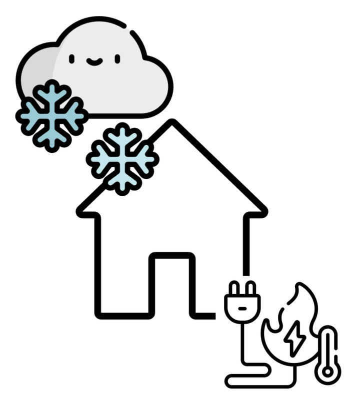
Estimating Heating Loads in Alaska using Remote Sensing and Machine Learning Methods



UNIVERSITY of WASHINGTON
eScience Institute
DATA SCIENCE FOR SOCIAL GOOD

Global Warming and Heating Load Estimates

Filling an Energy Use Data Gap

- ***Geospatial-first*** estimation approach
  - Leverage scale and granularity of satellite imagery
- Contrasts with micro-level approaches

UNIVERSITY *of* WASHINGTON

Our Task

Create a model that predicts heating loads for buildings in Alaska, accounting for local climate

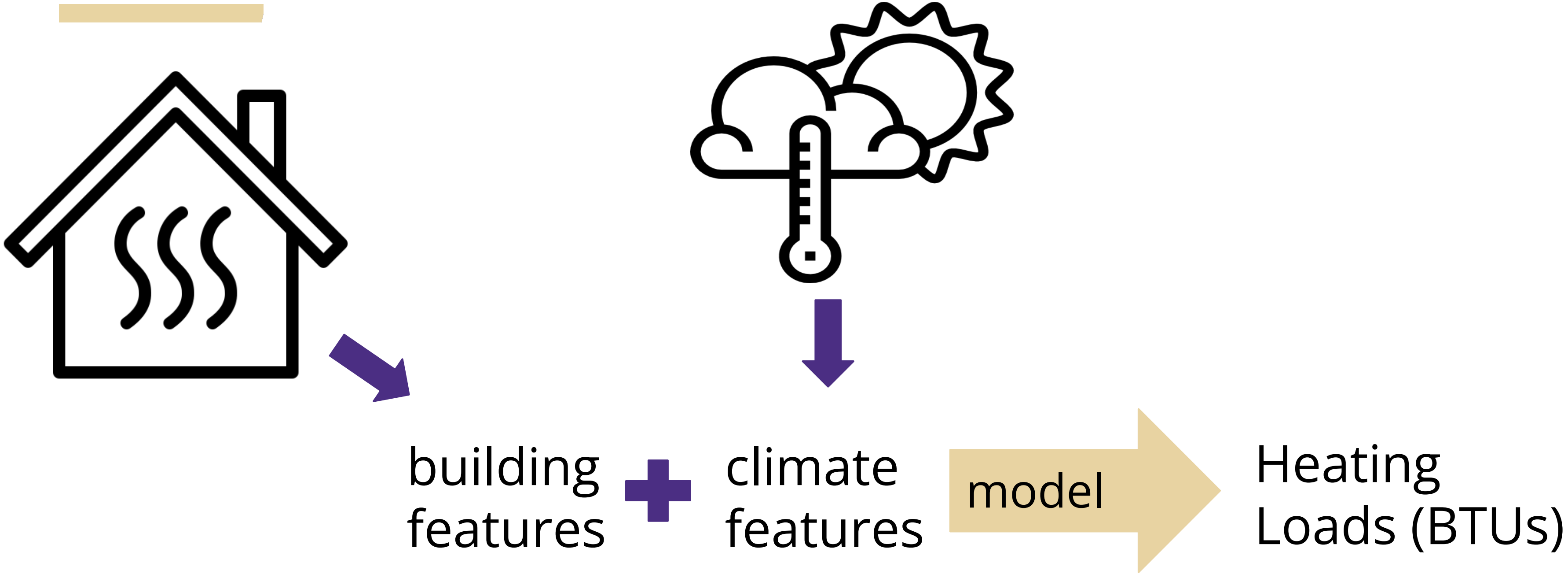
- Focus on Railbelt

Google Earth Engine for Input Features

> Local climate conditions
> Building Features
  - Height
  - Base Area
  - Age

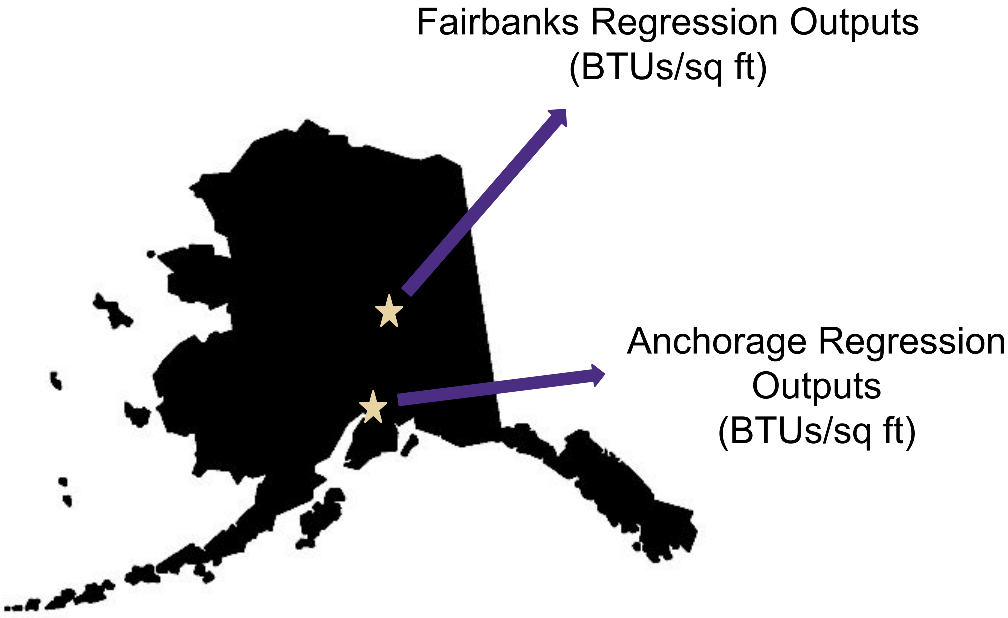
UNIVERSITY *of* WASHINGTON

Process Flowchart



Regression Model

- Capitalize on climate differences between Anchorage and Fairbanks
- Generalize to Railbelt



Models Estimated & Fit

Regression	Mean Squared Error
Linear	6.9503×10^{-3}
Ridge	6.976×10^{-3}
Ridge (degree 2 polynomial)	2.428×10^{-6}
Decision Tree	3.204×10^{-7}
Random Forest	1.221×10^{-7}

Better fit

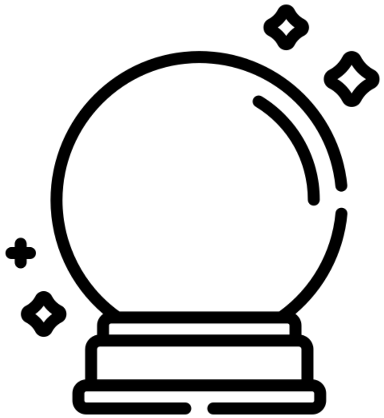
Data Sampling for Class Imbalance

- Avoid biasing model towards certain types of buildings
- Balancing Explored
  - Locations: Anchorage and Fairbanks
  - Building Age: years

Data Sampling Results

Regression	Mean Squared Error		
	No Balancing	Balanced Location	Balanced Age
Linear	6.950×10^{-3}	8.174×10^{-3}	**5.774×10^{-3}**
Ridge	6.976×10^{-3}	8.200×10^{-3}	**5.801×10^{-3}**
Ridge (degree 2 polynomial)	2.428×10^{-6}	2.660×10^{-6}	**1.214×10^{-6}**
Decision Tree	3.204×10^{-7}	4.326×10^{-8}	**3.321×10^{-9}**
Random Forest	1.221×10^{-7}	2.026×10^{-8}	**4.338×10^{-9}**

Results and Future Work



- Heating load estimates that capture variation in local climate
- Incorporating public energy retrofit database into models
- Hourly heating load estimates
- Widening scope to Alaska and beyond

Supporters

UNIVERSITY of WASHINGTON
eScience Institute

Micron®

W®
UNIVERSITY of WASHINGTON