

ANTICIPATING BUILDING CONSUMPTION

CITY OF SEATTLE

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1. PROBLEM STATEMENT

Carbon-Neutral City in Terms of GHG Emissions



OBJECTIVES

- ➤ Greenhouse Gas Emissions Neutrality by 2050
- ➤ Predict the energy consumption and GHG emissions of nonresidential buildings
- ➤ Evaluate the relevance of the Energy Star Score to assess the GHG emissions



1. Problem statement

2. PROVIDED DATA

Surveys conducted by city agents



SURVEYS

CONDUCTED IN 2016



On all buildings in the city

Extensive set of information for each building

Costly surveys

NumberofBuildings	NumberofFloors	PropertyGFATotal	PropertyGFAParking	PropertyGFABuilding(s)	ListOfAllPropertyUseTypes	LargestPropertyUseType	LargestPropertyUseTypeGFA
1.0	12	88434	0	88434	Hotel	Hotel	88434.0
1.0	11	103566	15064	88502	Hotel, Parking, Restaurant	Hotel	83880.0
1.0	41	956110	196718	759392	Hotel	Hotel	756493.0
1.0	10	61320	0	61320	Hotel	Hotel	61320.0
1.0	18	175580	62000	113580	Hotel, Parking, Swimming Pool	Hotel	123445.0
1.0	1	12294	0	12294	Office	Office	12294.0
1.0	1	16000	0	16000	Other - Recreation	Other - Recreation	16000.0
1.0	1	13157	0	13157	Fitness Center/Health Club/ Gym, Other - Recrea	Other - Recreation	7583.0
1.0	1	14101	0	14101	Fitness Center/Health Club/ Gym, Food Service,	Other - Recreation	6601.6
1.0	1	18258	0	18258	Fitness Center/Health Club/ Gym, Food Service,	Other - Recreation	8271.



STRUCTURAL ASSESSMENTS

2. Provided Data

ENERGY ASSESSMENTS





Excerpt

2. Provided Data

TARGET VARIABLES

SiteEnergyUse(kBtu)
7.226362e+06
8.387933e+06
7.258702e+07
6.794584e+06
1.417261e+07
9.320821e+05
9.502762e+05
5.765898e+06
7.194712e+05
1.152896e+06

TotalGHGEmissions		
249.98		
295.86		
2089.28		
286.43		
505.01		
20.94		
32.17		
223.54		
22.11		
41.27		

ENERGYSTARScore		
60	0.0	
61	1.0	
43	3.0	
56	5.0	
75	5.0	
46	6.0	
Na	aN	



2. Provided Data

3. DATA CLEANING AND PRELIMINARY ANALYSIS

Analysis of the dataset & Transformation of certain variables



DATA CLEANING AND PRELIMINARY ANALYSIS



Deleting columns that are not useful BuildingType PrimaryPropertyType PropertyName

Multifamily MR (5-9) Mid-Rise Multifamily Lyon Building

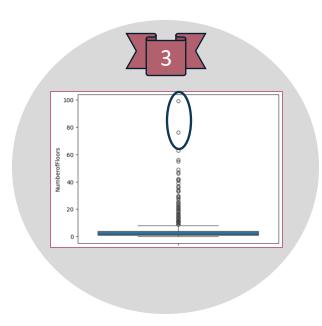
Multifamily MR (5-9) Mid-Rise Multifamily Place

Multifamily MR (5-9) Mid-Rise Multifamily Wintonia

Multifamily MR (5-9) Mid-Rise Multifamily LAKE CITY COURT

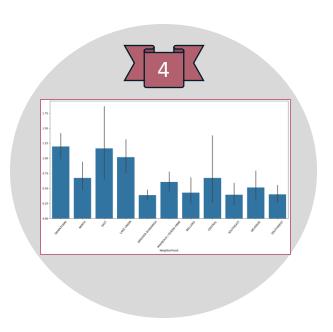
Multifamily MR (5-9) Mid-Rise Multifamily Tashiro_kaplan

Deleting residential buildings



Deleting some outliers

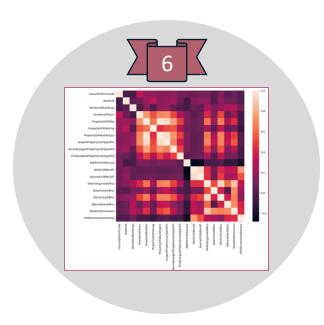
DATA CLEANING AND PRELIMINARY ANALYSIS



Relationship between target variables and textual variables (neighborhood)

LargestPropertyUseType 0
LargestPropertyUseTypeGFA 4
SecondLargestPropertyUseType 675
SecondLargestPropertyUseTypeGFA 675
ThirdLargestPropertyUseType 1152
ThirdLargestPropertyUseTypeGFA 1152
ENERGYSTARScore 530

Handling and replacement of missing values



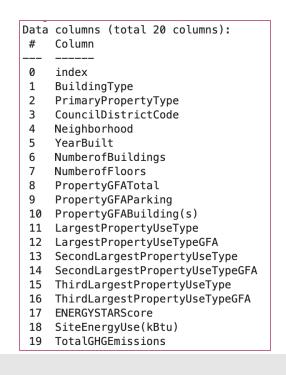
Correlation analysis between variables

DATA CLEANING AND PRELIMINARY ANALYSIS

FINAL REMOVAL OF COLUMNS



Removal of "non-target" columns and those unavailable at the time of building construction





REMAINING COLUMNS

3. Data Cleaning and Preliminary Analysis

CATEGORICAL VARIABLE TRANSFORMATION

LargestPropertyUseType	SecondLargestPropertyUseType	ThirdLargestPropertyUseType	
Convention Center	Parking	Financial Office	
Office	Laboratory	Non-Refrigerated Warehouse	
Hotel	Parking	Parking	
Office	Parking	Parking	
Hospital (General Medical & Surgical)	Parking	Other	
Retail Store	Other	Financial Office	
Office	Parking	Retail Store	
Office	Parking	Office	
Parking	Multifamily Housing	Medical Office	
Parking	Other - Entertainment/Public Assembly	Parking	
Retail Store	Office	Office	
Office	Parking	Restaurant	
Multifamily Housing	Hotel	Office	
Parking	Retail Store		
Office	Parking	Hotel	
Medical Office	Parking	Multifamily Housing	
Office	Retail Store	Multifamily Housing Data Center	
Non-Refrigerated Warehouse	Refrigerated Warehouse	Other/Specialty Hospital	
Office	Parking	Other Other	
Medical Office	Parking	Other	
Hospital (General Medical & Surgical)	Parking		
Office	Parking	Restaurant	
Office	Parking	Restaurant	
Office	Parking	Other	
Data Center	Office	Multifamily Housing	
Office	Parking	Multifamily Housing	
Office	Parking	Fitness Center/Health Club/Gym	
Office	Parking	Office	

Set of possible

values

```
7.5.1 LargestPropertyUseType
buildings['LargestPropertyUseType'].unique()
array(['Hotel', 'Police Station', 'Other - Entertainment/Public Assembly',
       'Library', 'Fitness Center/Health Club/Gym', 'Social/Meeting Hall',
       'Courthouse', 'Other', 'College/University',
       'Automobile Dealership', 'Office', 'Self-Storage Facility',
       'Non-Refrigerated Warehouse', 'K-12 School', 'Other - Mall',
       'Medical Office', 'Retail Store',
       'Hospital (General Medical & Surgical)', 'Museum',
       'Repair Services (Vehicle, Shoe, Locksmith, etc)',
       'Other - Lodging/Residential', 'Other/Specialty Hospital',
       'Financial Office', 'Distribution Center', 'Parking',
       'Multifamily Housing', 'Worship Facility', 'Restaurant',
       'Data Center', 'Laboratory', 'Supermarket/Grocery Store',
       'Urgent Care/Clinic/Other Outpatient', nan, 'Other - Services',
       'Strip Mall', 'Wholesale Club/Supercenter',
       'Refrigerated Warehouse', 'Manufacturing/Industrial Plant',
       'Other - Recreation', 'Lifestyle Center',
       'Other - Public Services', 'Fire Station', 'Performing Arts',
       'Residential Care Facility', 'Bank Branch', 'Other - Education',
       'Other - Restaurant/Bar', 'Food Service', 'Adult Education',
       'Other - Utility', 'Movie Theater',
       'Personal Services (Health/Beauty, Dry Cleaning, etc)',
       'Residence Hall/Dormitory', 'Pre-school/Daycare',
       'Prison/Incarceration'], dtype=object)
```

CATEGORICAL VARIABLE TRANSFORMATION

Reduction of possibilities

```
Largest value 1 = 'Office'
Largest_value_2 = 'Hospital'
Largest_value_3 = 'Warehouse'
Largest value 4 = 'School'
Largest_value_5 = 'Repair and Public Services'
Largest_value_6 = 'Food/Drink Services'
Largest_value_7 = 'Retail/Mall'
Largest value 8 = 'Recreational Venues'
# Creating a dictionnary to be able to use the replace methods to handle strings with parenthesis.
replacement_mapping = {
    'Medical Office': Largest value 1,
    'Office': Largest_value_1,
    'Financial Office': Largest value 1,
    'Hospital (General Medical & Surgical)': Largest value 2.
    'Other/Specialty Hospital': Largest_value_2,
    'Urgent Care/Clinic/Other Outpatient': Largest value 2,
    'Non-Refrigerated Warehouse': Largest_value_3,
    'Self-Storage Facility': Largest_value_3,
    'Distribution Center': Largest_value_3,
    'Refrigerated Warehouse': Largest_value_3,
    'College/University': Largest_value_4,
    'K-12 School': Largest_value_4,
    'Other - Education': Largest_value_4,
    'Adult Education': Largest_value_4,
    'Pre-school/Daycare': Largest_value_4,
    'Repair Services (Vehicle, Shoe, Locksmith, etc)': Largest value 5,
    'Other - Services': Largest_value_5,
    'Other - Public Services': Largest value 5,
    'Personal Services (Health/Beauty, Dry Cleaning, etc)': Largest_value_5,
    'Restaurant': Largest_value_6,
    'Other - Restaurant/Bar': Largest_value_6,
    'Food Service': Largest_value_6,
    'Supermarket/Grocery Store': Largest_value_6,
    'Other - Mall' : Largest_value_7,
    'Strip Mall' : Largest_value_7,
    'Retail Store' : Largest_value_7,
    'Wholesale Club/Supercenter' : Largest_value_7,
    'Other - Entertainment/Public Assembly' : Largest value 8,
    'Other - Recreation' : Largest_value_8,
    'Social/Meeting Hall' : Largest_value_8,
    'Movie Theater' : Largest_value_8
# Replacing the values
buildings['LargestPropertyUseType'] = buildings['LargestPropertyUseType'].replace(replacement_mapping)
```

CATEGORICAL VARIABLE TRANSFORMATION ENCODING

Removal of the original column

Addition of new columns

0 and 1

LargestPropertyUseType_Hotel	LargestPropertyUseType_Laboratory	LargestPropertyUseType_Library	LargestPropertyUseType_Lifestyle Center	LargestPropertyUseType_Manufacturing/ Industrial Plant
1.0	0.0	0.0	0.0	0.0
1.0	0.0	0.0	0.0	0.0
1.0	0.0	0.0	0.0	0.0
1.0	0.0	0.0	0.0	0.0
1.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0

3. Data Cleaning and Preliminary Analysis

ANALYSIS METRICS



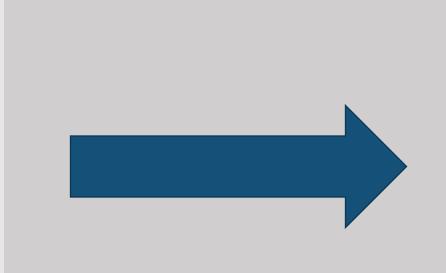
Initially: 3,376 rows × 46 columns

Residential: 1,668 rows × 46 columns

Outliers + Unnecessary columns:

 $1,477 \text{ rows} \times 20 \text{ columns}$

56% of rows & 57% of columns removed





ENCODING

Value transformation

1,477 rows × 112 columns

4. MODELING

Implementation of machine learning models



Models Selection

Models

Continuous valu
 Regression

- Linear Regression
- Random Forest
- Gradient Boosting
- Support Vector Regression

Metrics

- R² (Coefficient of determination)
- Mean Squared Error
- Execution Time
- Number of variables used

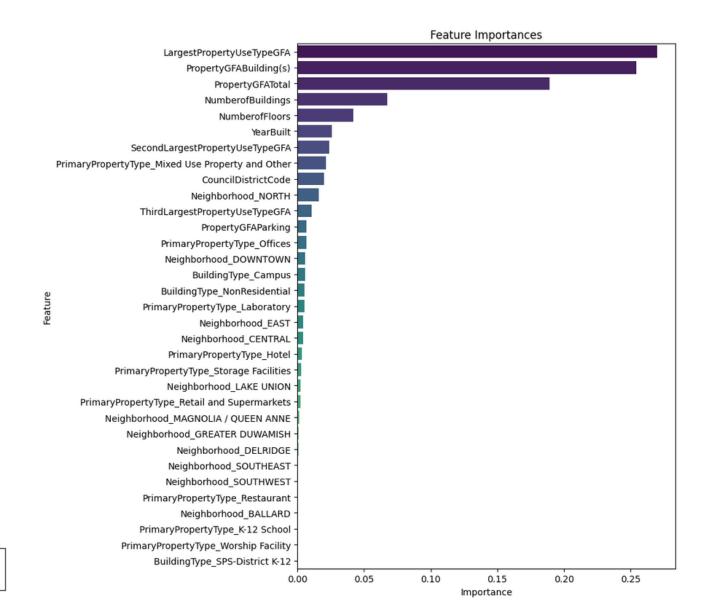
4. Modeling

PROCESS

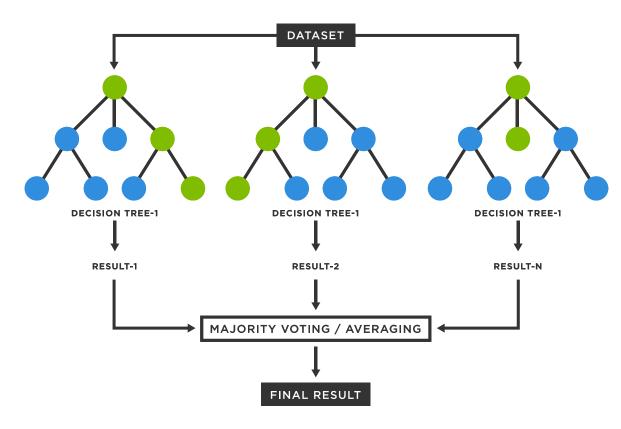
- ➤ All variables
- ➤ Selection of relevant variables
- >Selection of model hyperparameters (number of trees, tree depth, etc.)
- ➤ Results analysis and model execution time

RANDOM FOREST

Relevant variable selection



RANDOM FOREST SELECTION OF MODEL HYPERPARAMETERS



* Source : MétéoSuisse-Blog | 30 octobre 2022

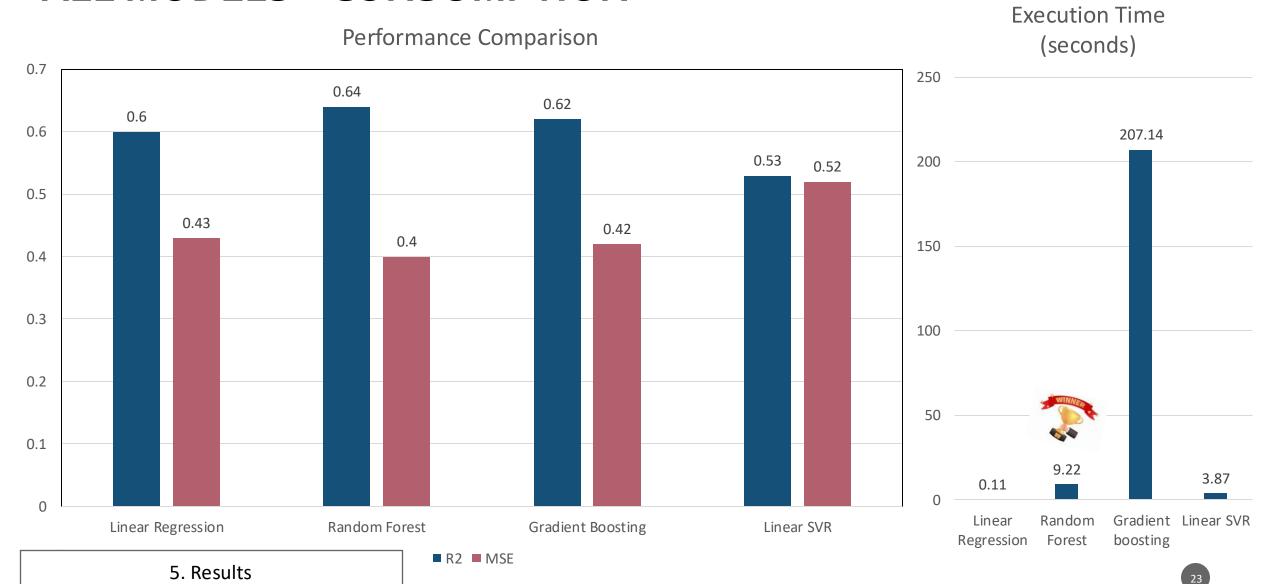
- Number of trees
- Maximum tree depth
- Minimum number of samples required to split an internal node
- Minimum number of samples required to be at a leaf node
- ➤ Threshold: Selection of variables with an importance score above a certain value

5. RESULTS

Models comparison



ALL MODELS – CONSUMPTION



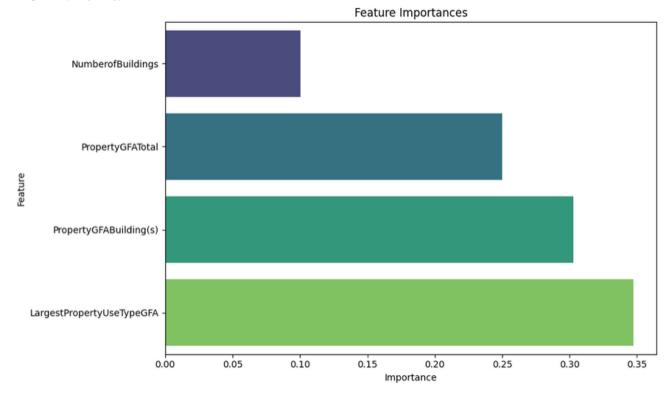
ALL MODELS – EMISSIONS



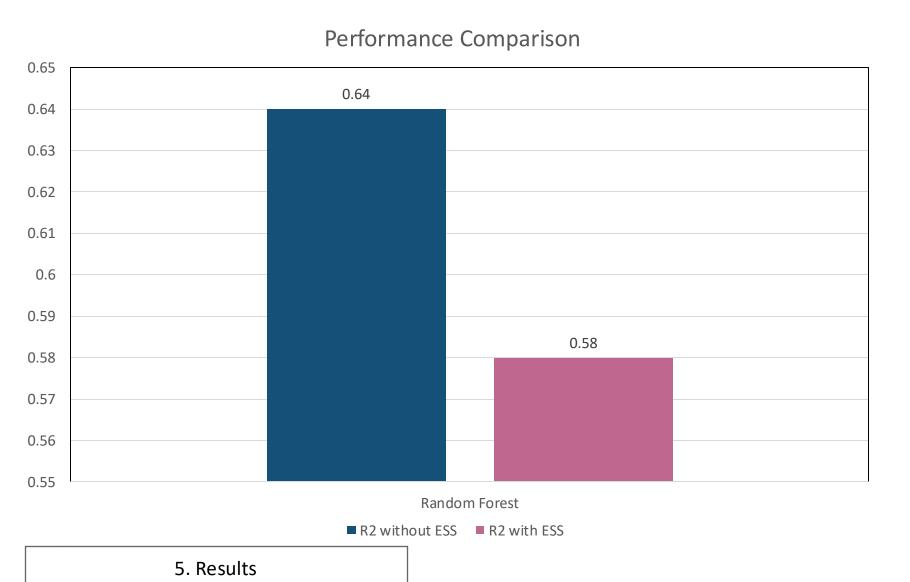
RANDOM FOREST- HYPERPARAMETERS

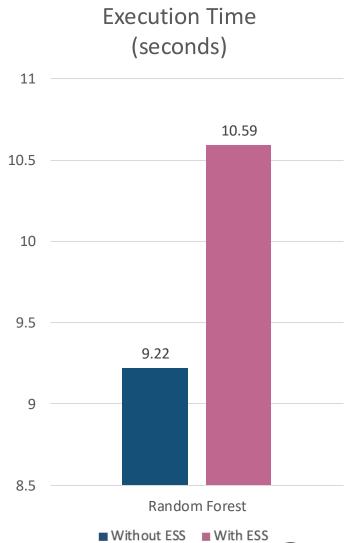
- \triangleright Number of trees 500
- ➤ Maximum tree depth None
- ➤ Minimum number of samples required to split an internal node 2
- ➤ Minimum number of samples required to be at a leaf node 1
- ➤ Threshold: Selection of variables with an importance score above a certain value Threshold set at 0.05

Feature Importances: NumberofBuildings: 0.1001 PropertyGFATotal: 0.2502 PropertyGFABuilding(s): 0.3026 LargestPropertyUseTypeGFA: 0.3471

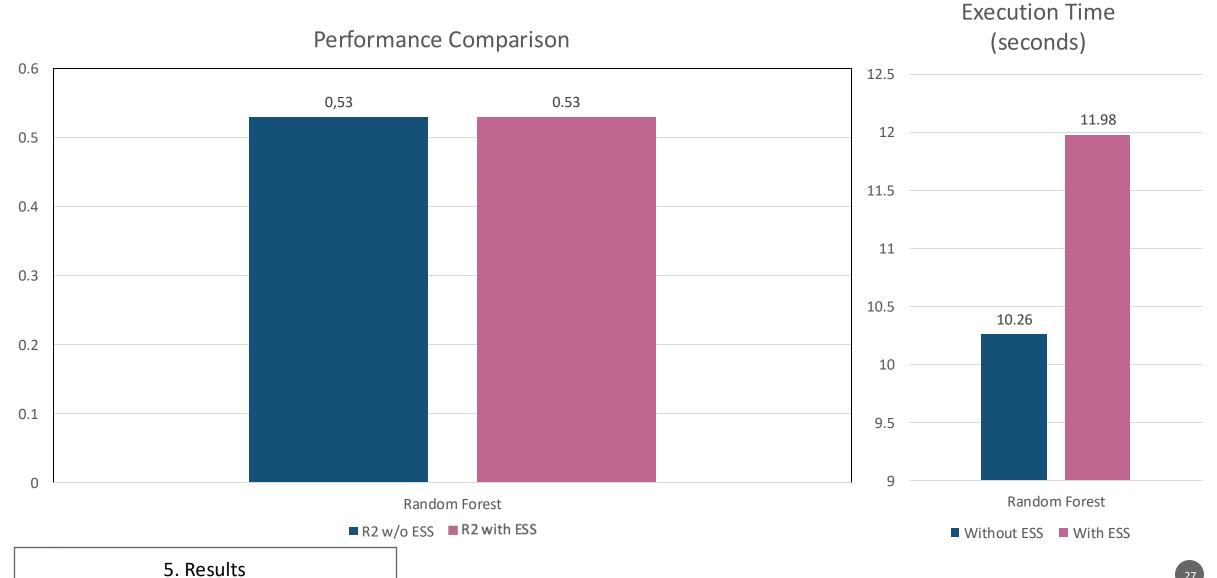


ENERGY STAR SCORE - CONSUMPTION





ENERGY STAR SCORE - ÉMISSIONS



ENERGY STAR SCORE



CONSUMPTION

Addition of the Energy Star Score to the input variables

Degrades the quality of the predictions





EMISSIONS

Addition of the Energy Star Score to the input variables

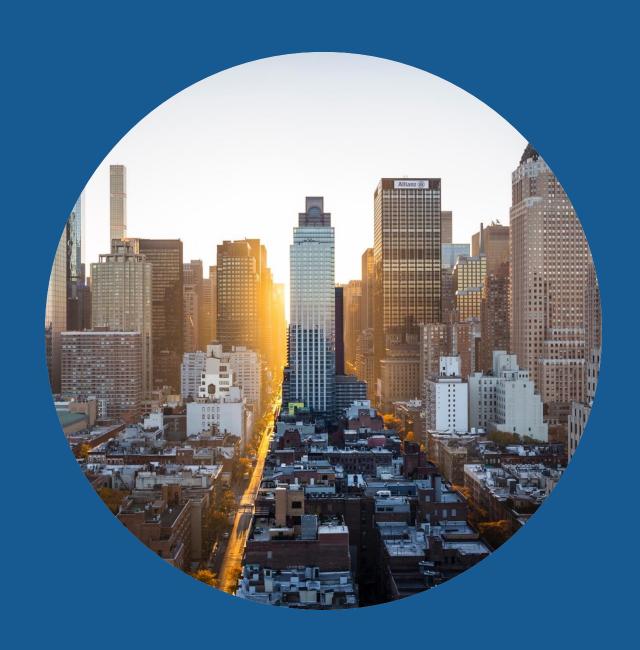
Has no impact on prediction performance

6. CONCLUSION



CONCLUSION

- ➤ Inconclusive results R² does not exceed 0.64 (At least 0.7 is usually required to deploy a model in production)
 - ➤ Limited number of buildings: (Non-residential buildings represent 1,668 rows a small sample)
- ➤ ML improvement opportunities:
 - > Improved feature engineering
 - ➤ More thorough hyperparameter tuning (Note: Some hyperparameter searches take a long time to complete)
 - > Testing other types of regression models



THANKYOU