GHG Emissions in Cambridge Buildings

CS 109A Final Project

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Problem Statement

Finalized Research Question

"How do building characteristics, such as size, age, and primary use type, impact energy use and greenhouse gas emissions in Cambridge, MA?"

- **Dataset**: Cambridge Building Energy Use Disclosure Ordinance (BEUDO) Data 2022
  - Data about ***buildings and their properties*** in Cambridge (year built, square footage, type of building, residential vs. non-residential, etc.)
  - Data about ***resource usage and emissions*** (energy usage, water usage, greenhouse gas emissions, etc.)

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EDA Visualizations

Data Cleaning

Total Records: 851 buildings

Cleaning Steps:

- Removed columns with > 50% missing values.
- Imputed missing values for Year Built and Property Area with means
  - Assuming averages which maintains any correlations within the variables

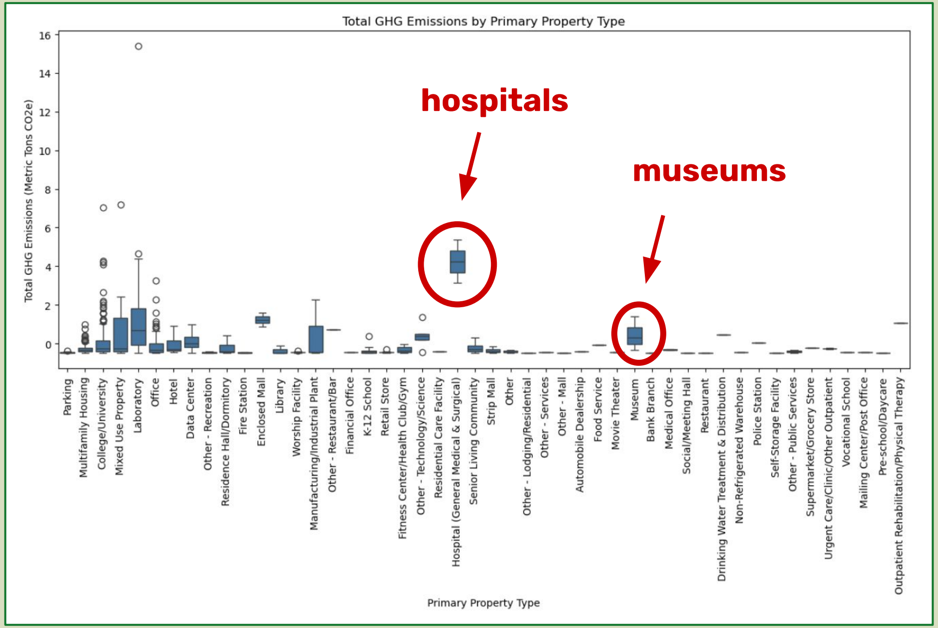
NEXT: EDA to determine good predictors

Total GHG Emissions vs. Property Type

Key Insights:

Total Greenhouse Gas (GHG) Emissions:

- Differs significantly by property type
- Higher emissions: Non-residential categories like hospitals and offices.
- Lower emissions: Residential and smaller properties.

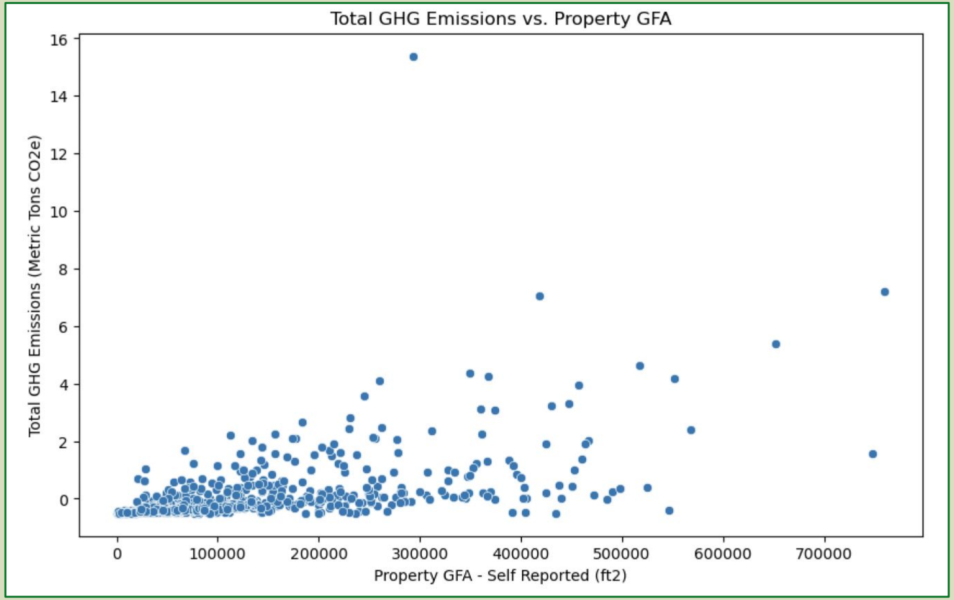


Total GHG Emissions vs. Property Area

Key Insights:

- Larger properties tend to have higher absolute emissions.
- Emissions vary more as property size increases

Outliers: Large buildings with unexpectedly low emissions likely use renewable energy.

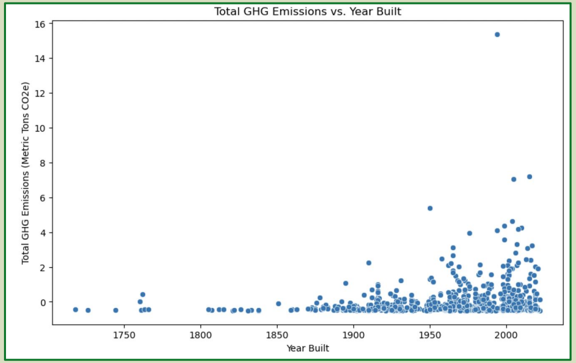


Total GHG Emissions vs. Year Built

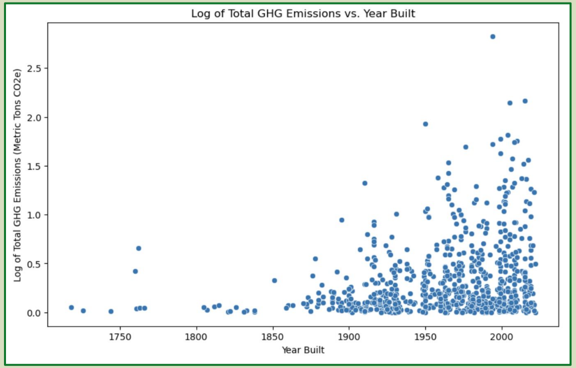
Key Insights:

- **Positive trend** for GHG emissions on average, but **increase in variability** as year built increases
- High concentration of low GHG emissions across all years
- **Weak overall correlation**: Building age alone is not a strong predictor.

Normal scale



Log scale



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Baseline Model

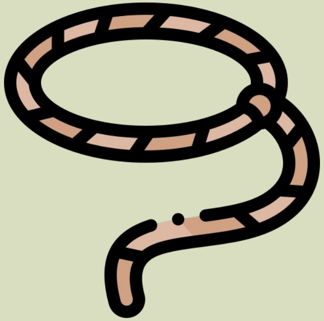
Baseline Model: Lasso Regression

Rationale

- Lasso assumes linear relationship (our relationships have a positive, almost linear trend)
- Shrinks coefficients of less relevant variables to zero → Provides an **interpretable model**

Predictors and Target

- **Predictors**: 'Property Area', 'Year Built', 'Dataset Category'
- **Target**: ‘Total GHG Emissions’



Baseline Model: Pipeline

Baseline Model Pipeline:

1. **Data preprocessing**:
   a. Imputation, scaling, and encoding.
2. **Model training**:
   a. GridSearchCV to find the best alpha value (alpha = 10^{-5})
   b. Train the Lasso algorithm
3. **Evaluation**: Assessing cross-validated RMSE and R^2 metrics

Baseline Model: Results & Analysis

Performance in Context

- **RMSE**: 0.76
    - Smaller than the standard deviation of the target variable (1.000629) and is a small fraction of the range (20.4) → model is performing reasonably well in predicting values
- **R^2**: 0.4
    - Pretty low, only explains 40% of the variability in the target variable
- **Key Predictors**: Property Area and Dataset Category
    - Makes sense: most clear and "linear" relationships to target variable

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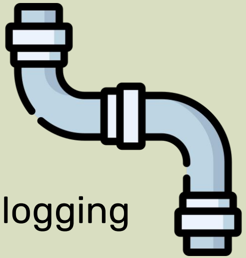
Final Model

Final Model: Random Forest

Steps to Improve Baseline Model

1. **Switch to Random Forest:** Can handle more complex, non-linear relationships; models interactions between predictors; reduces variance
2. **Feature Selection & Engineering**: Experimenting with adding an important feature from our original analysis, **'Primary Property Type'**, and adding interaction terms
3. **Taking Logs:** Experimenting with logging response variables and predictors to convert exponential trends into linear understandings
4. **Optimal Parameters**: Grid search to find best n_estimators (100-500)

Final Pipeline



Data preprocessing

→ Add combination of estimator, interaction terms, extra features, and logging

→ Training, & Evaluation

Final Model Pipeline - Results

Best Model:

450 Estimators, No Interaction Terms, Include Property Type, Log X and y

- **Scores**:
  - **OOB R^2 -** 0.690
  - **RMSE -** 0.373
  - **Train R^2 -** 0.861
- **Key predictors**:
  - Property Area (followed by Laboratory and Year Built)

Combination	Log_X	Log_Y	OOB R^2	RMSE	R^2	Best_Params
{'interaction_terms': False, 'include_property_type': False}	FALSE	FALSE	0.338106719550621	0.2832159947536660	0.9197887003156920	{'random_forest__n_estimators': 100}
{'interaction_terms': False, 'include_property_type': False}	TRUE	FALSE	0.3160021416595370	0.29059178417217900	0.9155564149716300	{'random_forest__n_estimators': 150}
{'interaction_terms': False, 'include_property_type': False}	FALSE	TRUE	0.5437126004395560	0.40248935784183800	0.8380023168240650	{'random_forest__n_estimators': 450}
{'interaction_terms': False, 'include_property_type': False}	TRUE	TRUE	0.5370711806825500	0.4045506177907470	0.8363387976451250	{'random_forest__n_estimators': 300}
{'interaction_terms': True, 'include_property_type': False}	FALSE	FALSE	0.3004761816986500	0.2901329058375100	0.9158228969502830	{'random_forest__n_estimators': 100}
{'interaction_terms': True, 'include_property_type': False}	TRUE	FALSE	0.30748118550667300	0.28923906610001000	0.9163407626415940	{'random_forest__n_estimators': 100}
{'interaction_terms': True, 'include_property_type': False}	FALSE	TRUE	0.520936600079633	0.4211339867580890	0.8226461651972380	{'random_forest__n_estimators': 450}
{'interaction_terms': True, 'include_property_type': False}	TRUE	TRUE	0.5263772679090560	0.408552690303497	0.8330846992457750	{'random_forest__n_estimators': 500}
{'interaction_terms': False, 'include_property_type': True}	FALSE	FALSE	0.44651043083281500	0.2668378385327570	0.9287975679271670	{'random_forest__n_estimators': 450}
{'interaction_terms': False, 'include_property_type': True}	TRUE	FALSE	0.45182379784099300	0.25555472414268900	0.934691782968354	{'random_forest__n_estimators': 150}
{'interaction_terms': False, 'include_property_type': True}	FALSE	TRUE	0.6884901024645230	0.3654923083820490	0.866415372513561	{'random_forest__n_estimators': 500}
{'interaction_terms': False, 'include_property_type': True}	TRUE	TRUE	0.6903692515713370	0.3726355494274600	0.8611427473028950	{'random_forest__n_estimators': 450}
{'interaction_terms': True, 'include_property_type': True}	FALSE	FALSE	0.44801780551072400	0.26222575383646800	0.9312219195796660	{'random_forest__n_estimators': 400}
{'interaction_terms': True, 'include_property_type': True}	TRUE	FALSE	0.4419559488864530	0.26742271662480300	0.9284850906330100	{'random_forest__n_estimators': 450}
{'interaction_terms': True, 'include_property_type': True}	FALSE	TRUE	0.6796364017342340	0.3749816289958010	0.8593887779156550	{'random_forest__n_estimators': 450}
{'interaction_terms': True, 'include_property_type': True}	TRUE	TRUE	0.6752541933591420	0.3755284757102870	0.8589783639307090	{'random_forest__n_estimators': 450}

Final Model Pipeline - Analysis

Scores

- The **OOB R^2** (0.690) recognizes that the model is statistically significant in terms of generalizability against unseen data
- The **RMSE** (0.373) infers our model is interpreting trends with minimal error
- The train **R^2** (0.861) shows that our model is capable of explaining 86.1% of the variability of emissions

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Results/Inferences

Model Performance Comparison

	Lasso Regression	**Random Forest**
R^2	0.40	0.69
RMSE	0.76	0.37
Key Predictors	Property Area, Dataset Category	Property Area, Laboratory, Year Built

Results and Inferences

- **Larger buildings** are more energy-intensive
- **Non-linear relationships** between predictors and GHG emissions, because:
  - Log-transformation of predictors improved the model
  - Random forest performed much better than Lasso regression
- **Non-residential buildings** are primary contributors to emissions, especially certain energy-intensive property types (like laboratories)
- **Building age** offers information when interactions with other features are considered, indicating that factors like expansion or usage change may be impactful

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Future Work

Future Work / Next Steps

Actionable Outcomes:

- Targets large non-residential buildings and energy-intensive property types for emission reduction initiatives.
- Focus efforts on a small number of outliers, due to non-linearity of problem

Future Work:

- Individually log or square root every combination of predictor variables to account for exponential or logarithmic variable trends in the final model.
- Compare against other water or energy variables, such as water or electricity usage, in Cambridge buildings.

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Characteristics vs. Property Type

Key Insights:

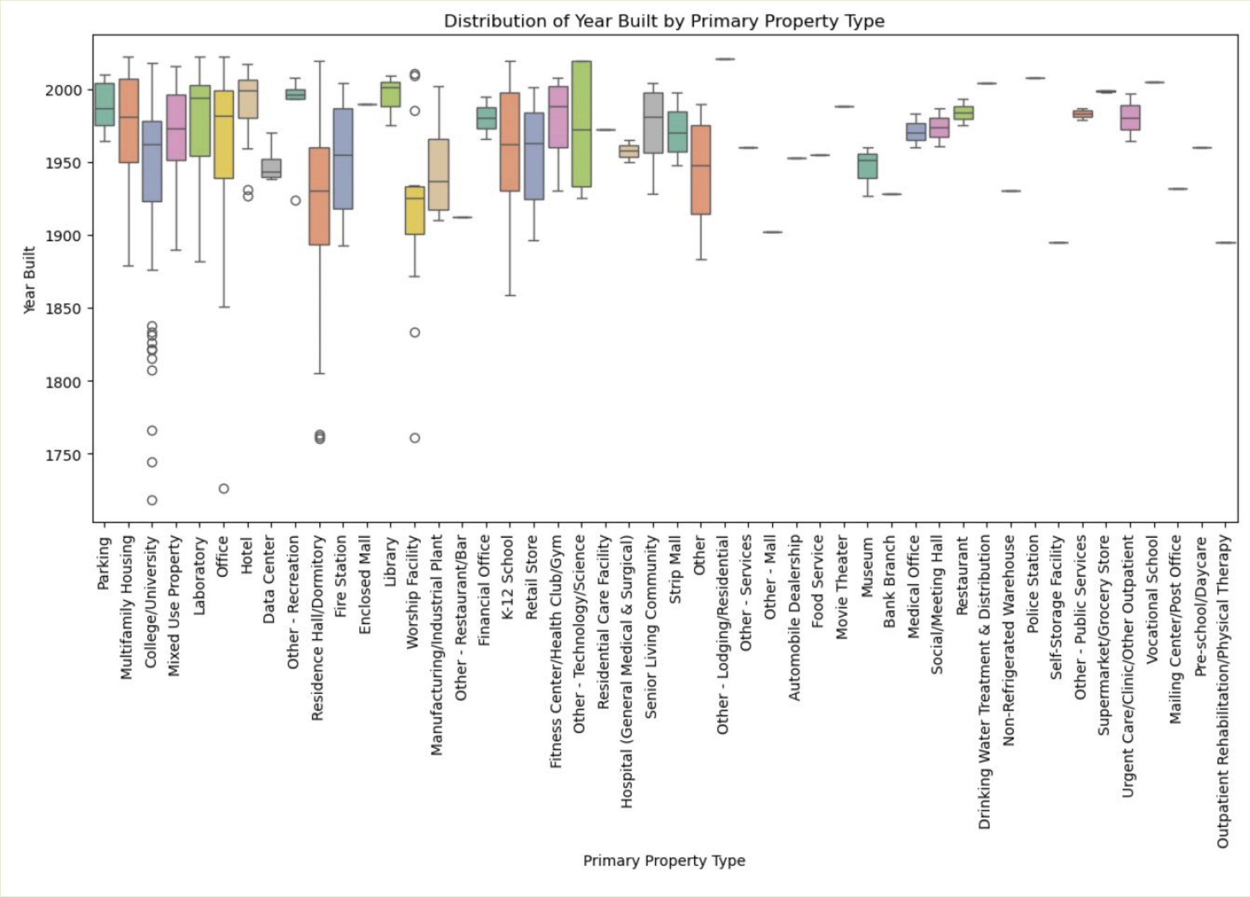
- Property floor area varies widely across property types.
  - Large properties: College/University, Enclosed Mall.
  - Smaller properties: Bank Branch, Medical Offices.

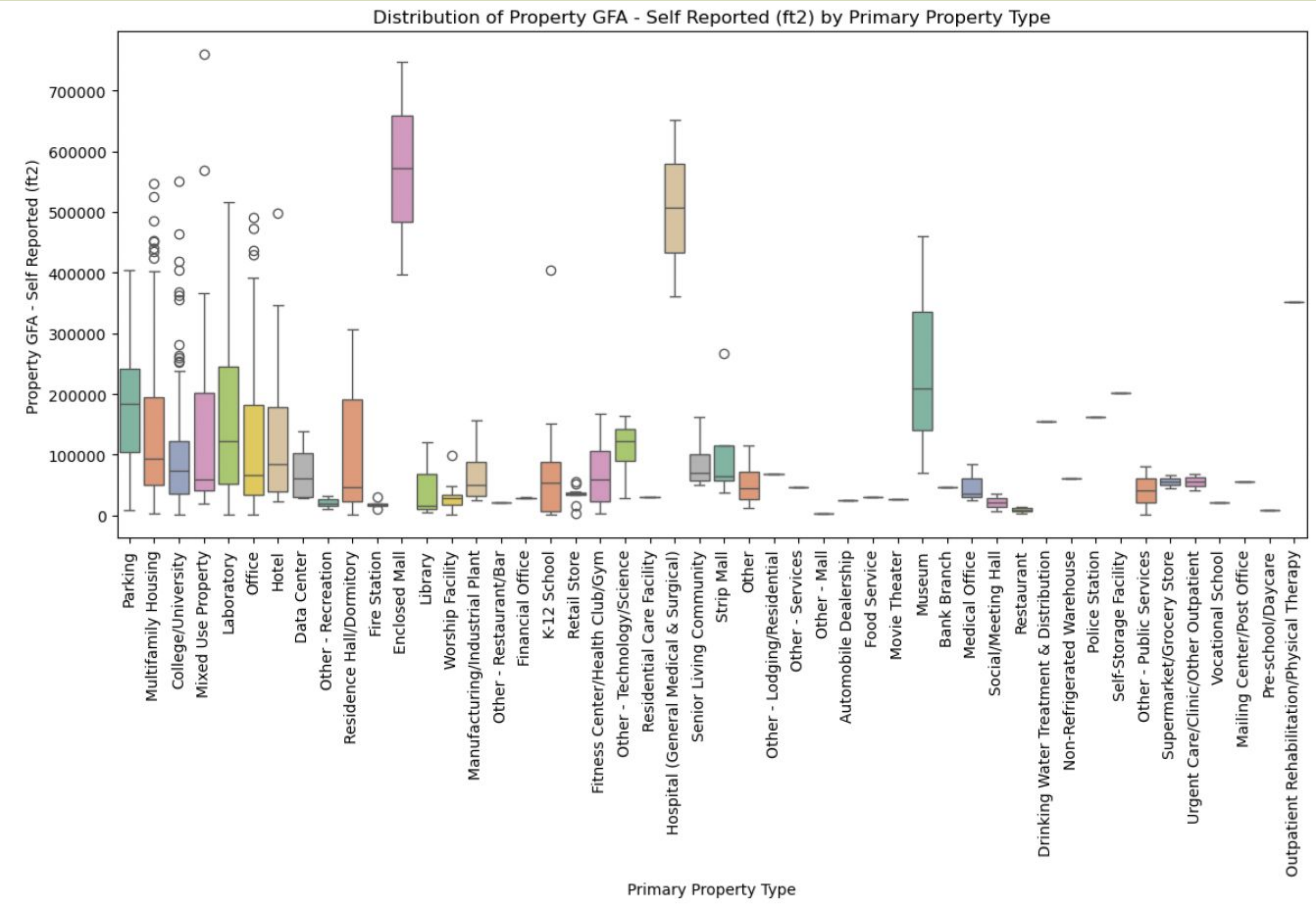
Year Built trends:

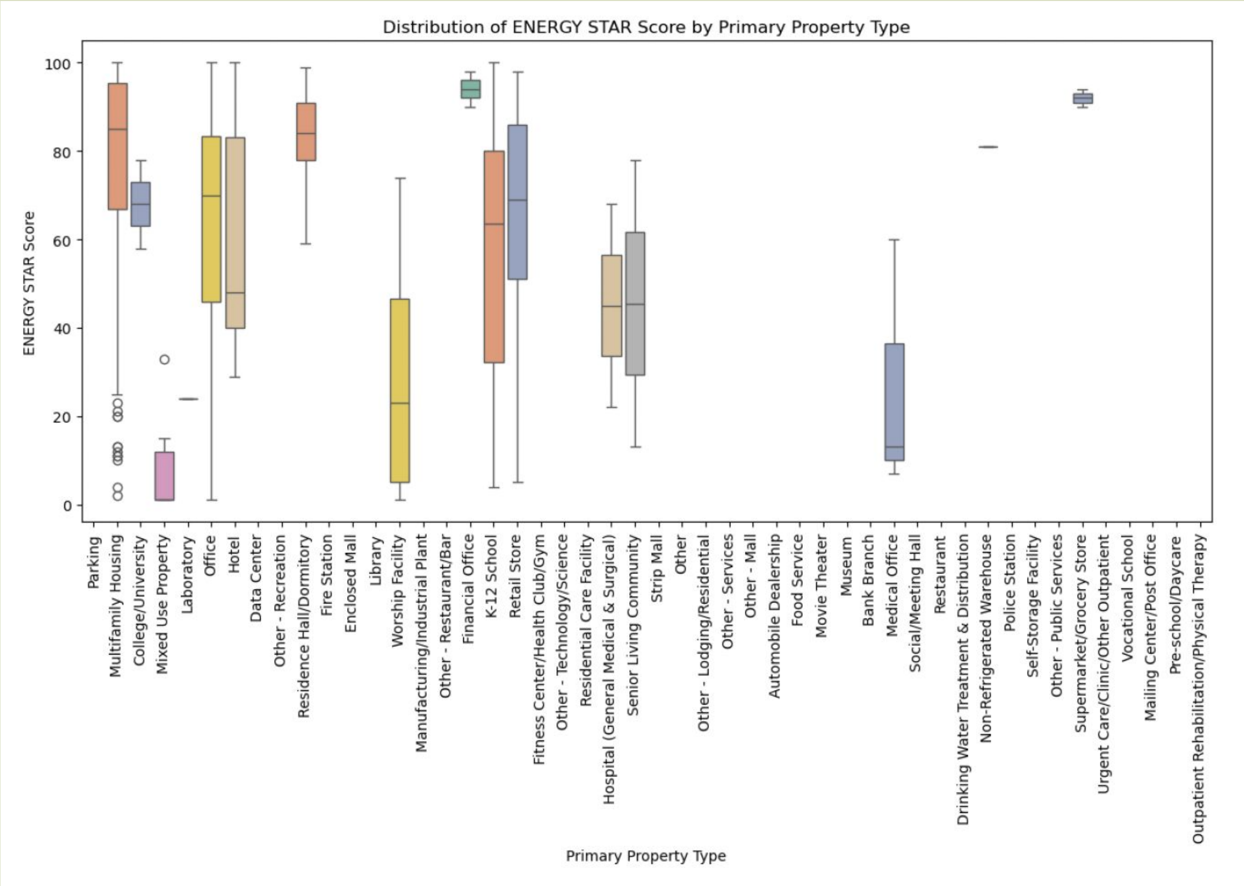
- Older: Religious worship facilities, universities.
- Newer: Hotels, recreation facilities.

ENERGY STAR Scores:

- High: Residence Halls/Dormitories, Financial Offices.
- Low: Mixed-Use Properties, Medical Offices.


Distribution of Year Built by Primary Property Type
Year Built
2000
1950
1900
1850
1800
1750
Primary Property Type
Parking
Multifamily Housing
College/University
Mixed Use Property
Laboratory
Office
Hotel
Data Center
Other - Recreation
Residence Hall/Dormitory
Fire Station
Enclosed Mall
Library
Worship Facility
Manufacturing/Industrial Plant
Other - Restaurant/Bar
Financial Office
K-12 School
Retail Store
Fitness Center/Health Club/Gym
Other - Technology/Science
Residential Care Facility
Hospital (General Medical & Surgical)
Senior Living Community
Strip Mall
Other
Other - Lodging/Residential
Other - Services
Other - Mall
Automobile Dealership
Food Service
Movie Theater
Museum
Bank Branch
Medical Office
Social/Meeting Hall
Restaurant
Drinking Water Treatment & Distribution
Non-Refrigerated Warehouse
Police Station
Self-Storage Facility
Other - Public Services
Supermarket/Grocery Store
Urgent Care/Clinic/Other Outpatient
Vocational School
Mailing Center/Post Office
Pre-school/Daycare
Outpatient Rehabilitation/Physical Therapy


Distribution of Property GFA - Self Reported (ft2) by Primary Property Type
Property GFA - Self Reported (ft2)
0
100000
200000
300000
400000
500000
600000
700000
Parking
Multifamily Housing
College/University
Mixed Use Property
Laboratory
Office
Hotel
Data Center
Other - Recreation
Residence Hall/Dormitory
Fire Station
Enclosed Mall
Library
Worship Facility
Manufacturing/Industrial Plant
Other - Restaurant/Bar
Financial Office
K-12 School
Retail Store
Fitness Center/Health Club/Gym
Other - Technology/Science
Residential Care Facility
Hospital (General Medical & Surgical)
Senior Living Community
Strip Mall
Other
Other - Lodging/Residential
Other - Services
Other - Mall
Automobile Dealership
Food Service
Movie Theater
Museum
Bank Branch
Medical Office
Social/Meeting Hall
Restaurant
Drinking Water Treatment & Distribution
Non-Refrigerated Warehouse
Police Station
Self-Storage Facility
Other - Public Services
Supermarket/Grocery Store
Urgent Care/Clinic/Other Outpatient
Vocational School
Mailing Center/Post Office
Pre-school/Daycare
Outpatient Rehabilitation/Physical Therapy
Primary Property Type


Distribution of ENERGY STAR Score by Primary Property Type
ENERGY STAR Score
100
80
60
40
20
0
Parking
Multifamily Housing
College/University
Mixed Use Property
Laboratory
Office
Hotel
Data Center
Other - Recreation
Residence Hall/Dormitory
Fire Station
Enclosed Mall
Library
Worship Facility
Manufacturing/Industrial Plant
Other - Restaurant/Bar
Financial Office
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Outpatient Rehabilitation/Physical Therapy
Primary Property Type