

# **Final Project for Group 2 - Energy Efficiency**

Energy Efficiency Dataset by Athanasios Tsanas, Angeliki Xifara from  
the UC Irvine Machine Learning Repository

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# Research Question and Data

## Research Question

Can we create a Machine Learning model to evaluate the heating and cooling demands of a residential building using only its engineering design variables?

Variable	Mean	Std	Min	Max
Relative_Compactness (X1)	0.7642	0.1058	0.62	0.98
Surface_Area (X2)	671.71	88.09	514.50	808.50
Wall_Area (X3)	318.50	43.63	245.00	416.50
Roof_Area (X4)	176.60	45.17	110.25	220.50
Overall_Height (X5)	5.25	1.75	3.50	7.00
Orientation (X6)	3.50	1.12	2.00	5.00
Glazing_Area (X7)	0.2344	0.1332	0.00	0.40
Glazing_Area_Distribution (X8)	2.8125	1.5510	0.00	5.00
Heating_Load (Y1)	22.31	10.09	6.01	43.10
Cooling_Load (Y2)	24.59	9.51	10.90	48.03

Data collected from UC Irvine Machine Learning Repository.

# Methods

Machine Learning Models used to evaluate Heating and Cooling demands:

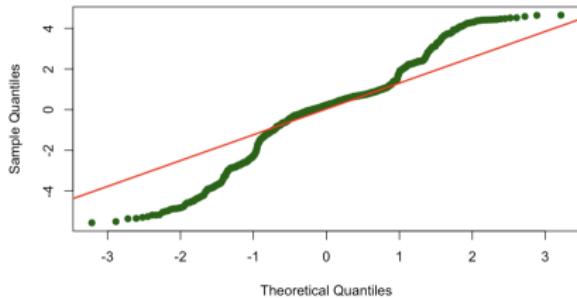
- Ridge Regression
  - Serves as a baseline to capture linear relationships
  - Performed 10-fold CV over  $\lambda \in [0, 50]$ ; recorded optimal  $\lambda(0.25)$  and corresponding to the minimum MSE
- Lasso Regression (Ridge + Lasso)
  - Select interaction terms using Lasso regularization (combined with Ridge)
  - Performed 10-fold CV over  $\alpha \in [0, 1]$  and  $\lambda \in [0, 50]$ ; recorded the optimal  $(\alpha, \lambda)$  and choosing  $(\alpha = 1, \lambda = 0.002)$  which has minimum MSE.
- Spline Regression with Lasso Regularization:
  - Fitting a spline regression with the mgcv library.
  - Regularize using a L1 regularization.
- KNN:
  - Motivation - "Similar" residential structures may have similar energy load.
  - Run 10-fold CV for  $k \in [1, 50]$ , using the best  $k(5)$  with the lowest MSE.
- Random Forest: As proposed by the Initial Researchers.

# Results

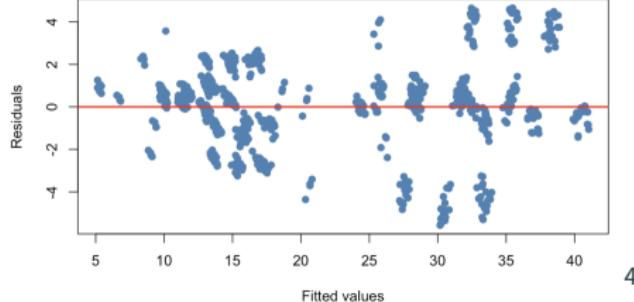
Models with 10-fold Cross Validation error for Heating and Cooling load.

Model	Cooling load	Heating load
Random Forest	1.03	6.59
Spline & Lasso	1.09	3.07
KNN	6.05	10.66
Ridge & Lasso	7.3	4.85
Ridge Regression	10.26	8.64

QQ Plot of Residuals for heating

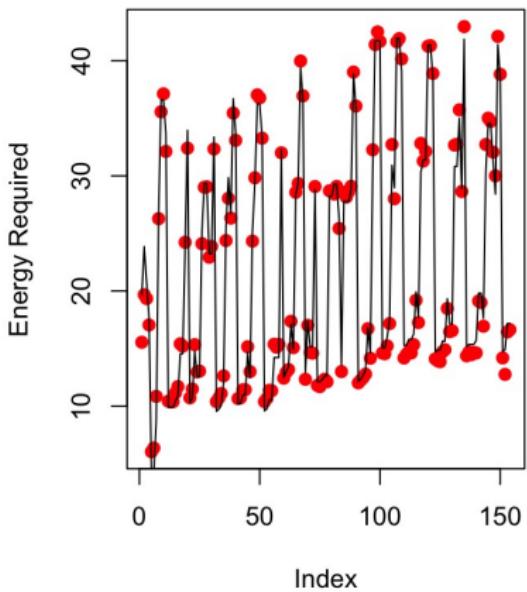


Ridge+Lasso: Residuals vs Fitted for heating



# Conclusion

Actual vs. Predicted Heating Load (Y1)



Actual vs. Predicted Cooling Load (Y2)

