

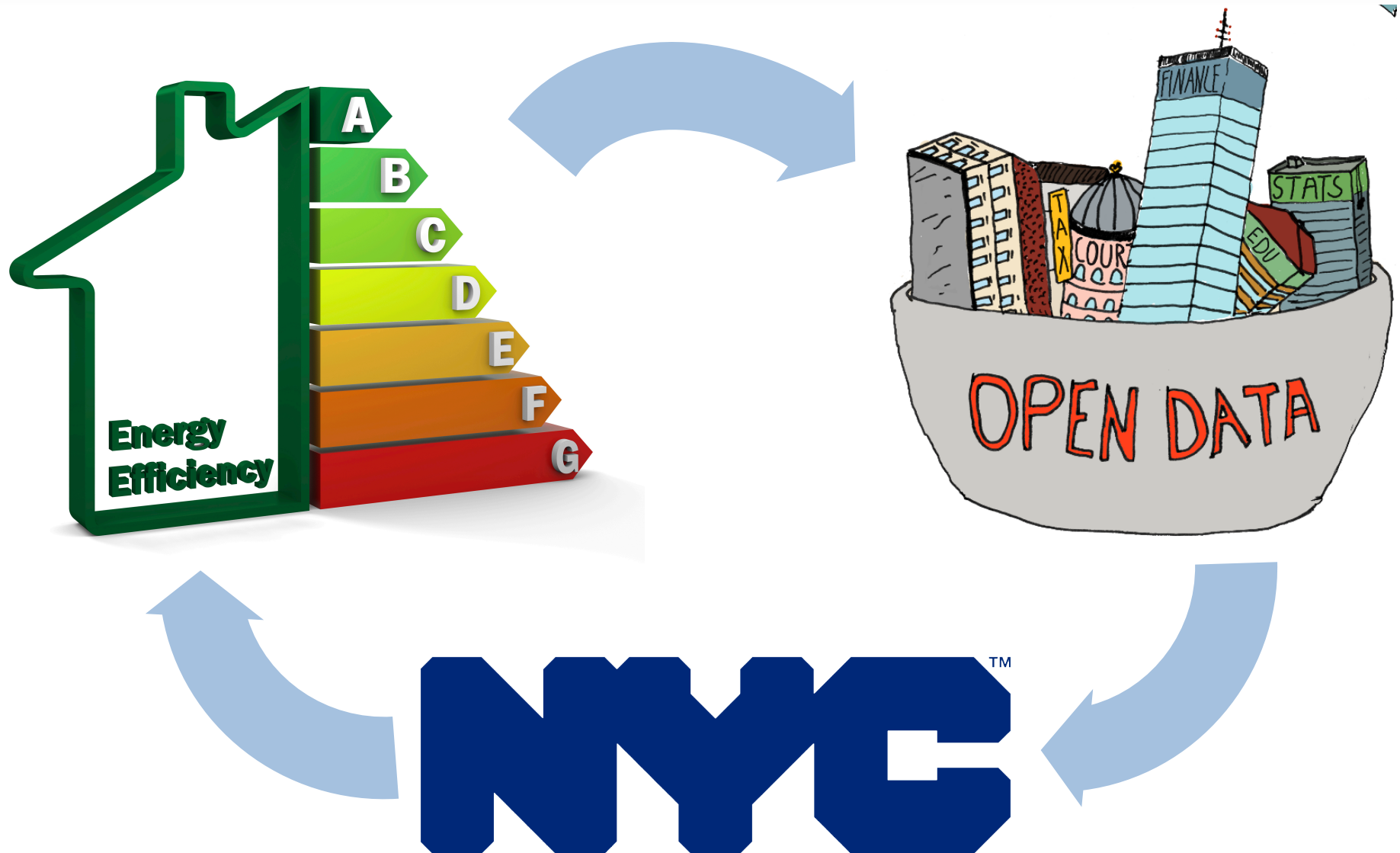
# Final Project Presentation

## GA Data Science 18

Theodore Love

4/20/2015

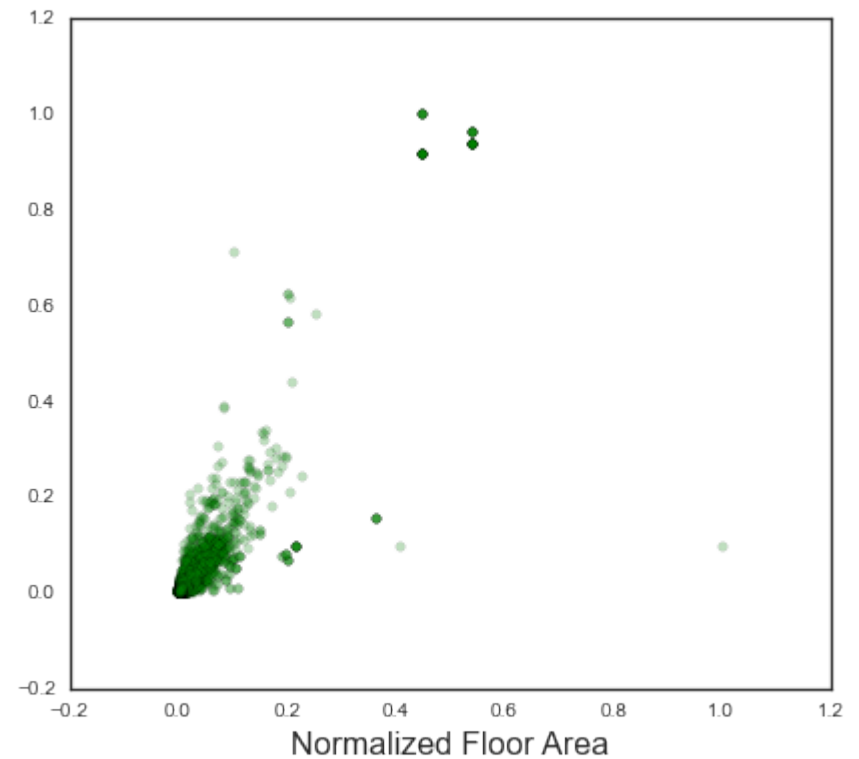
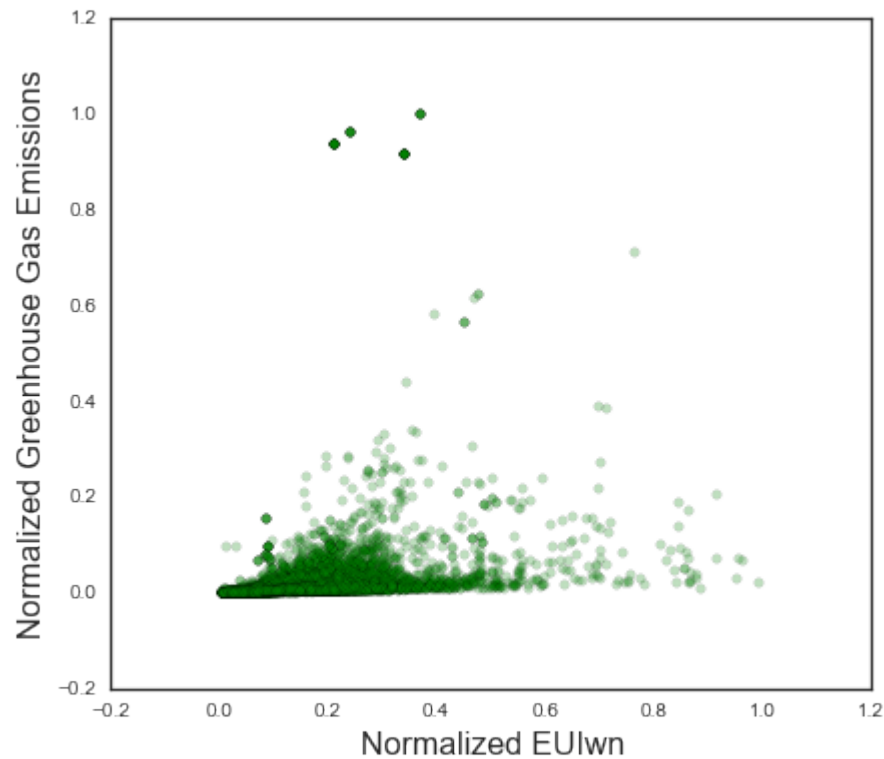
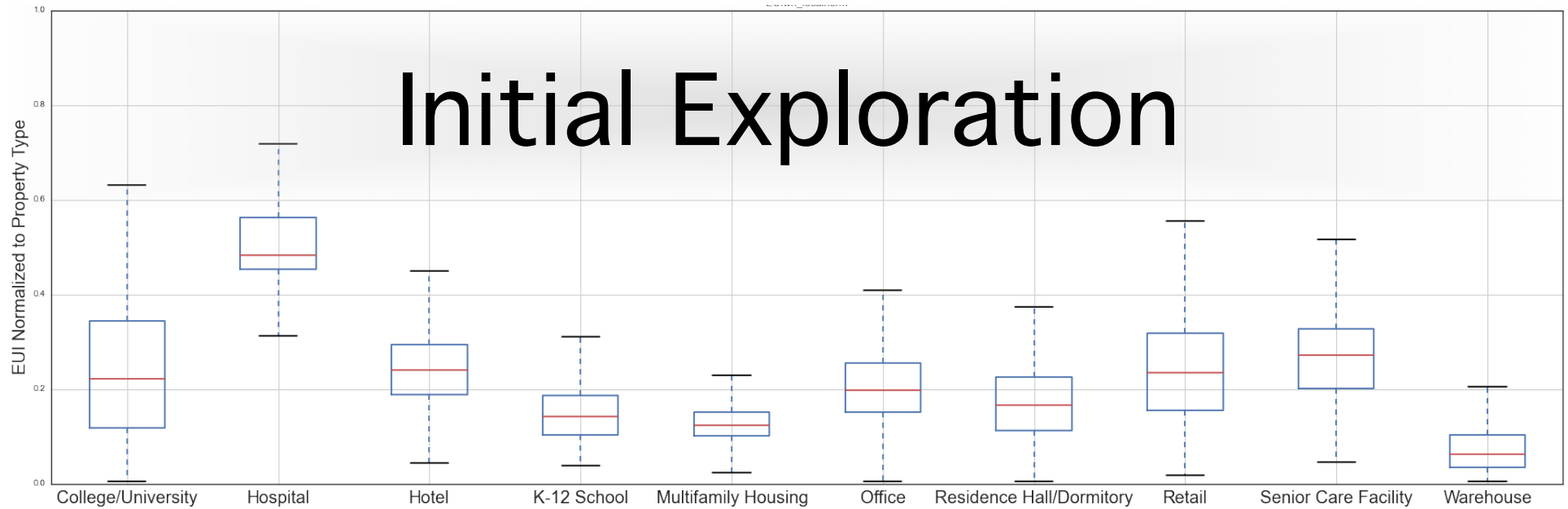
# The Inspiration



# Local Law 84

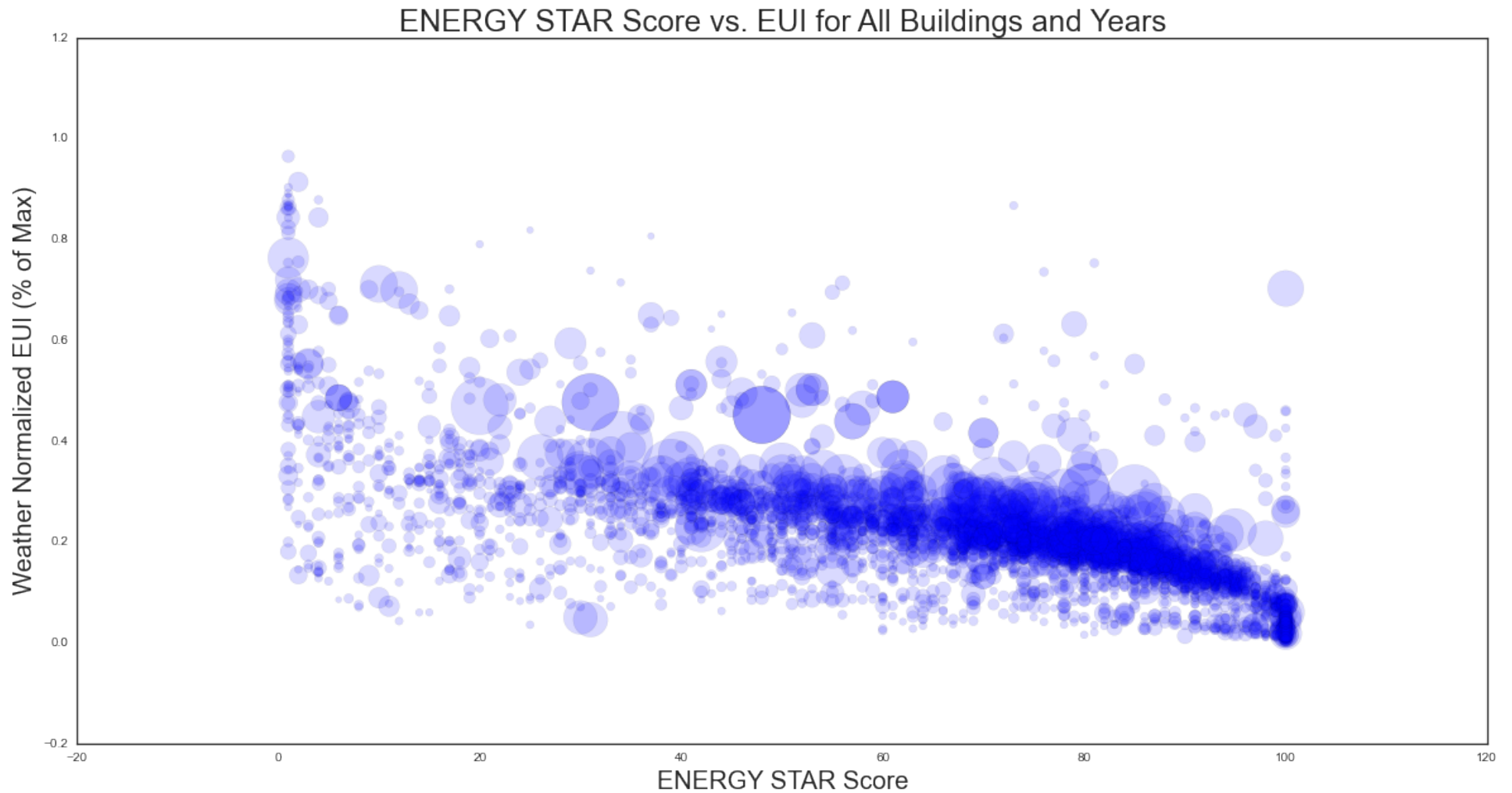


# Initial Exploration

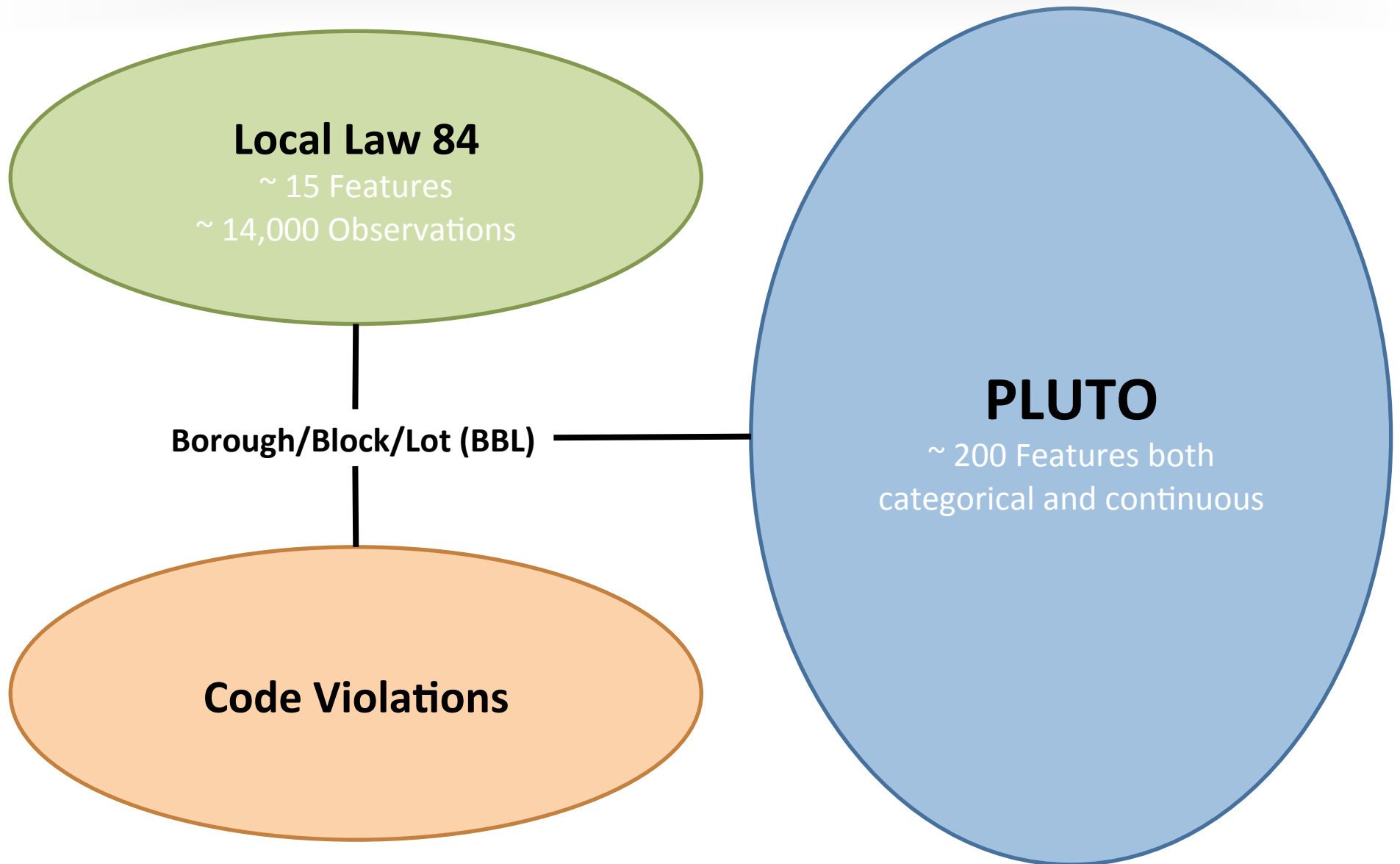




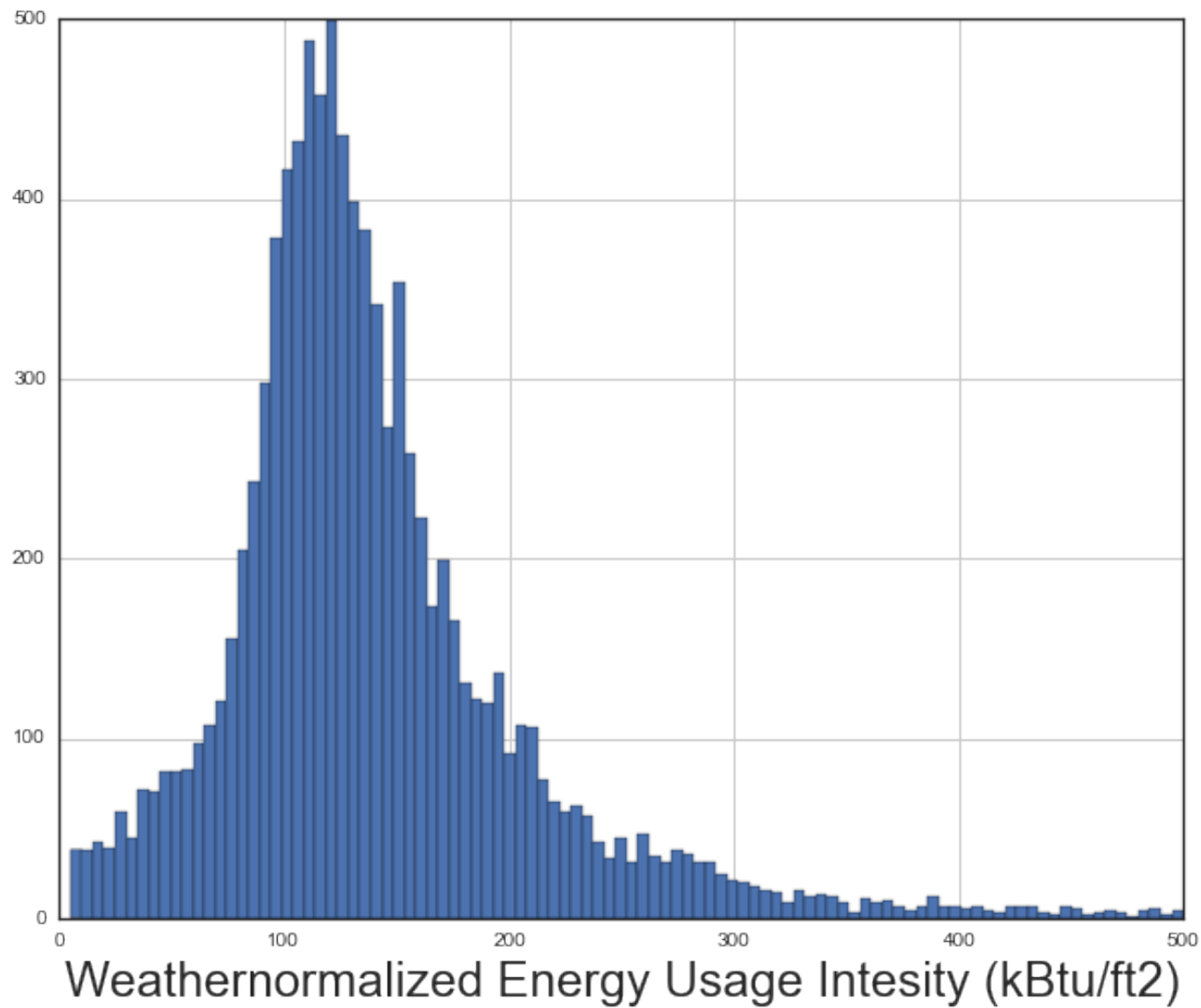
# Existing Benchmarks



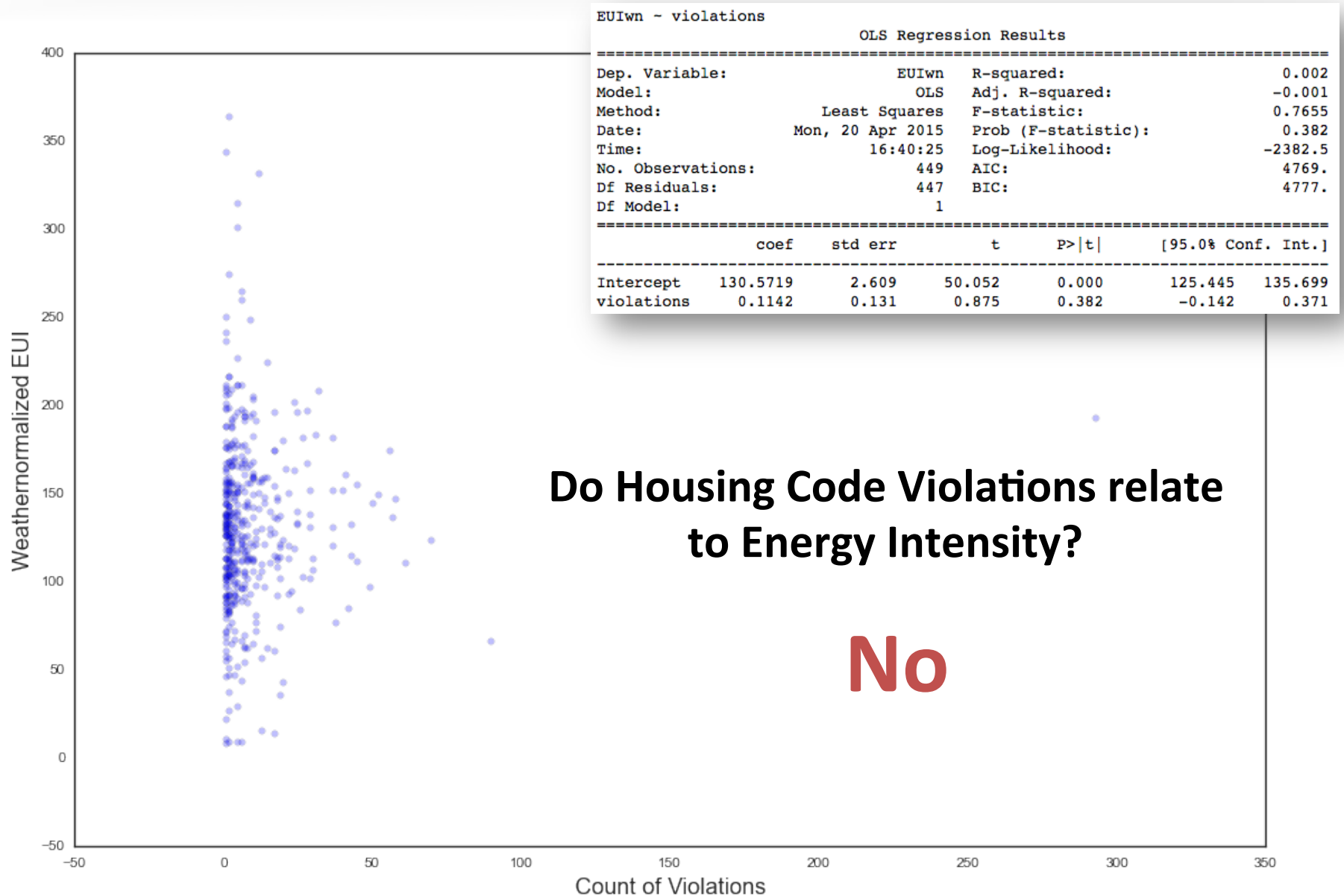
# Going Further with New Data



# Let's Try to Predict EUI

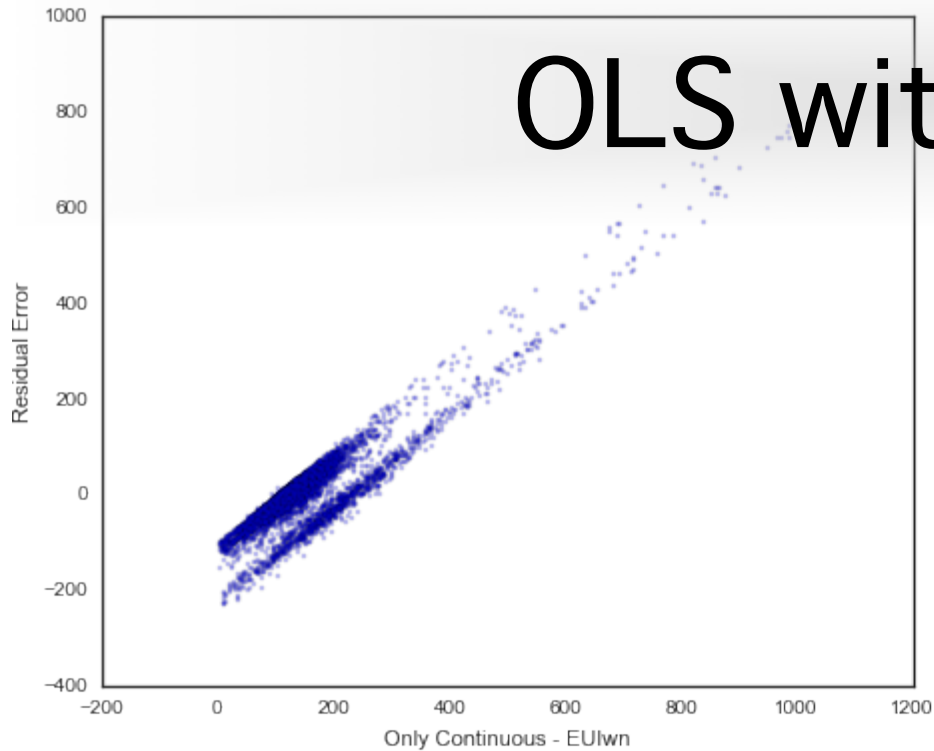


# A Dead End

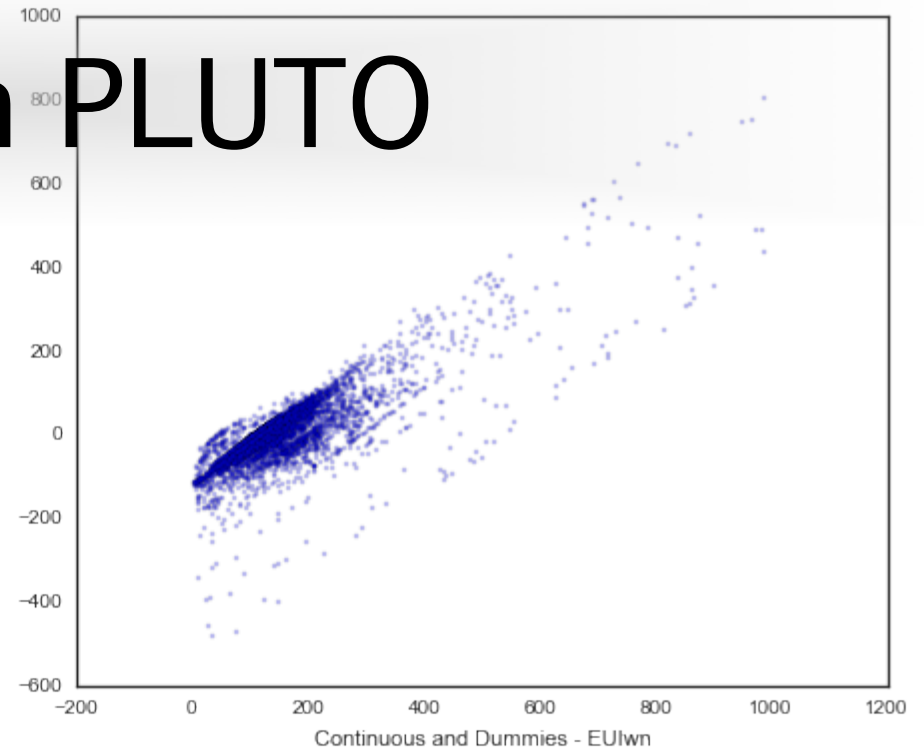




# OLS with PLUTO



OLS Regression Results					
Dep. Variable:	EUIwn	R-squared:	0.220		
Model:	OLS	Adj. R-squared:	0.219		
Method:	Least Squares	F-statistic:	212.6		
Date:	Mon, 20 Apr 2015	Prob (F-statistic):	0.00		
Time:	17:01:21	Log-Likelihood:	-39550.		
No. Observations:	6811	AIC:	7.912e+04		
Df Residuals:	6801	BIC:	7.919e+04		
Df Model:	9				
	coef	std err	t	P> t	[95.0% Conf. Int.]
Intercept	114.9118	1.916	59.969	0.000	111.156 118.668
PerComArea	-18.1909	4.605	-3.950	0.000	-27.219 -9.163
PerOfficeArea	120.2945	5.997	20.058	0.000	108.538 132.051
PerOtherArea	129.8724	6.077	21.372	0.000	117.960 141.784
PerRetailArea	154.0383	9.447	16.305	0.000	135.519 172.558
PerGarageArea	125.3753	14.756	8.497	0.000	96.450 154.301
Easements	19.8924	6.129	3.245	0.001	7.877 31.908
NumBldgs	0.8138	0.160	5.079	0.000	0.500 1.128
NumFloors	1.2586	0.146	8.595	0.000	0.972 1.546
MaxAllwFAR	-1.3232	0.367	-3.601	0.000	-2.044 -0.603
Omnibus:	5182.231	Durbin-Watson:	1.994		
Prob(Omnibus):	0.000	Jarque-Bera (JB):	164207.190		
Skew:	3.351	Prob(JB):	0.00		
Kurtosis:	26.102	Cond. No.	237.		



OLS Regression Results						
=====						
Dep. Variable:	EUIwn	R-squared:	0.359			
Model:	OLS	Adj. R-squared:	0.356			
Method:	Least Squares	F-statistic:	111.5			
Date:	Wed, 18 Mar 2015	Prob (F-statistic):	0.00			
Time:	23:14:04	Log-Likelihood:	-38881.			
No. Observations:	6811	AIC:	7.783e+04			
Df Residuals:	6776	BIC:	7.807e+04			
Df Model:	34					
=====						
	coef	std err	t	P> t	[95.0% Conf. Int.]	
-----						
Intercept	119.5677	2.098	56.999	0.000	115.455	123.680
PerOfficeArea	66.9291	3.782	17.697	0.000	59.515	74.343
PerOtherArea	39.5388	5.277	7.493	0.000	29.194	49.883
PerRetailArea	48.5308	10.524	4.612	0.000	27.901	69.161
PerGarageArea	46.2411	16.258	2.844	0.004	14.371	78.111
Easements	15.8513	5.595	2.833	0.005	4.884	26.818
NumFloors	1.2730	0.113	11.266	0.000	1.051	1.494
I1	350.1366	13.971	25.061	0.000	322.748	377.525
● ● ●						
O6	143.0251	51.820	2.760	0.006	41.443	244.608
G1	97.2183	25.589	3.799	0.000	47.056	147.381
F9	-56.6767	14.451	-3.922	0.000	-85.006	-28.347
=====						
Omnibus:	4195.869	Durbin-Watson:	1.994			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	129991.633			
Skew:	2.436	Prob(JB):	0.00			
Kurtosis:	23.840	Cond. No.	826.			

# Tree Regressions with Full PLUTO Data

	features	importance
147	LandUse_05	0.129002
77	BldgClass_I1	0.080447
25	YearBuilt	0.066685
19	AssessLand	0.038579
20	AssessTot	0.037660
26	YearLastWork	0.037520
150	LandUse_08	0.036264
3	ComArea	0.030964
1	LotArea	0.030778
15	LotFront	0.029329
16	LotDepth	0.027269
18	BldgDepth	0.027257
23	BuiltFAR	0.026796
12	NumFloors	0.025325
22	ExemptTot	0.024598
17	BldgFront	0.024171
14	UnitsTotal	0.023993
2	BldgArea	0.019196
5	OfficeArea	0.017562
30	PerRetailArea	0.016927

Hospitals and Health

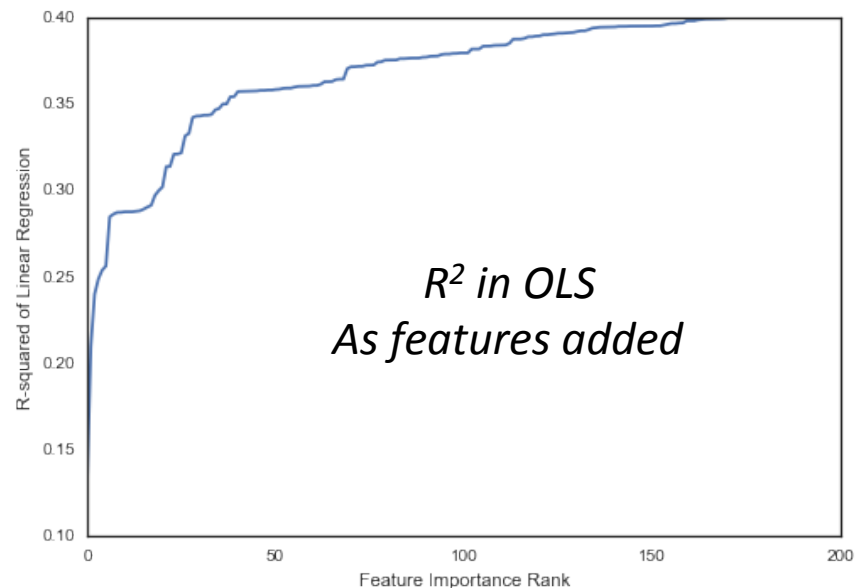
Commercial & Office Buildings

Age of Building

Value of building/land

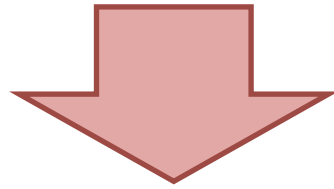
Public Facilities & Institutions

Size/usage percent of building



# Optimization of Decision Tree Regression

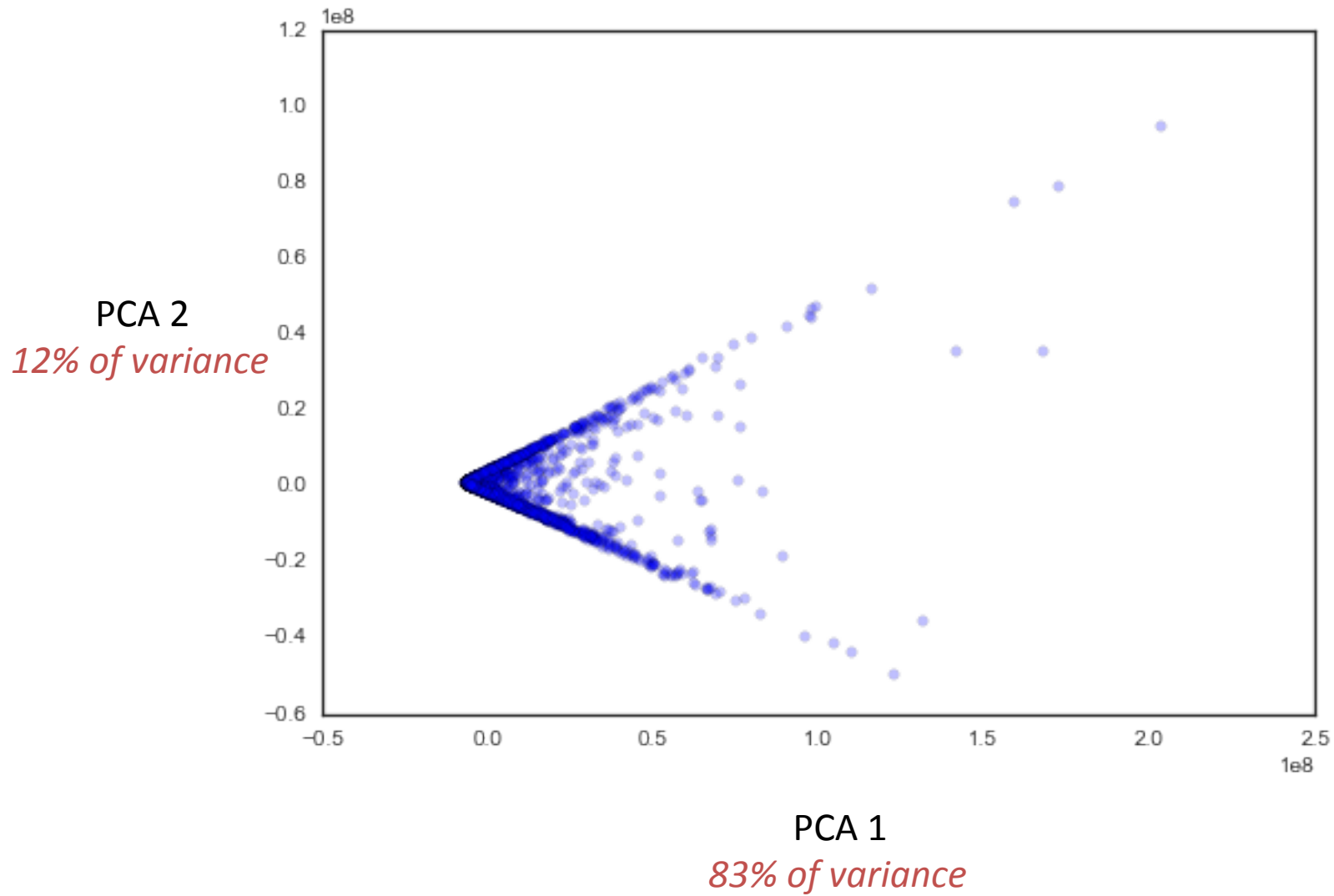
Cross-validation found over fitting issues across sub-samples even with low depths.



## Random Forest Regression

$R^2$  from 0.23 to 0.29 with std dev  $\sim 0.03$

# Quick PCA



# Next Steps

- Further examination of PCA
- Exploration of residuals and classification of high users
- See how regressions works on new data
- Prepare white paper (BECC Conference)

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