Great Energy Predictor

Team: High on Data

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Agenda

- Project Overview
- Data Description and Handling
- Exploratory Data Analysis
- Modeling and Prediction
- Recommendations and Conclusion



Project Description

Background

Today, significant investments are being made to improve building efficiencies but owners makes payments based on the difference between their real energy consumption and what they would have used without any retrofits. The latter values come from a model.

Objective

We have chosen a kaggle case competition focusing on building accurate models of metered building energy usage provided by ASHRAE, an institute that serves to advance the arts and sciences of heating, ventilation, air conditioning, refrigeration and their allied fields.

https://www.kaggle.com/c/ashrae-energy-prediction/data



Technology Stack



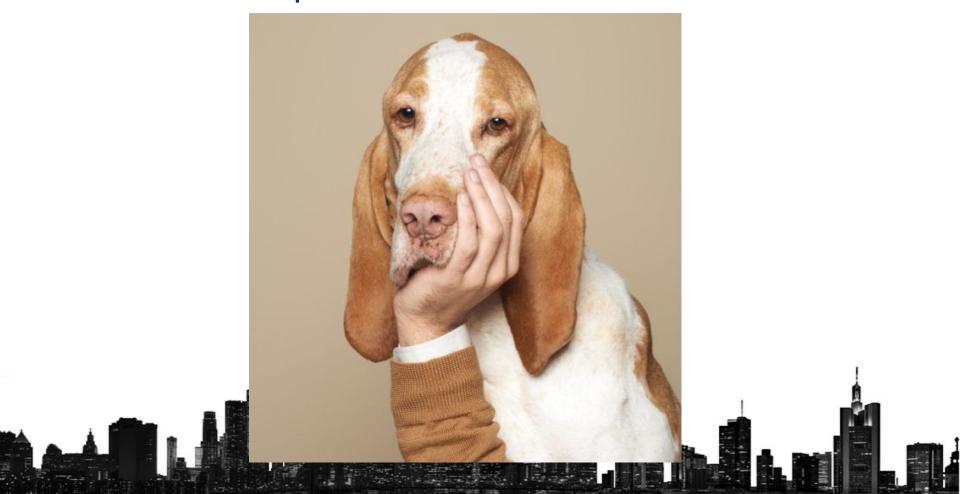
Data Description

Data collected over 3 years across 16 sites for around 1500 buildings.

- Building metadata
 - Floor count, area, age, primary use, site, etc.
- Weather data
 - Site level hourly data of temperature, wind speed, precipitation, cloud coverage
- Meter Readings
 - Building level hourly data of energy consumption readings collected from 4 different meters
 - 20 million training data points and 40 million test data points



60 million data points - Databricks & Colab were like

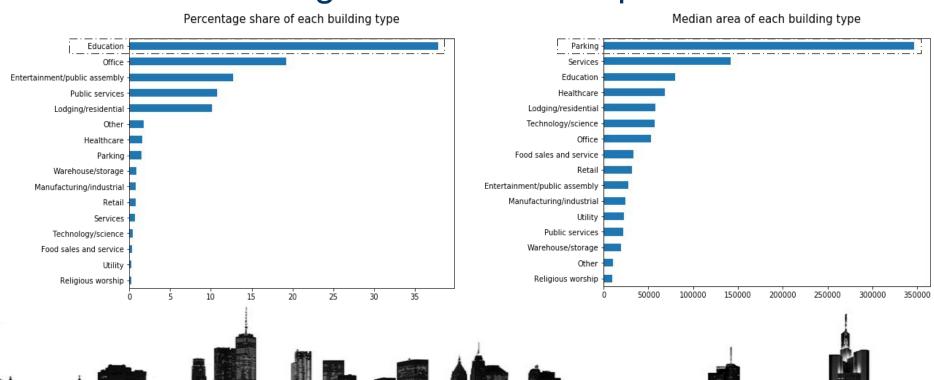


Data Size Reduction

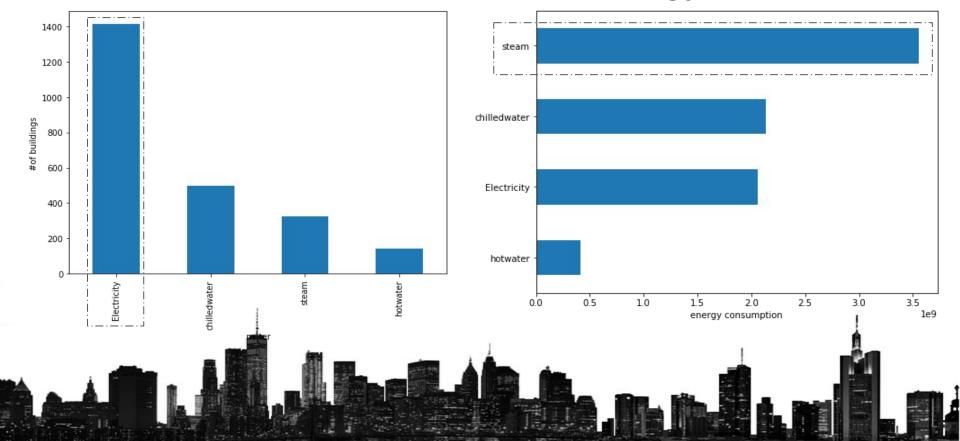
- 60 million data points Around 8 GBs of data before feature engineering
- Reduced data size by almost 50%
 - int64 -> int32 and int16
 - float64 > float32 and float16
 - Removed columns with >70% nulls
 - Label Encoding categorical features to int8



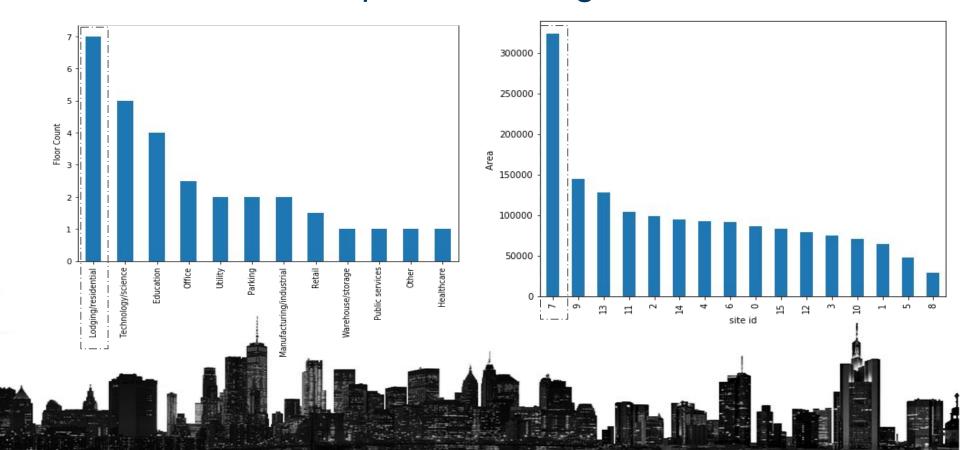
Educational buildings have maximum presence while Parking takes the most space



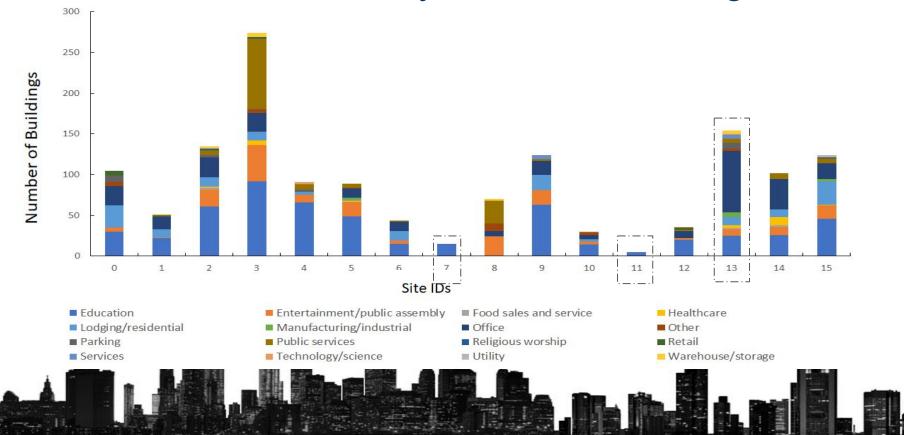
Electricity meter is omnipresent while Steam consumes the most energy



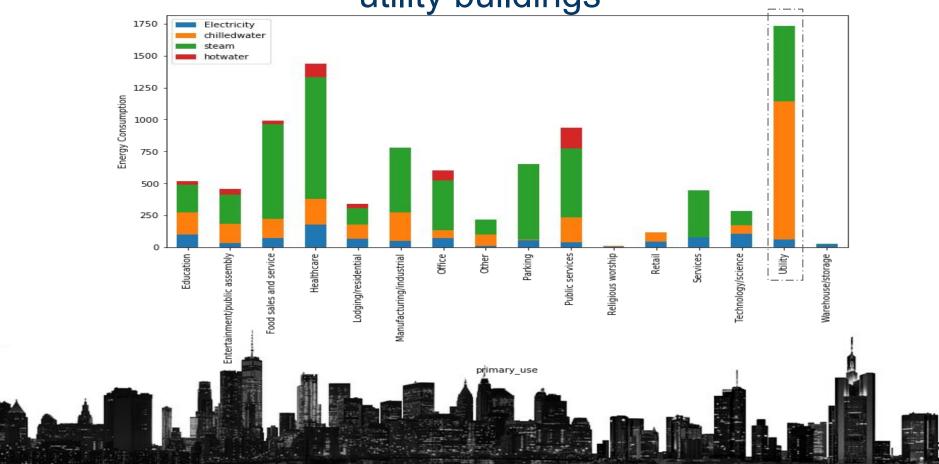
Residential/Lodging are tallest & Site 7 has more spread buildings



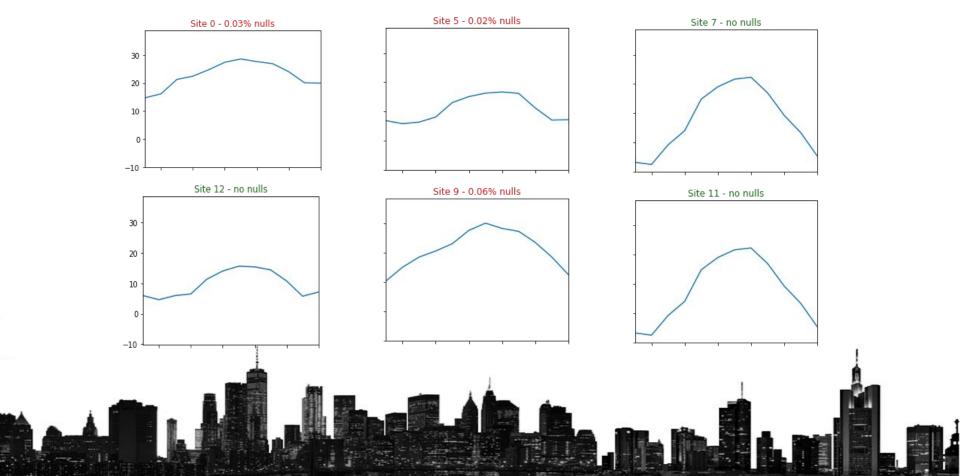
Sites 7 & 11 predominantly have educational buildings while Site 13 mostly has office buildings



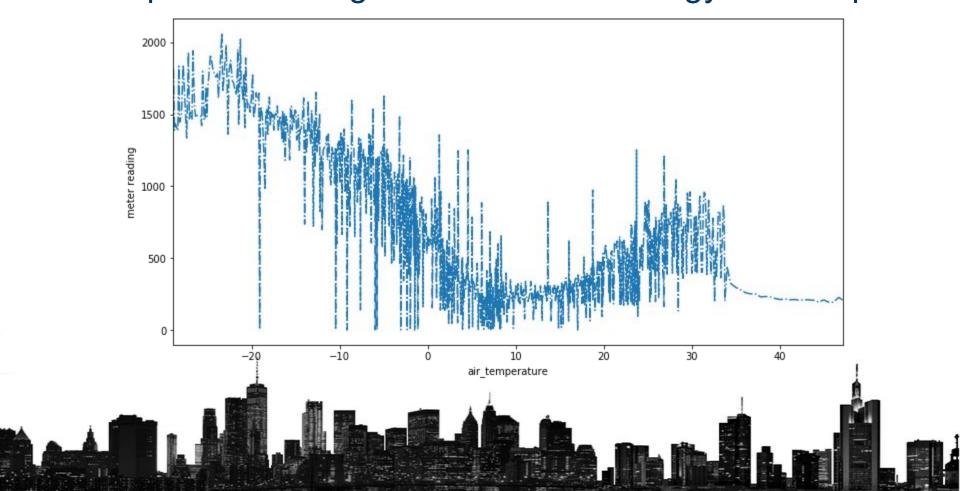
Chilled water was the most consumed energy in utility buildings



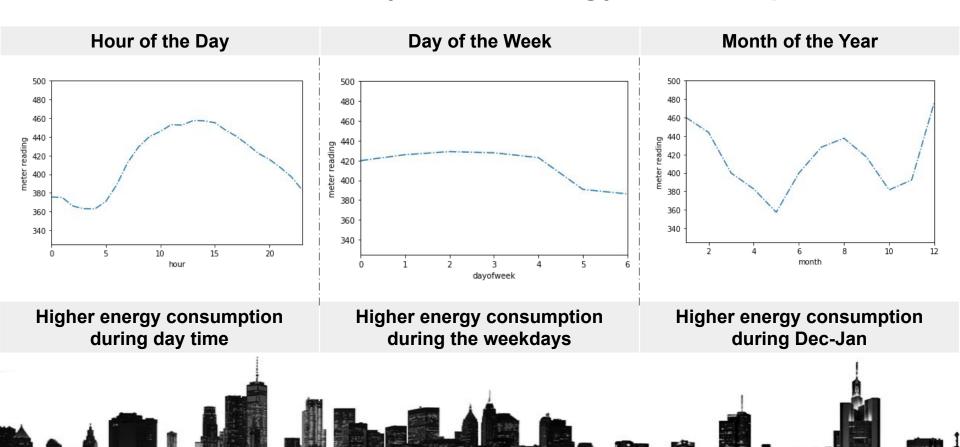
Monthly Weather patterns (Air Temperature) across Sites



Air Temperature is a good indicator of energy consumption

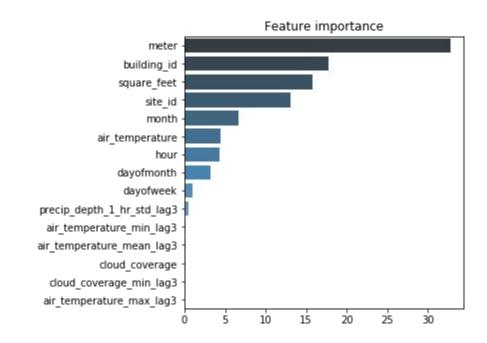


Time Series Analysis of Energy Consumption



Modeling - CatBoost

- Train and Validation
 - H1 vs H2
 - o 3 fold CV
- 500 boosting trees
- Parameters
 - Learning rate: 0.05
 - o Max depth: 8
- Train Score: 0.84
- Validation Score: 1.29
- Test Score: 1.34

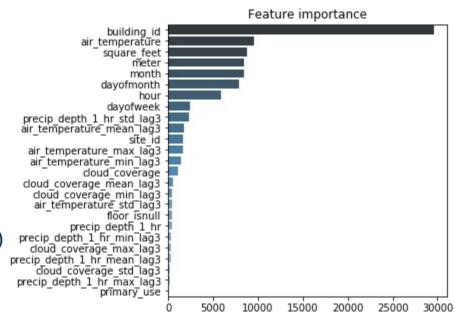




Modeling - LGBM

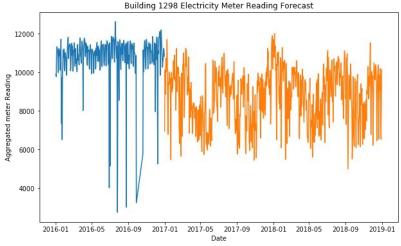
- 3 fold cross validation
- Tuned Parameters
 - Learning rate: 0.03
 - Feature Fraction: 0.85
 - o Reg Lambda: 0.2
 - o Max depth: 10
- Train Score: 0.55
- Validation Score: 1.02
- Test Score: 1.11 (Kaggle Top 40%)
- Test Score Post-Processing: 1.01

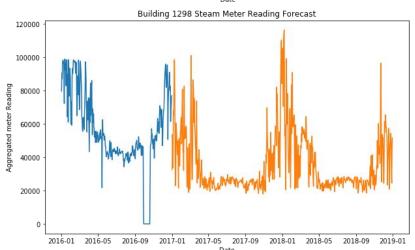
(Kaggle Top 20%)

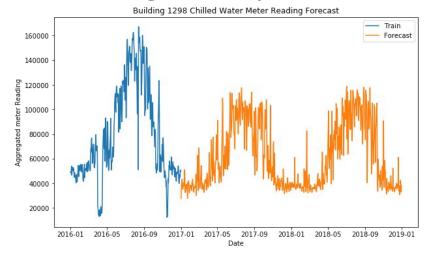


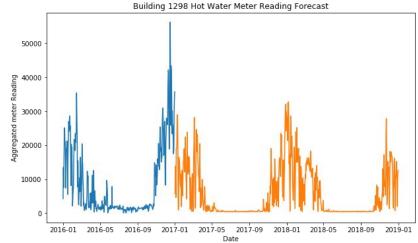


Model Prediction (for Building 1298)

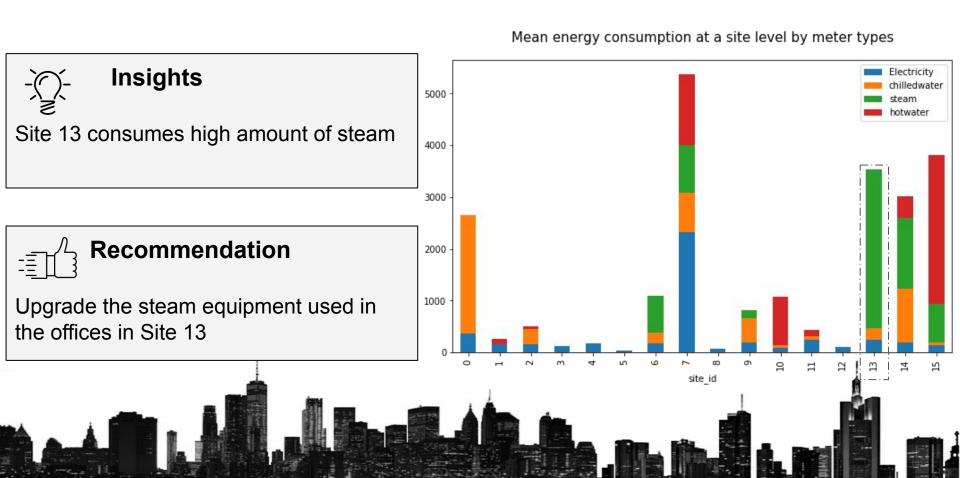








Recommendation



Recommendation

Mean energy consumption at a site level by meter types



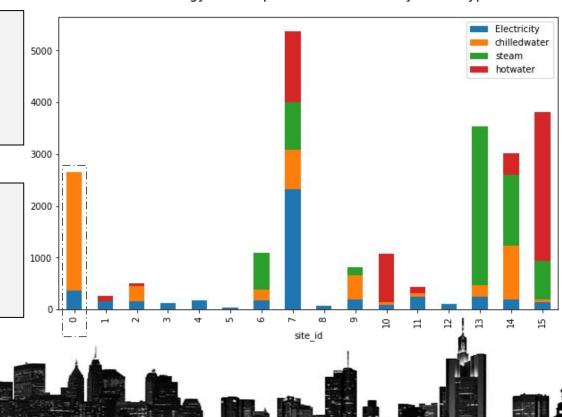
Insights

Site 0 consumes most amount of chilled water, at least 6 times more than others



Recommendation

Upgrade the chilled water system in the educational and residential buildings



Recommendation

Mean energy consumption at a site level by meter types



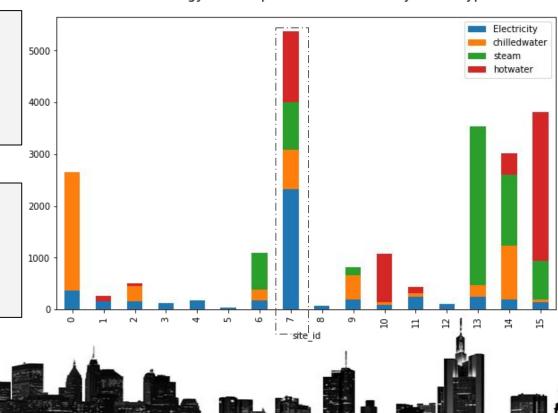
Insights

Site 7 has the highest energy consumption across all sites



Recommendation

Upgrade all the old equipments in the educational buildings in this site



Next Steps

- Different approaches yet to be tried:
 - Train for each meter
 - Train for each site
- Try to utilize external data
- Tune parameters further
- Try stacking CatBoost and LGBM outputs
- Try H20.ai Auto ML algorithm for benchmarking





Questions?