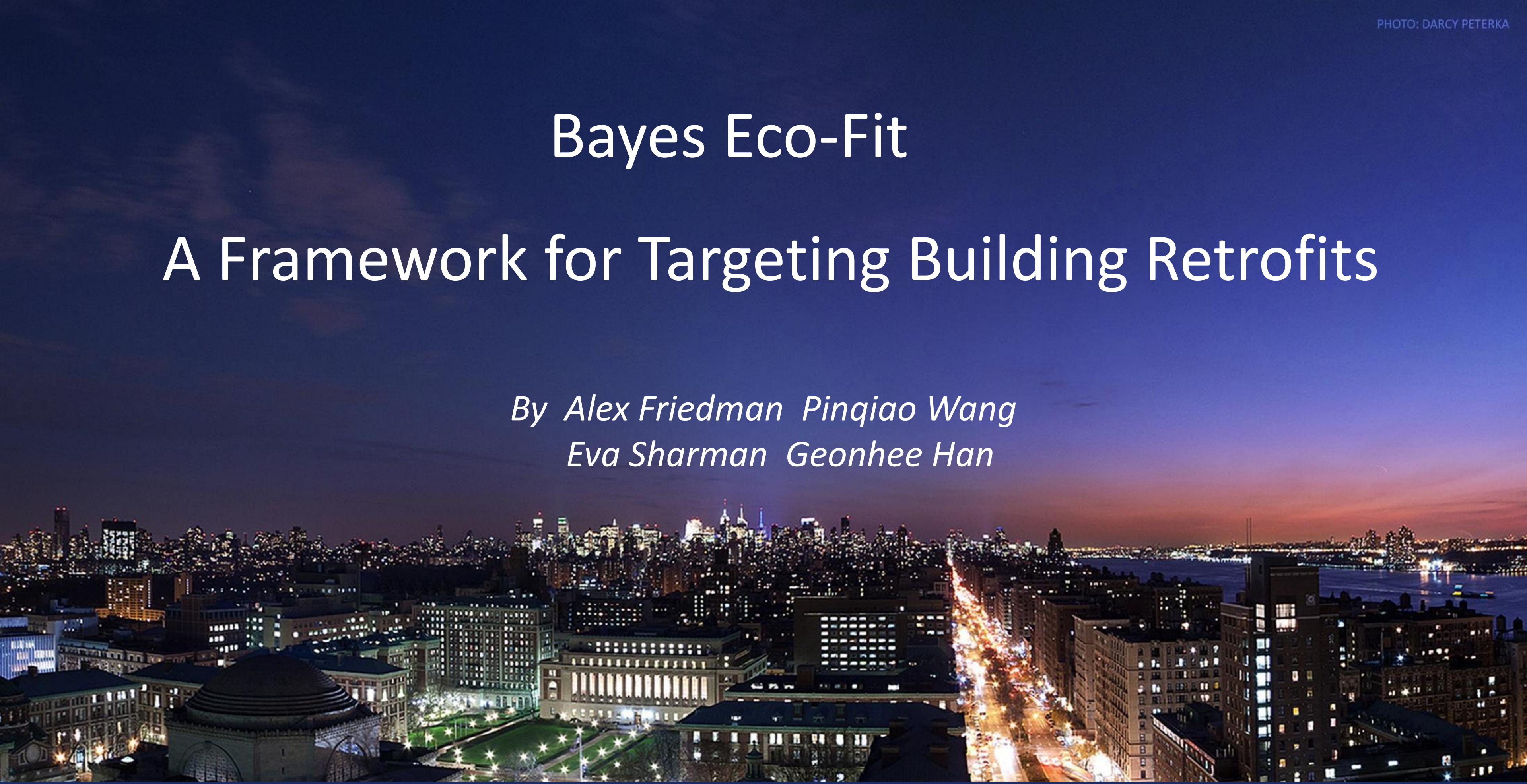

PHOTO: DARCY PETERKA

Bayes Eco-Fit

A Framework for Targeting Building Retrofits

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A Summary

"Six million New York buildings account for ⅓ of statewide greenhouse gas emissions (GE)." Successful building energy conservation measures are crucial to lower GE.

- Such measures are costly to implement.
- Energy star score is an existing efficiency metric but may inadequately describe building-level performance.
- It is crucial to *accurately* spot energy inefficiency at a local building level in a time- and cost-economical manner.
- We provide a framework for practitioners to easily identify these targets.

Motivation

& Initial Data Exploration

Exploration and Early Stage Data Visualization

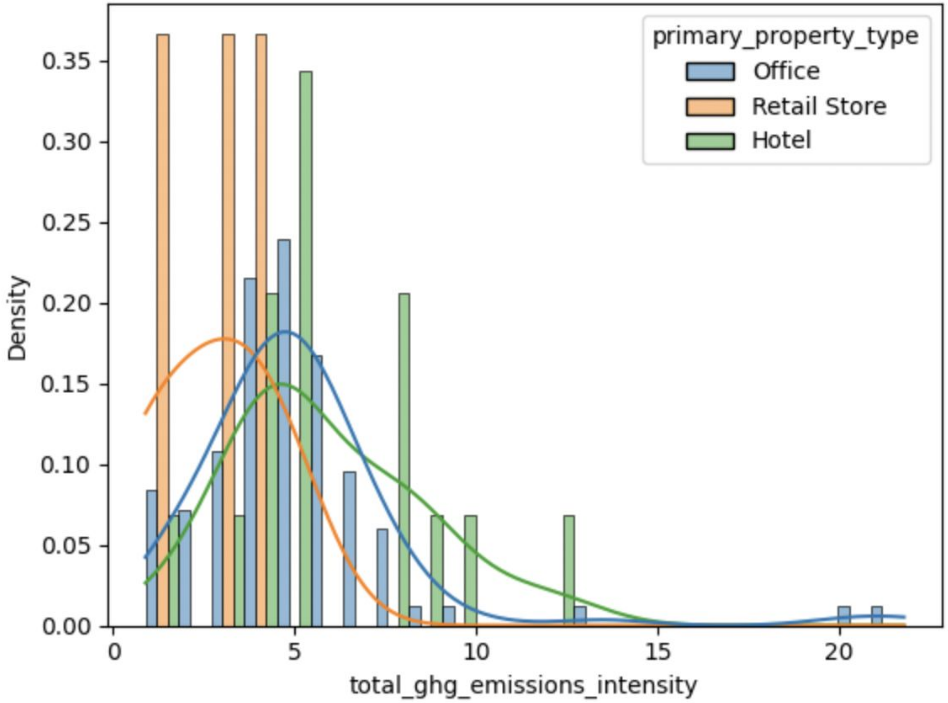
	parent_property_id	parent_property_name	year_ending	automobile_dealership_gross	medical_office_number_of	estimated_data_flag_fuel_3
0	Not Applicable: Standalone Property	Not Applicable: Standalone Property	2021-12-31T00:00:00.000	NaN	NaN	NaN
1	20599688	Stellar - Campus West 93rd Street	2021-12-31T00:00:00.000	NaN	NaN	No
2	Not Applicable: Standalone Property	Not Applicable: Standalone Property	2021-12-31T00:00:00.000	NaN	17.93	No
3	Not Applicable: Standalone Property	Not Applicable: Standalone Property	2021-12-31T00:00:00.000	NaN	NaN	No
4	Not Applicable: Standalone Property	Not Applicable: Standalone Property	2021-12-31T00:00:00.000	NaN	NaN	No
...	...	...	...	...	...	...

Observation 1:

Very hard to “make sense” of the data.

What are the key factors?

Exploration and Early Stage Data Visualization



Observation 2:

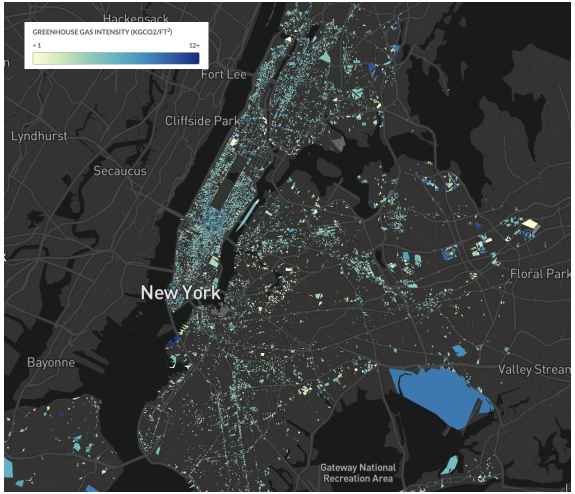
Cross-categorical heterogeneity in outcome distribution.

<u>How can we model this?</u>

This leads to our Goals/RQ……

- **What factors** do and don't explain NYC greenhouse gas emission intensity?

- Given characteristics of major buildings, can we
  - **Identify** "local outliers" with poor energy efficiency?
  - **Recommend** non-trivial candidates: buildings with high energy star scores despite poor efficiency?



GHG Intensity, 2017. NYC Mayor's Office of Sustainability.

How can we understand GHG emission intensity of NYC buildings through analysis of 2021 energy and usage factors?

Data & Model

Data Cleaning

(1) Carefully/manually drop extraneous columns, drop properties without associated row data, replace missing values, and alternate invalid observations.
(2) Conceptually partition the data column-wise.
(3) Remove outliers in a distribution-agnostic manner

Location

Property & Use

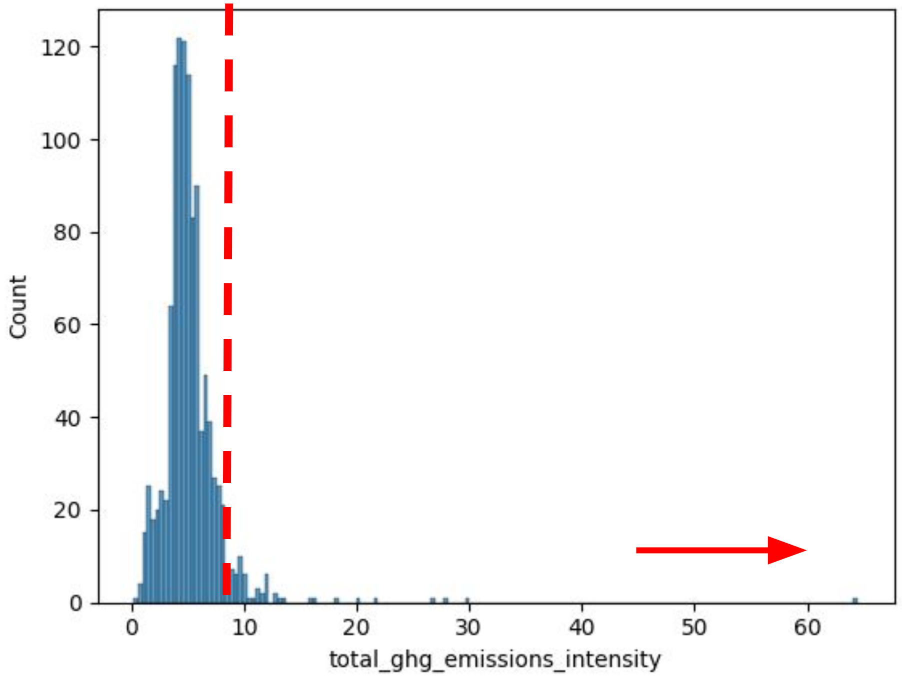
Energy Use Metrics;
Data Quality Flags; …

	property_id	latitude	longitude	borough	primary_property_type	largest_property_use_type	largest_property_use_type_1	year_built	number_of_buildings	occupancy	...
0	21205224	40.769272	-73.913633	QUEENS	Multifamily Housing	Multifamily Housing	25000	2010	1	100	...
1	2665352	40.790503	-73.96792	MANHATTAN	Multifamily Housing	Multifamily Housing	260780	1970	1	100	...
2	2665400	40.792758	-73.965171	MANHATTAN	Multifamily Housing	Multifamily Housing	324378	1943	1	100	...
7	2665443	40.837333	-73.94006	MANHATTAN	Multifamily Housing	Multifamily Housing	52428	1958	1	100	...
8	2665447	40.837275	-73.94423	MANHATTAN	Multifamily Housing	Multifamily Housing	70384	1973	1	100	...
...	...	...	...	...	...	...	...	...	...	...	...
1980	4095518	40.670965	-73.862535	BROOKLYN	Senior Living Community	Senior Living Community	42000	1975	1	100	...
1981	22480734	40.692915	-73.98815	BROOKLYN	K-12 School	K-12 School	76200	1927	1	100	...
1983	6275883	40.693963	-73.992561	BROOKLYN	Multifamily Housing	Multifamily Housing	88941	2010	1	100	...
1985	14719028	40.782735	-73.977327	MANHATTAN	Multifamily Housing	Multifamily Housing	94659	1924	1	100	...
1997	21967832	40.754847	-73.987833	MANHATTAN	Hotel	Hotel	179000	2021	1	55	...

1098 rows × 68 columns

Probabilistic Model: Bayesian Hierarchical Truncated Normal

A hierarchical model allows one to jointly estimate parameters for all subsets and categories of data. It also performs the best for skewed, truncated and multi-levelled data. This model has the advantage over estimating subset parameters individually since it may reduce some noise.



$$\underbrace{y_i}_{\text{Greenhouse Intensity}} = y_i^* \mathbb{I}\{y_i^* \geq 0\},$$

$$y_i^* \sim N(\mu_i, \sigma^2),$$

$$\mu_i = \alpha + \underbrace{[\boldsymbol{X\beta}]_i}_{\text{Local Variations}} .$$

$$\sigma_i \sim \text{Exponential}(\tau_i), \quad \tau_i \sim \text{Exponential}(1).$$

Modeling

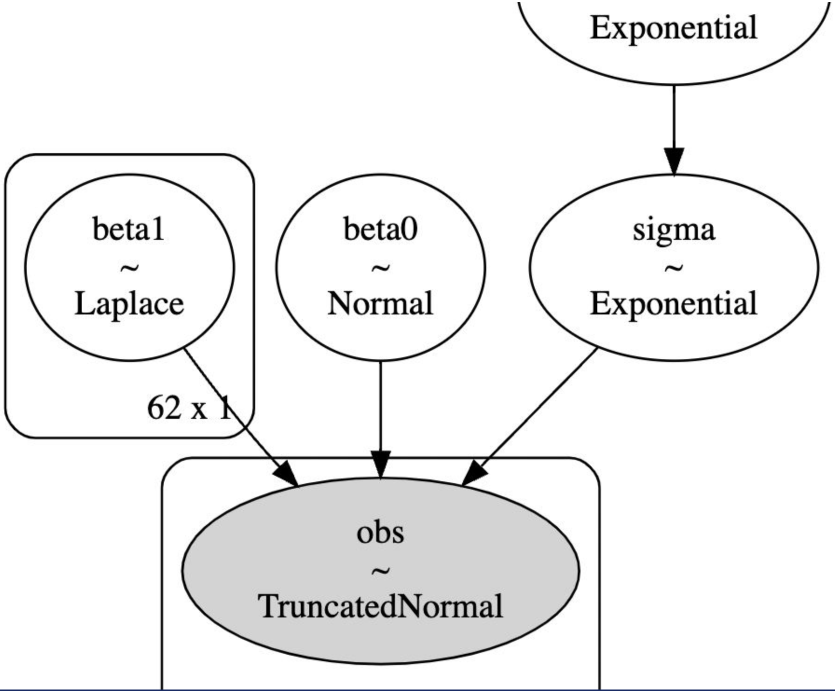
(1) What factors do/don't explain GHG emission intensity?

"Bayesian Lasso" for Variable Selection.

$$\boldsymbol{\beta} = \begin{bmatrix} \boldsymbol{\beta}_{\text{num}} \\ \boldsymbol{\beta}_{\text{cat}} \end{bmatrix}, \quad \beta_i \sim \text{Laplace}(0, 1).$$

Considerations:

- (Mild) shrinkage effect of coefficients;
- Computational ease over "SOTA" priors.



Modeling

(2) Identifying “Local Outliers” with a Multilevel Structure

$$\boldsymbol{X} = \begin{bmatrix} \boldsymbol{X}_{\text{num}} & \boldsymbol{X}_{\text{cat}} \end{bmatrix},$$

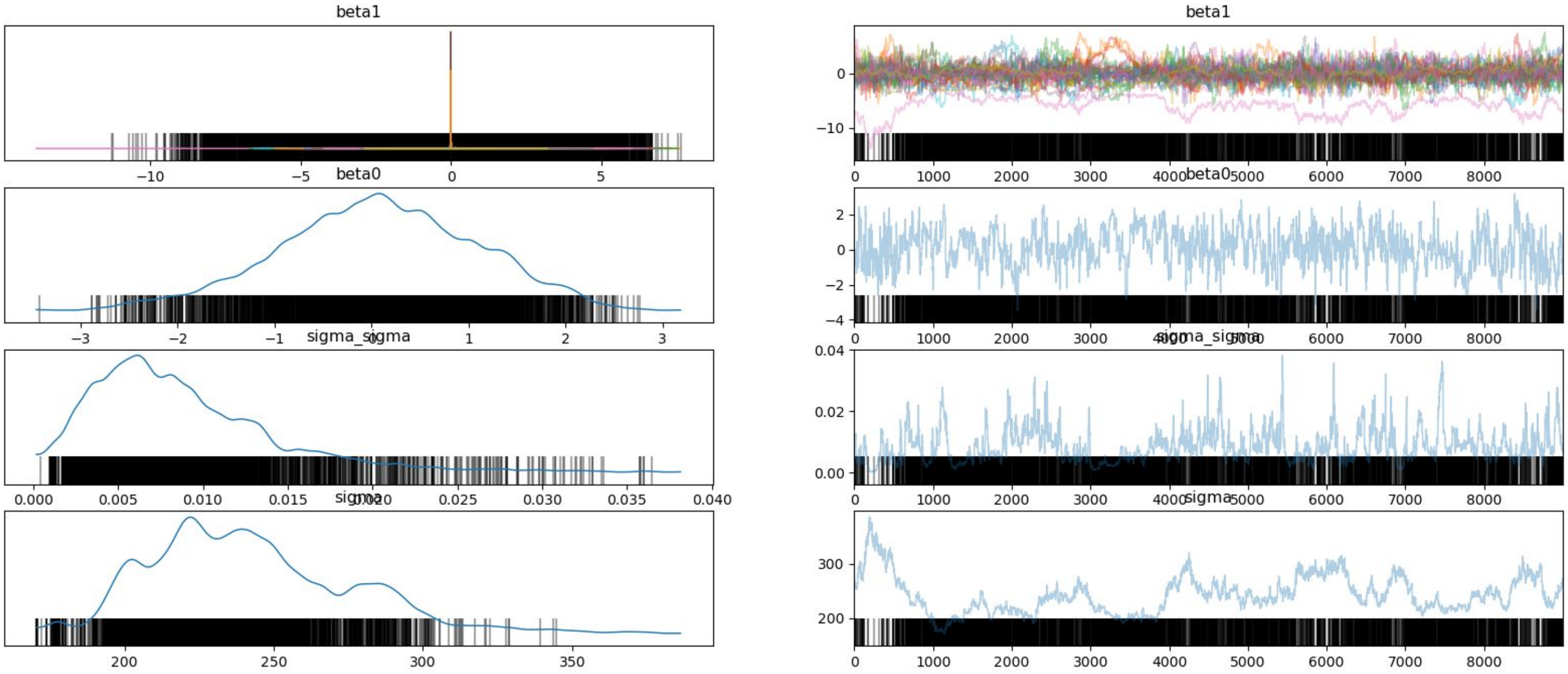
$$\boldsymbol{X}_{\text{num}} \in \mathbb{R}^{N \times K_{\text{num}}},$$

$$\boldsymbol{X}_{\text{cat}} = \begin{array}{c} \begin{matrix} \text{(Manhattan)} & \text{(Queens)} & \dots & \text{(Bronx)} & \text{(Multifamily Housing)} & \dots & \text{(K-12 School)} \end{matrix} \\ \begin{bmatrix} 1 & 0 & \dots & 0 & 1 & \dots & 0 \\ 0 & 1 & \dots & 0 & 0 & \dots & 1 \\ \vdots & & & & & & \\ 0 & 0 & \dots & 1 & 1 & \dots & 0 \end{bmatrix} \end{array}$$

- Examine data relative to predictive distribution.
- Considering location, property & use details, various energy use metrics, and data quality flags, which buildings are “local underperformers”?

Model Performance

- Mean Acceptance Rate: 0.75
- We visually inspect convergence



Major Findings

And policy recommendations

Findings

Notable factors that contribute to GHG emission intensity

	(-)	(~0)	(+)
Property Type / Characteristics	Year Built [-5.91]		# of Bldgs [0.63] Manhattan [0.6] Residence Hall/Dorm [0.26]
Usage Metrics	Natural Gas Use (therms) [-1.44] Electricity Use - Grid Purchase	Fuel Oil #1 Use (kBtu) Natural Gas Use (kBtu) Electricity Use Grid Purchase	Source EUI (kBtu/Ft) [0.85]

An Example: Identifying “Local Outliers” (High Emission: low pdf, Obs > Pred)

Locally…	Borough	Type	Year Built	Occup.	Star Score	Site EUI ($kBtu/ft^2$)	GHG Intensity
Lower	Manhattan	Multifam. Housing	1911	100	1	1207.4	5.7
Lower	Manhattan	Office	2013	60	49	75.8	64.5
Higher	Queens	Multifam. Housing	1961	90	88	86.2	4
Higher	Brooklyn	Multifam. Housing	1964	100	70	106.3	4.4

Future Directions & Approaches

Data Suggestions

- Quality: a more systematic Bayesian approach may be taken for missing data.
- Spatio-Temporal Modeling: exploit spatial correlation and temporal variations.

Policy & Research Recommendations

- Incentivize energy-efficient improvements to tenements, especially in older properties & affordable housing.
- Investigate disparity in energy cost burden through additional demographic data.
- Prioritize clean-energy implementation plans that allow for building-level use of green power.
- Re-evaluate Energy Star scoring in a more holistic manner.

Thank you !