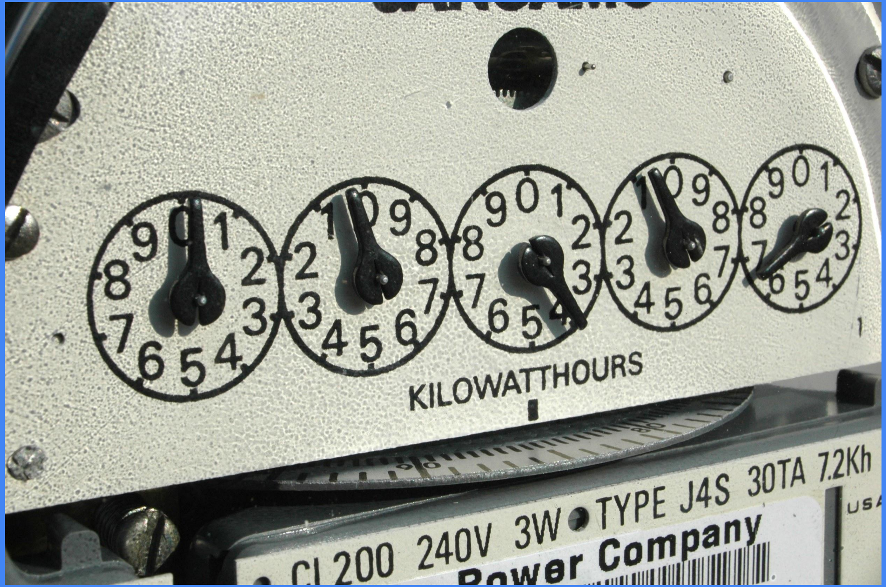
Can We Accurately Model Building Energy Usage?



By Justin Tyrrell

About me

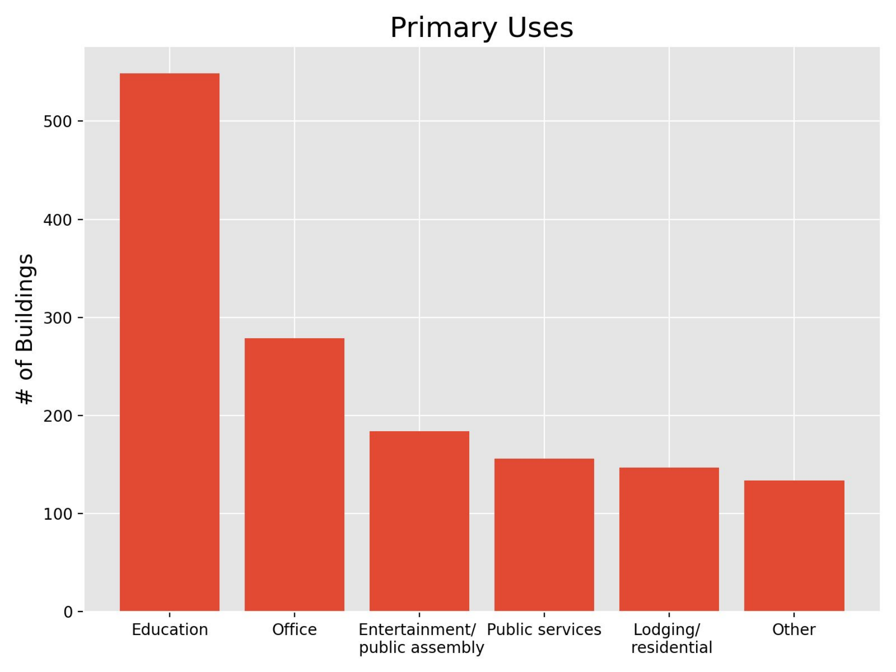
- Outdoors
  - Kayaking
  - Hiking
  - Biking
- Concerts
- Environmental Studies
- Career
  - Energy Efficiency
  - Environmental Health
  - Data Science

Why Should We Care?

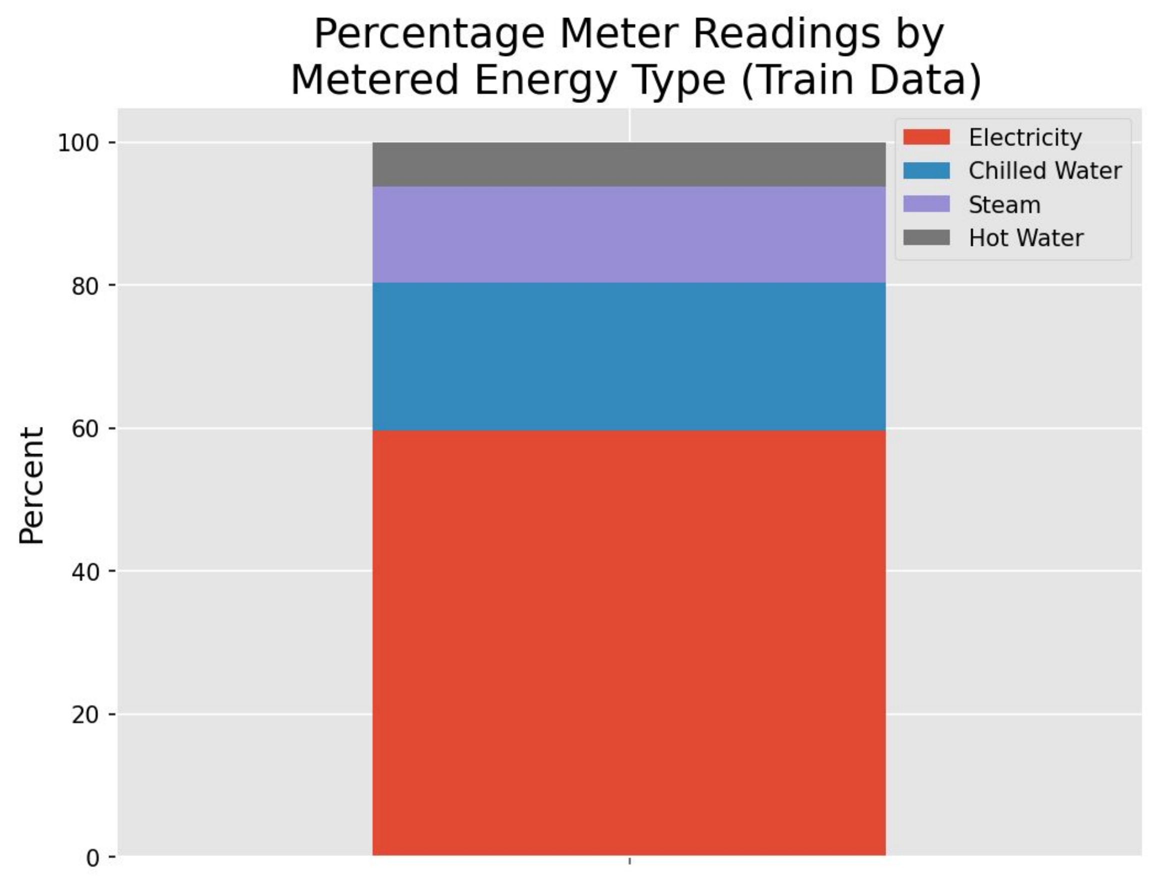
- Current administration's focus on Climate Change
- Reducing energy consumption
- Energy efficiency
- Accurately modeling baseline usage

The Data

- Metadata
  - Includes unique building ID, site ID, primary use, and metered energy use type
- Energy usage and weather
  - Hour by hour for each building/ site ID for 1 year
- Kaggle Competition
  - 20,000,000+ rows in train
  - 40,000,000+ rows in test

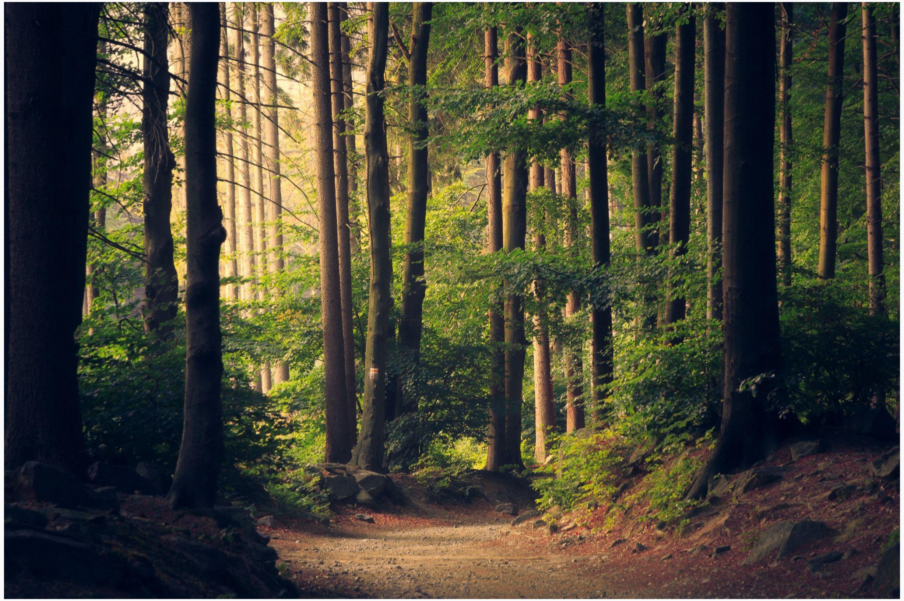


The Data

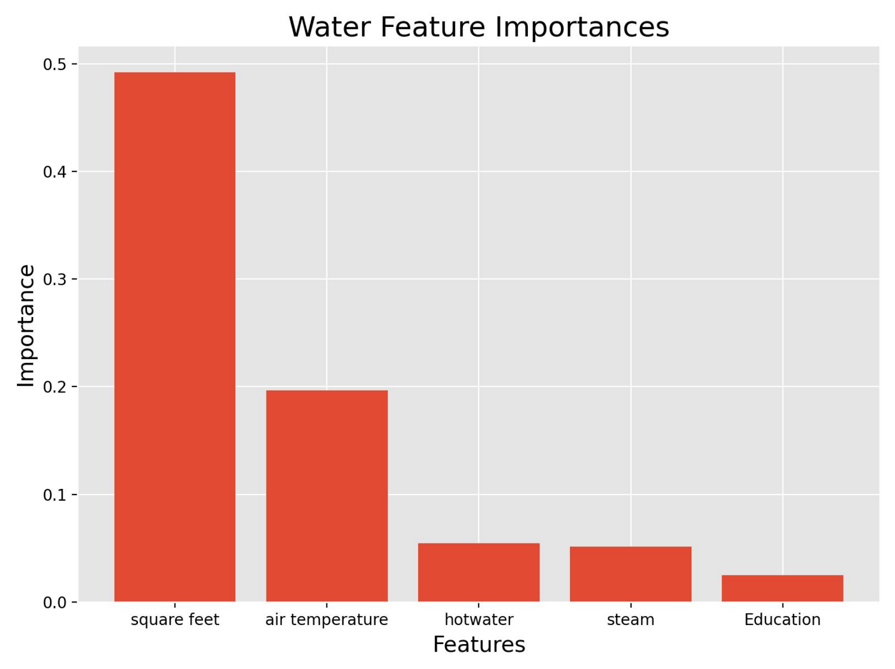

Percentage Meter Readings by
Metered Energy Type (Train Data)
Percent
0
20
40
60
80
100
Electricity
Chilled Water
Steam
Hot Water

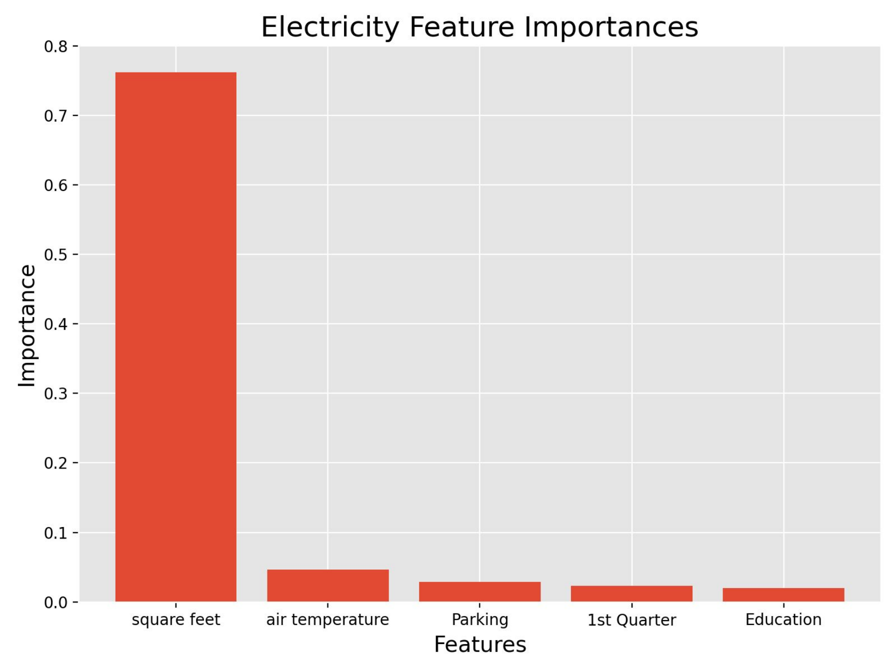
Building the Model

- Random Forest Regressor
  - Root Mean Squared Log Error (RMSLE)
- Split data into:
  - Water Usage Types
  - Electricity
- My RMSLE: 0.855
- Kaggle Winning RMSLE: 0.931



Feature Importances





Conclusions

- Initial results from modeling train data are promising
  - My RMSLE: 0.855
  - Kaggle Winning RMSLE: 0.931
- Square footage and temperature important to water metered energy types
- Square footage most important for electricity
- AWS EC2 instance crucial for future work

Questions?

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Appendices

1. Sources
2. Future Direction
3. Data Visualizations
4. Additional Feature Importance Plots

Sources

- Data - https://www.kaggle.com/c/ashrae-energy-prediction/leaderboard
- Energy stats - https://www.eia.gov/
- Biden admins climate goals - https://www.nytimes.com/live/2021/04/22/us/biden-earth-day-climate-summit

Future Direction

- Run my cleaning script and model on the test dataset using an AWS EC2 instance and then submit the predictions to Kaggle
- Depending on how this model predicts on the test data it could be useful to use a Grid Search to try other models
- Look into imputing the missing values from one or more of the dropped columns in the weather data
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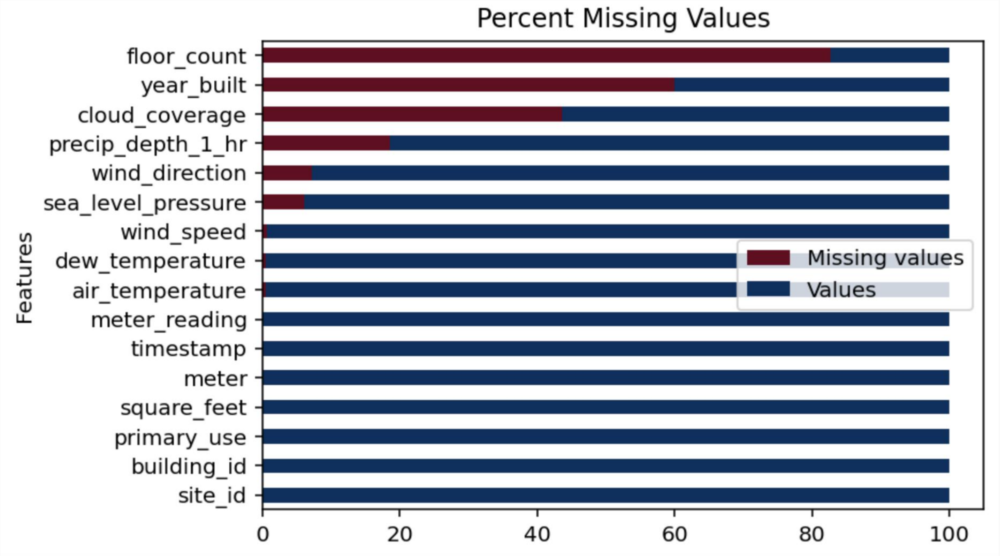
Cleaning and Featurization

- Missing values
  - imputing missing temperatures
- Timestamp data, Primary usage, and meter columns
  - One hot encoding
- Usage conversion for site 0



Building Metadata

building_meta.csv		
Variable Name	**Data Type**	**Description**
site_id	int	Foreign key for the weather files.
building_id	int	Foreign key for training.csv
primary_use	object (string)	Indicator of the primary category of activities for the building based on EnergyStar property type definitions
square_feet	int	Gross floor area of the building
year_built	float	Year building was opened
floor_count	float	Number of floors of the building

Primary uses included Education, Entertainment/public assembly, Food sales and service, Healthcare, Lodging/residential, Manufacturing/industrial, Office, Other, Parking, Public services, Retail, Services, Technology/science, Utility, and Warehouse/storage.

Energy Usage and Usage Type

train.csv		
Variable Name	**Data Type**	**Description**
building_id	int	Foreign key for the building metadata.
meter	int	The meter id code. Read as {0: electricity, 1: chilledwater, 2: steam, 3: hotwater}. Not every building has all meter types.
timestamp	object (string)	When the measurement was taken
meter_reading	float	The target variable. Energy consumption in kWh (or equivalent). Note that this is real data with measurement error, which we expect will impose a baseline level of modeling error. UPDATE: as discussed here, the site 0 electric meter readings are in kBTU.

Over 20 million rows of data

Weather Data

weather_[train/test].csv		
Variable Name	**Data Type**	**Description**
site_id	int	
timestamp	object (string)	When the measurement was taken
air_temperature	float	Degrees Celsius
cloud_coverage	float	Portion of the sky covered in clouds, in oktas
dew_temperature	float	Degrees Celsius
precip_depth_1_hr	float	Millimeters
sea_level_pressure	float	Millibar/hectopascals
wind_direction	float	Compass direction (0-360)
wind_speed	float	Meters per second

Cleaned Data

	square_feet	meter_reading	air_temperature	q1	q2	q3	q4	afternoon	early_morning	evening	...	Office	Other	Parking	Public services	Retail	Services
0	7432	0.0	25.0	1	0	0	0	0	1	0	...	0	0	0	0	0	0
1	2720	0.0	25.0	1	0	0	0	0	1	0	...	0	0	0	0	0	0
2	5376	0.0	25.0	1	0	0	0	0	1	0	...	0	0	0	0	0	0
3	23685	0.0	25.0	1	0	0	0	0	1	0	...	0	0	0	0	0	0
4	116607	0.0	25.0	1	0	0	0	0	1	0	...	0	0	0	0	0	0