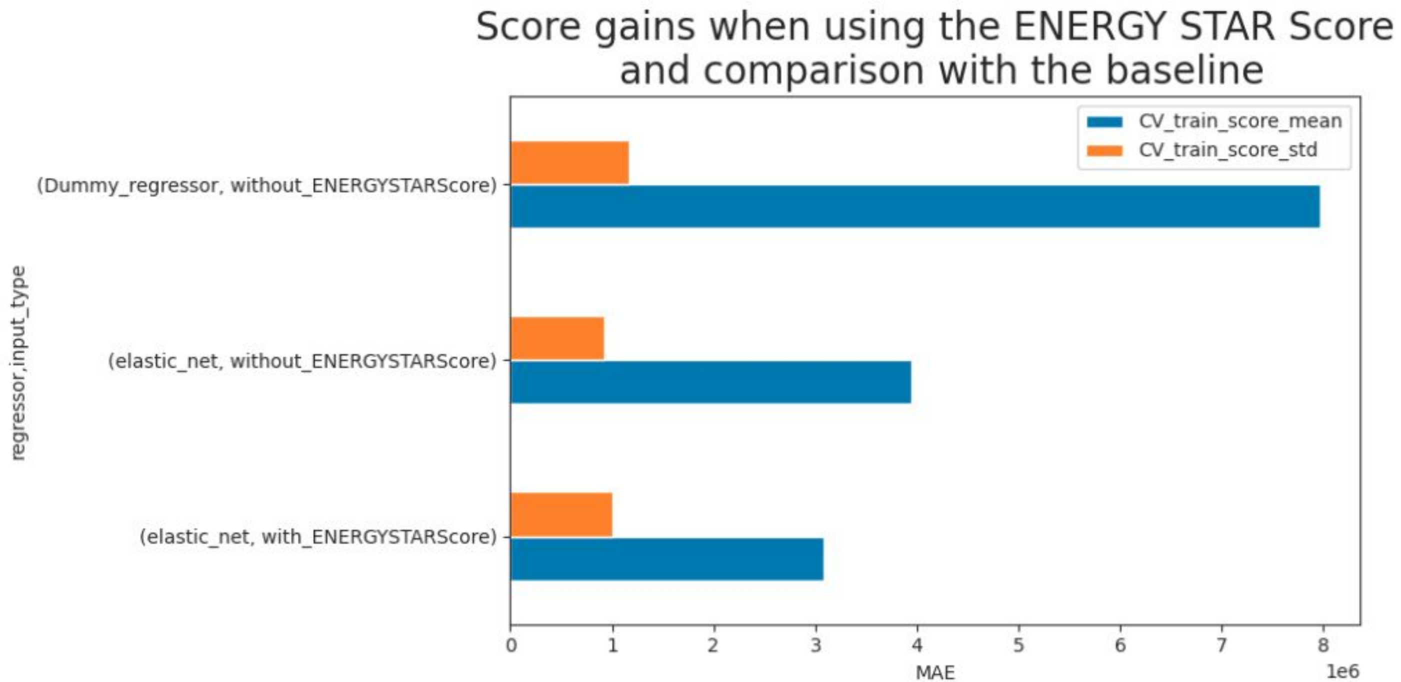
# Energy Star score

# What is the Energy Star Score ?

- available for 65 % of the selected properties.
- currently being generated by colleagues (expensive/time consuming).
- range between 0 and 100

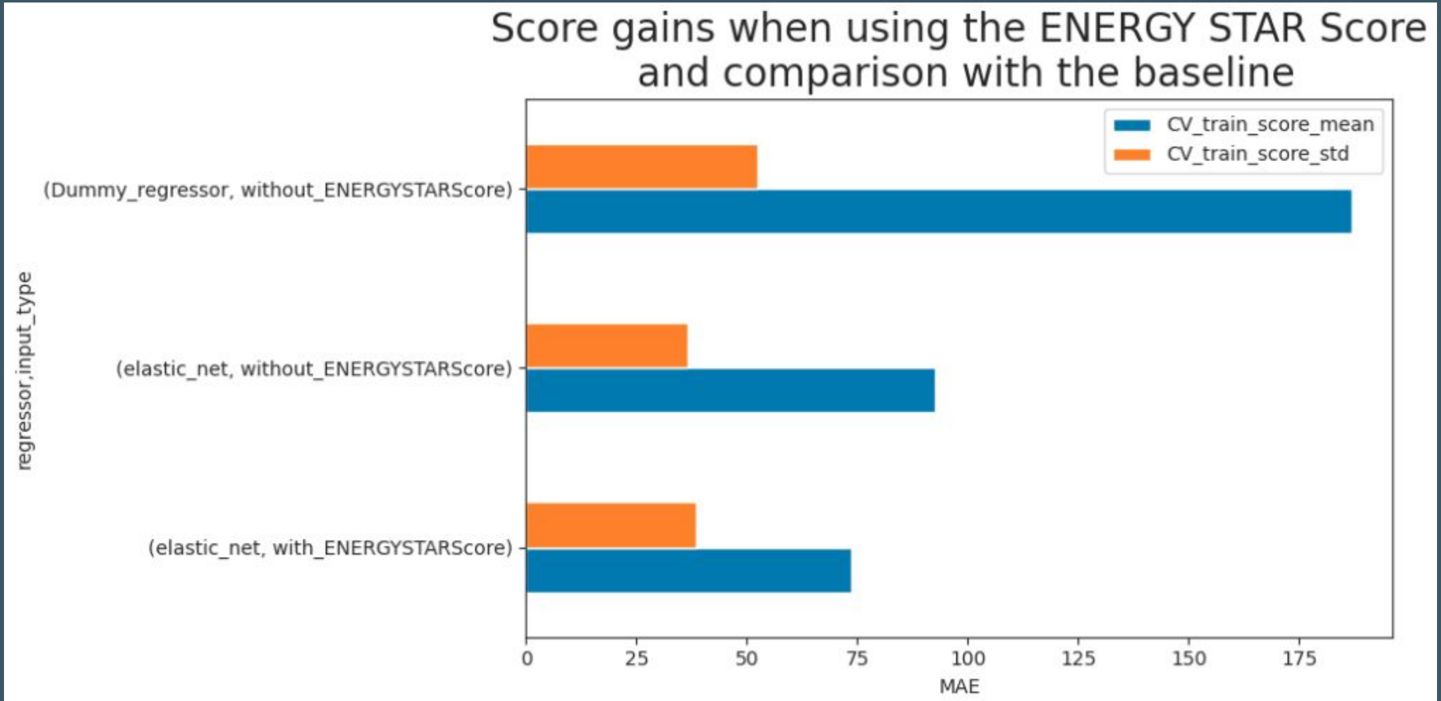


# Impact on the best model : ElasticNet (Energy consumptions)



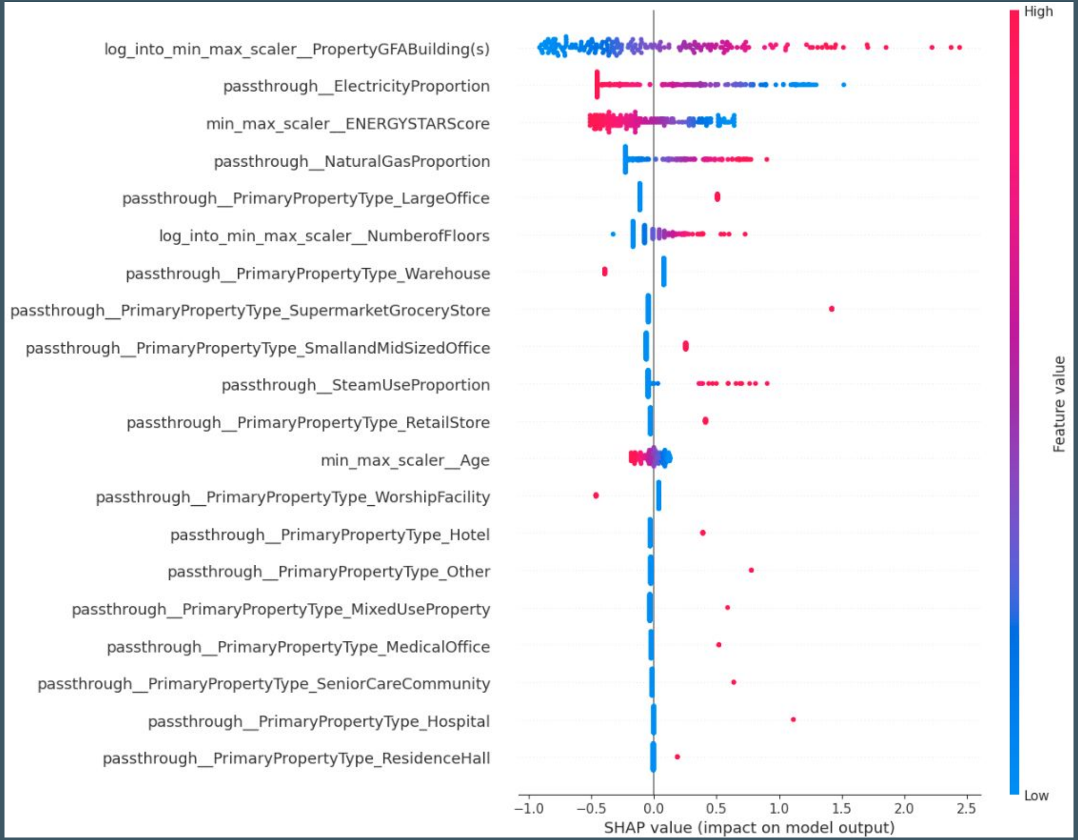
- Adding the Energy Star Score to the inputs of the model increases the performance (~21,9% gain)
- Ultimately, the model has an MAE which is ~38,7% of the baseline's MAE.

# Impact on the best model : ElasticNet (GHG emissions)



- Adding the Energy Star Score to the inputs of the model increases the performance (~20,4% gain)
- Ultimately, the model has an MAE which is ~39,4% of the baseline's MAE.

# Features importance in the model : (GHG emissions)



*(Read the most important features from top to bottom.)*

- Energy Star Score ranked 3.

-> Not surprising considering the gains.

- Energy sources proportions are important.

# Conclusion

- For both predictions, the ElasticNet gives the best performance.
- In both cases, adding the Energy Star Score in the model's inputs improves the performance (~20% gain).

# Going further ?

Some ideas to improve the performance ?

- Address the energy sources proportions problem on some properties.
- Introduce location information.
- Retrieve number of buildings (very correlated with GFA).
- Continue to build the Energy Star Score for the missing non-residential properties.

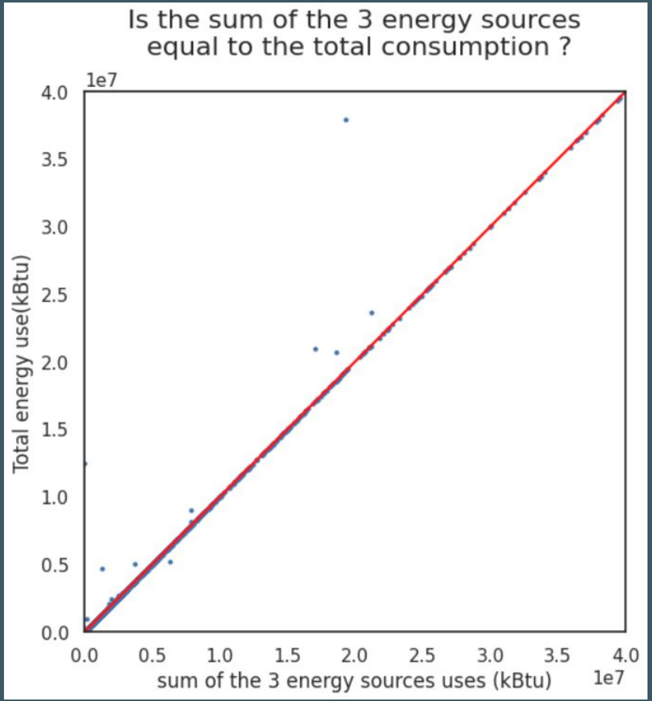
Feature engineering :

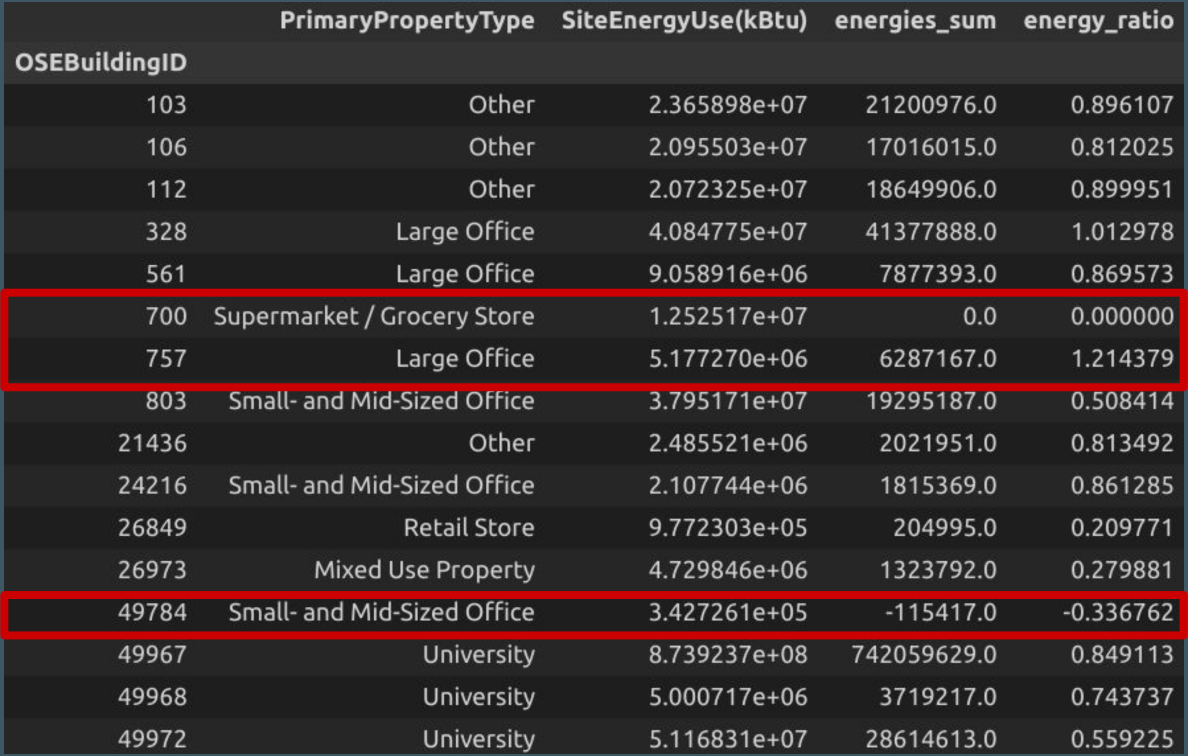
- map each class of Primary, secondary and third type use (quite detailed) with the one-hot encoded variable classes AND weight the 1 with the respective GFA proportion.

# Thank you for listening

# Appendices

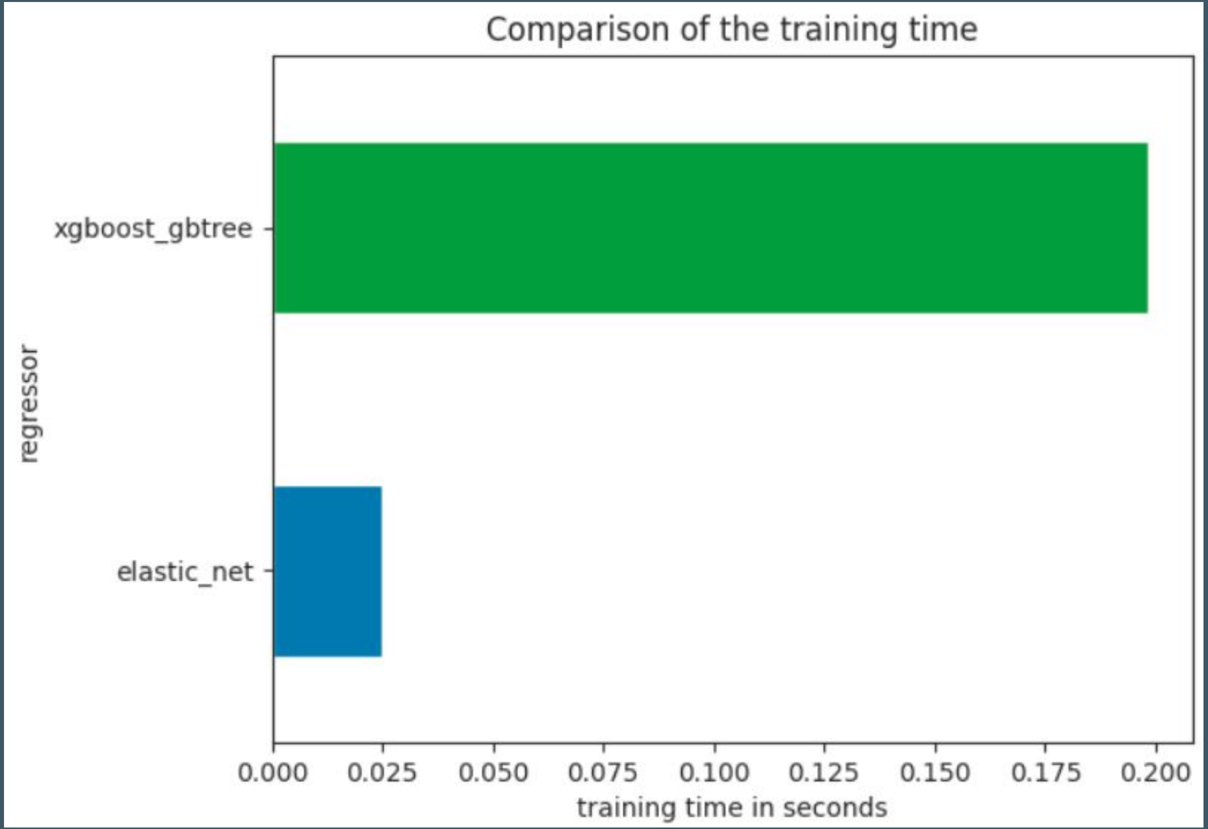
# Energy source proportions outliers ?



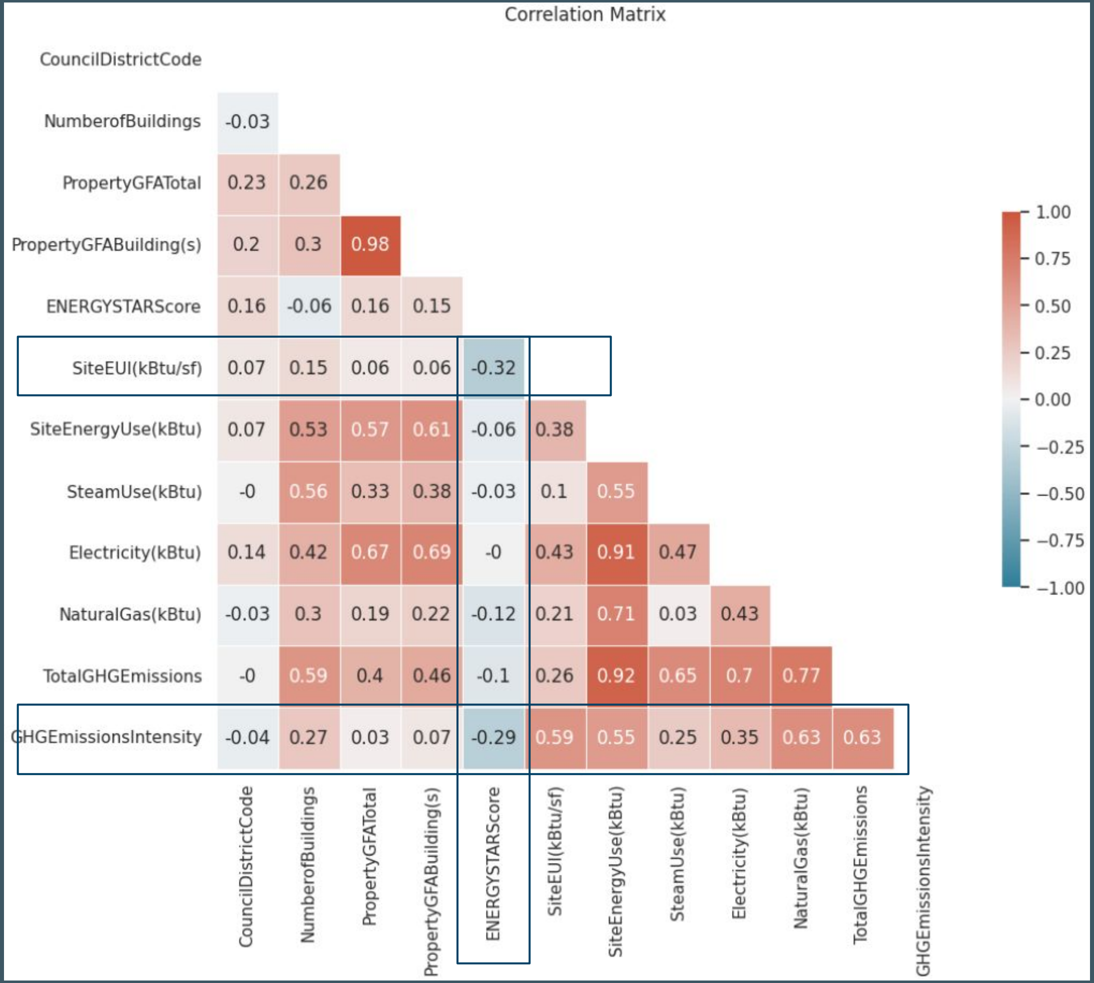


| | PrimaryPropertyType | SiteEnergyUse(kBtu) | energies_sum | energy_ratio |
|---|---|---|---|---|
| OSEBuildingID | | | | |
| 103 | Other | 2.365898e+07 | 21200976.0 | 0.896107 |
| 106 | Other | 2.095503e+07 | 17016015.0 | 0.812025 |
| 112 | Other | 2.072325e+07 | 18649906.0 | 0.899951 |
| 328 | Large Office | 4.084775e+07 | 41377888.0 | 1.012978 |
| 561 | Large Office | 9.058916e+06 | 7877393.0 | 0.869573 |
| 700 | Supermarket / Grocery Store | 1.252517e+07 | 0.0 | 0.000000 |
| 757 | Large Office | 5.177270e+06 | 6287167.0 | 1.214379 |
| 803 | Small- and Mid-Sized Office | 3.795171e+07 | 19295187.0 | 0.508414 |
| 21436 | Other | 2.485521e+06 | 2021951.0 | 0.813492 |
| 24216 | Small- and Mid-Sized Office | 2.107744e+06 | 1815369.0 | 0.861285 |
| 26849 | Retail Store | 9.772303e+05 | 204995.0 | 0.209771 |
| 26973 | Mixed Use Property | 4.729846e+06 | 1323792.0 | 0.279881 |
| 49784 | Small- and Mid-Sized Office | 3.427261e+05 | -115417.0 | -0.336762 |
| 49967 | University | 8.739237e+08 | 742059629.0 | 0.849113 |
| 49968 | University | 5.000717e+06 | 3719217.0 | 0.743737 |
| 49972 | University | 5.116831e+07 | 28614613.0 | 0.559225 |

I Discarded the 3 properties highlighted here. Not all, in order to keep some universities in the dataset.
Explanations for the other ratios ?

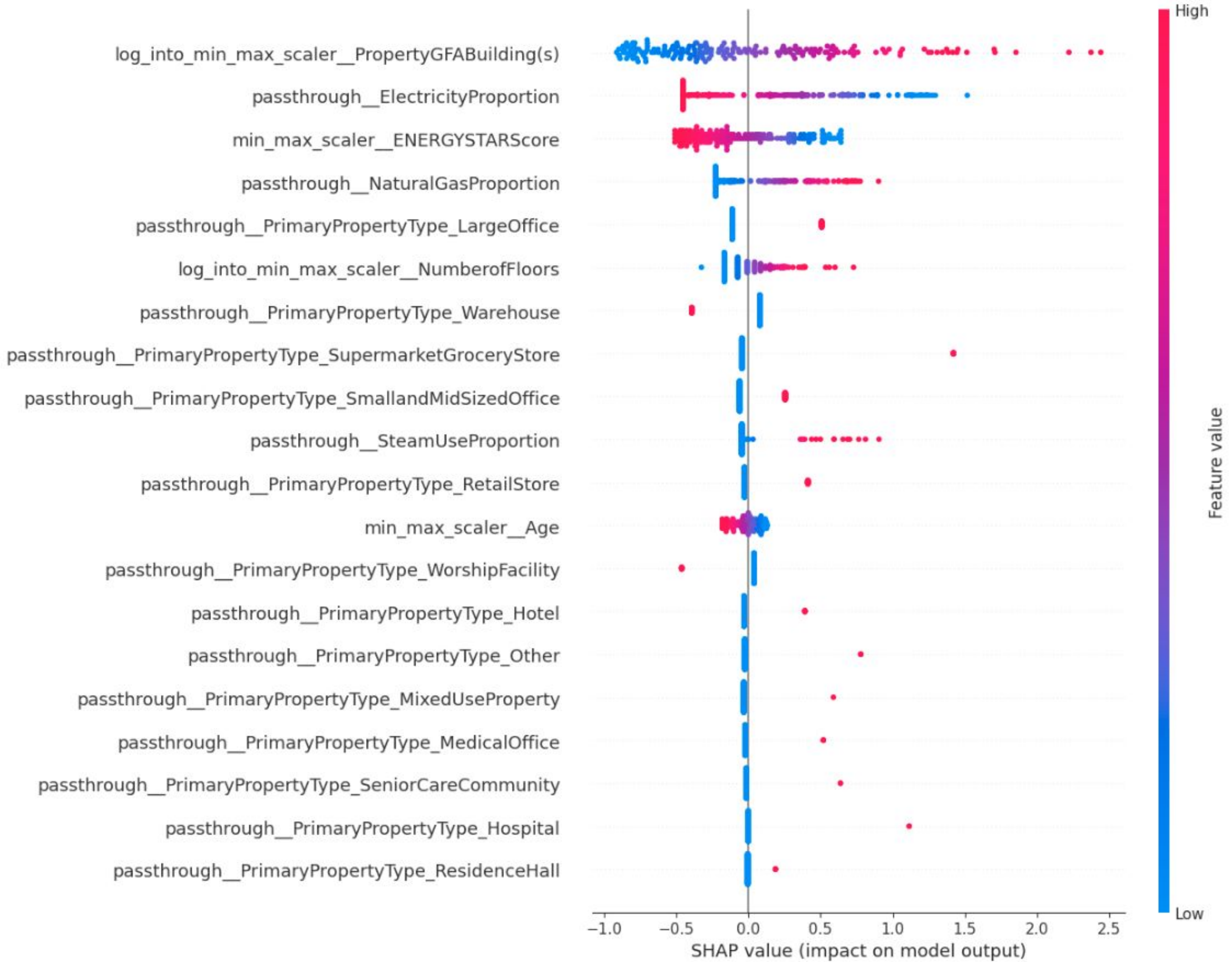


The Xgboost which could be a reasonable alternative to linear models is about 8 times longer to train on the training set.



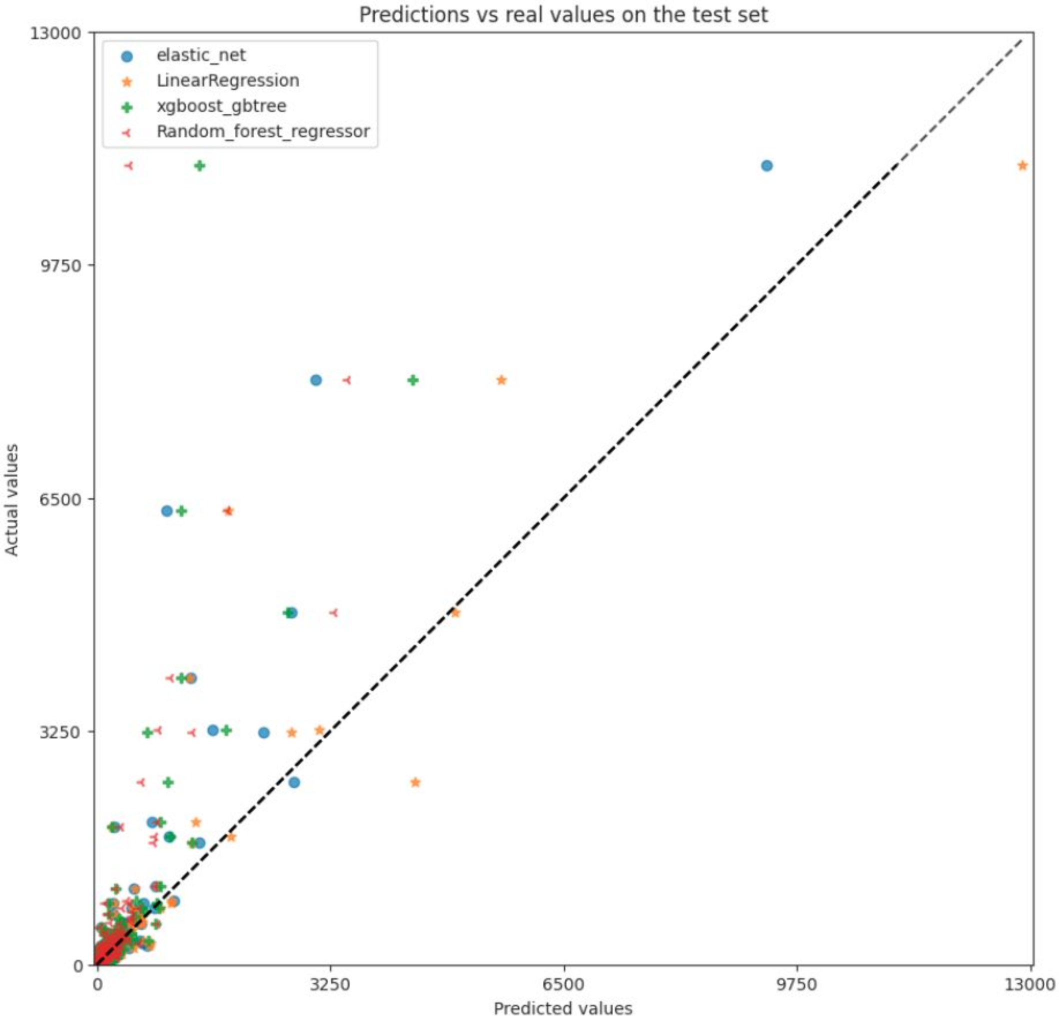
| | CouncilDistrictCode | NumberofBuildings | PropertyGFATotal | PropertyGFABuilding(s) | ENERGYSTARScore | SiteEUI(kBtu/sf) | SiteEnergyUse(kBtu) | SteamUse(kBtu) | Electricity(kBtu) | NaturalGas(kBtu) | TotalGHGEmissions | GHGEmissionsIntensity |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CouncilDistrictCode | | | | | | | | | | | | |
| NumberofBuildings | -0.03 | | | | | | | | | | | |
| PropertyGFATotal | 0.23 | 0.26 | | | | | | | | | | |
| PropertyGFABuilding(s) | 0.2 | 0.3 | 0.98 | | | | | | | | | |
| ENERGYSTARScore | 0.16 | -0.06 | 0.16 | 0.15 | | | | | | | | |
| SiteEUI(kBtu/sf) | 0.07 | 0.15 | 0.06 | 0.06 | -0.32 | | | | | | | |
| SiteEnergyUse(kBtu) | 0.07 | 0.53 | 0.57 | 0.61 | -0.06 | 0.38 | | | | | | |
| SteamUse(kBtu) | -0 | 0.56 | 0.33 | 0.38 | -0.03 | 0.1 | 0.55 | | | | | |
| Electricity(kBtu) | 0.14 | 0.42 | 0.67 | 0.69 | -0 | 0.43 | 0.91 | 0.47 | | | | |
| NaturalGas(kBtu) | -0.03 | 0.3 | 0.19 | 0.22 | -0.12 | 0.21 | 0.71 | 0.03 | 0.43 | | | |
| TotalGHGEmissions | -0 | 0.59 | 0.4 | 0.46 | -0.1 | 0.26 | 0.92 | 0.65 | 0.7 | 0.77 | | |
| GHGEmissionsIntensity | -0.04 | 0.27 | 0.03 | 0.07 | -0.29 | 0.59 | 0.55 | 0.25 | 0.35 | 0.63 | 0.63 | |

High Energy Star score could mean lower values for both predictions.



*Features importance and explainability with shap in the ElasticNet configured for GHG emission predictions*

It confirms the assumption made with the correlation matrix about the Energy StarScore. The higher the Energy Star Score, the less polluter is the the property.

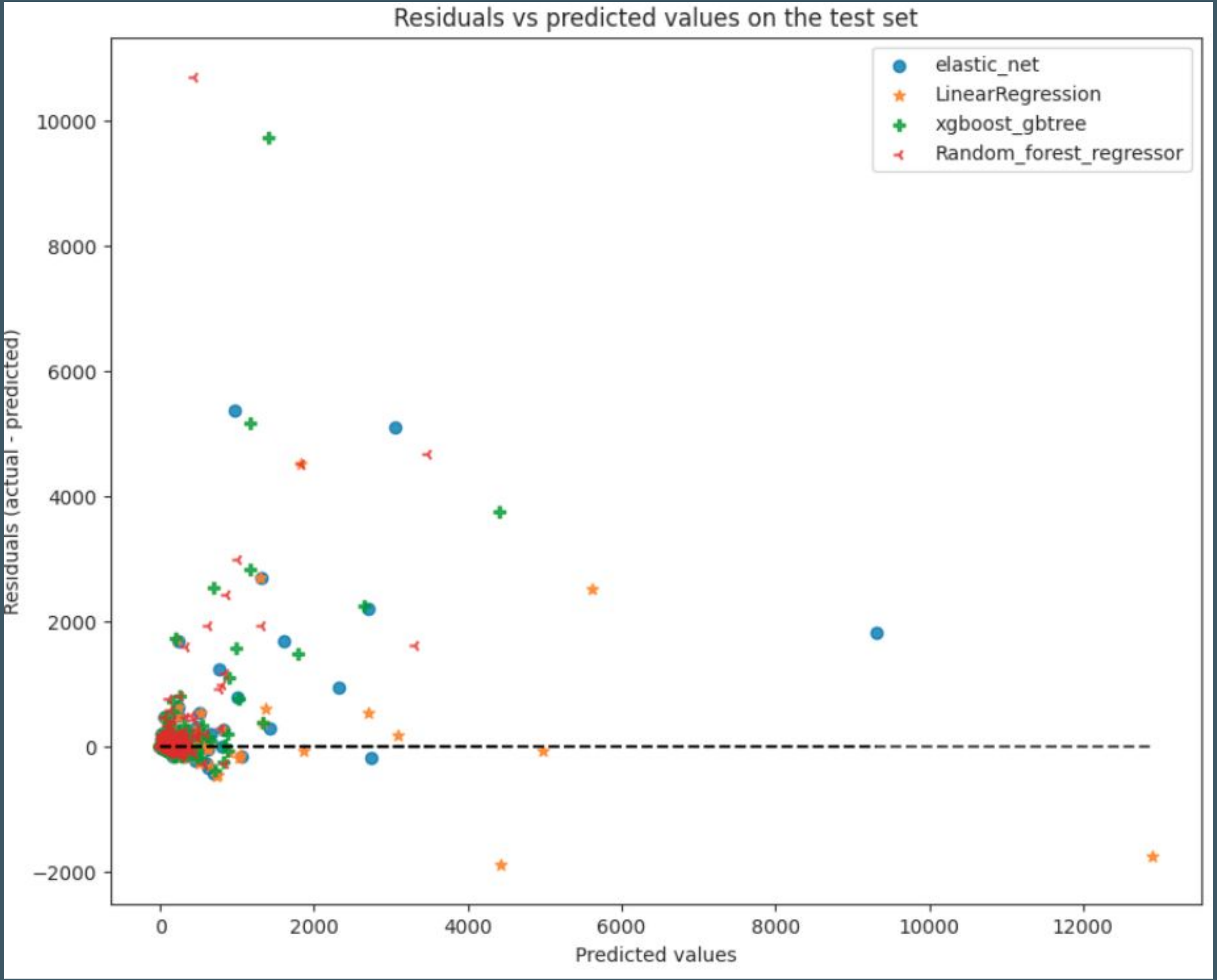


Linear models perform better for high values because they are not well represented in the dataset ?

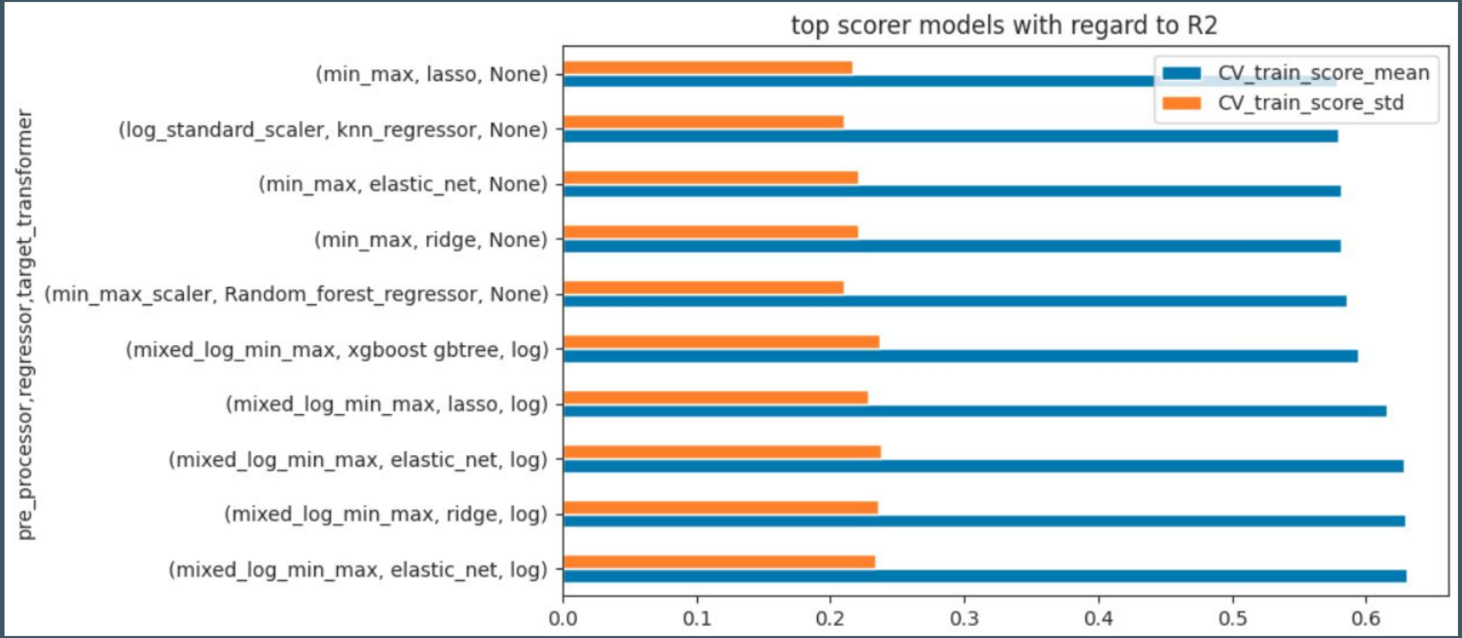
Better capacity to extrapolate.

Would more data help tree-based to perform better?

-> We will not get more data, because such properties are not going to be built massively.

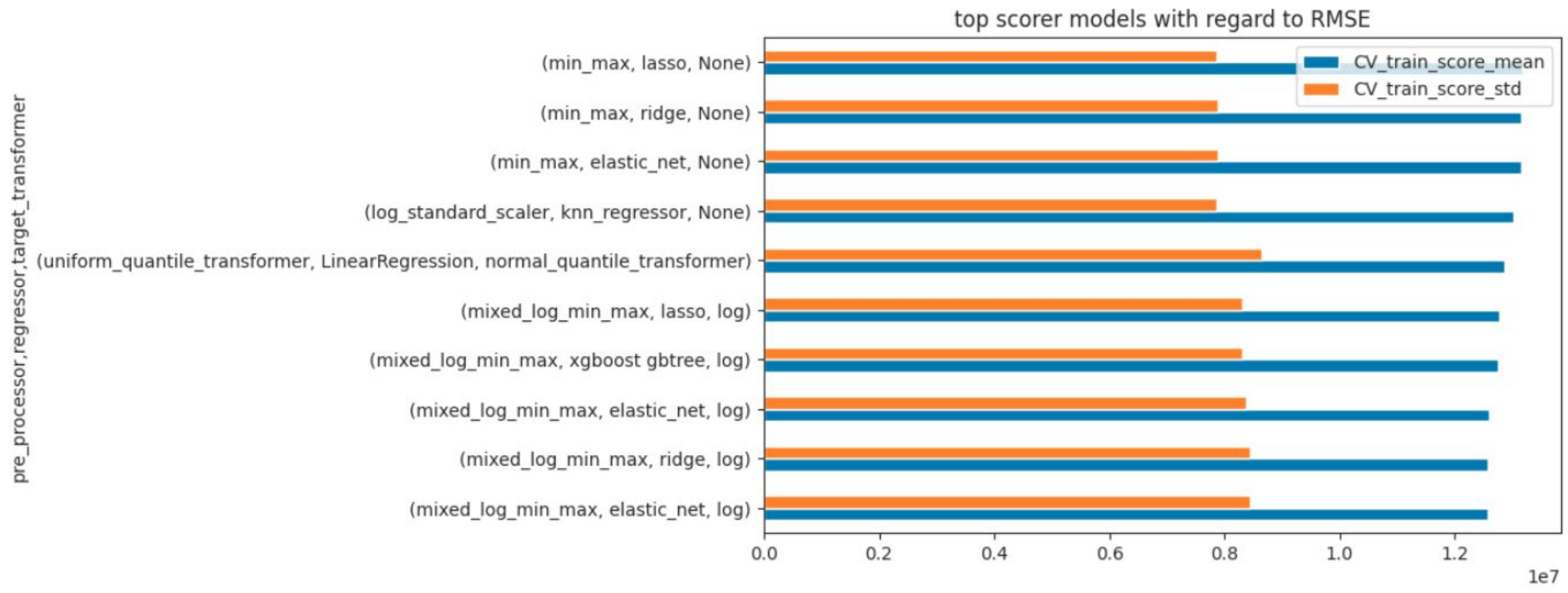

Residuals vs predicted values on the test set
elastic_net
LinearRegression
xgboost_gbtree
Random_forest_regressor
Residuals (actual - predicted)
10000
8000
6000
4000
2000
0
−2000
0
2000
4000
6000
8000
10000
12000
Predicted values

# Energy prediction (R2)



- Dummy regressor : R2 ~ 0
- Regardless of the regressor, a log transformation on both skewed inputs and the target gave the best results.
- Linear models give better results than tree-based models.

# Energy prediction (RMSE)



- Dummy regressor : RMSE ~ 3e7 kBtu
- Idem