Predicting Pittsburgh Single Family Home Prices

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Problem Statement

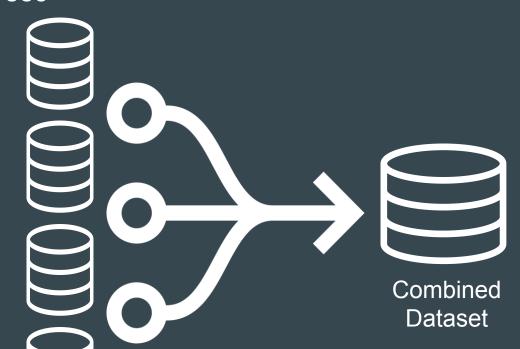
 Given current real estate market difficulties, use non-conventional data to predict home prices

- Input -> Output
- Criteria for Success

External Data Sources



Home Data





Crime Stats



School Stats



ACS Survey

Features



Redfin Dataset Description

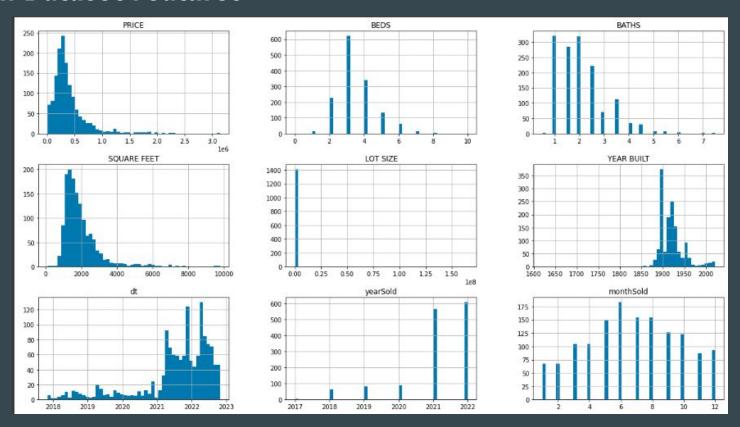
• 1989 x 29

- Categorical:
 - O Nominal: 13
 - o Ordinal: 2

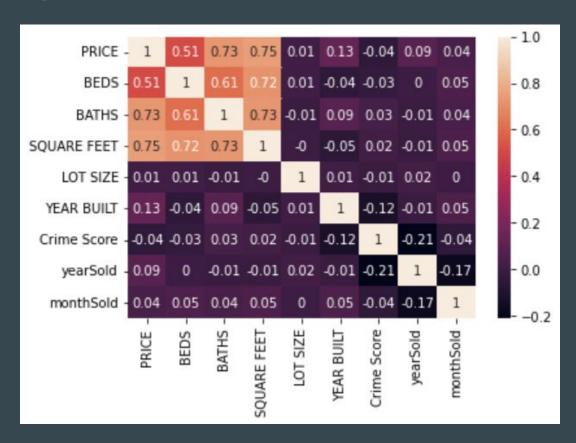
- Numerical:
 - Discrete: 4
 - o Continuous: 10



Redfin Dataset Features



Redfin Data Exploration



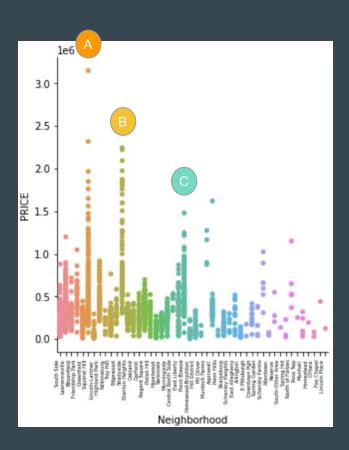
Baseline Model

Baseline Model – Features

Beds	Price	Year Sold
Square Feet	Bath	Month Sold
Neighborhood	Lot Size	One-Hot Encode Neighborhood
Location	Year Built	

1989 x 55

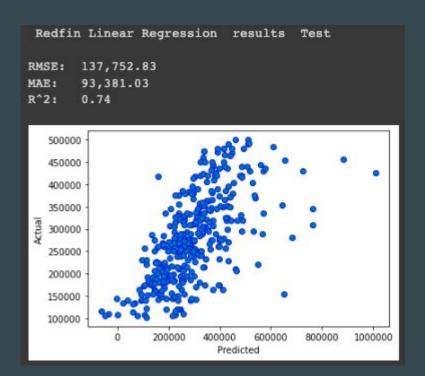
- A Squirrel Hill
- B Shadyside
- C Point Breeze



Baseline Model – Preliminary Results

• Linear Regression

• Split 75% train (1491) 25% test (498)



The Approach — Search for New Features



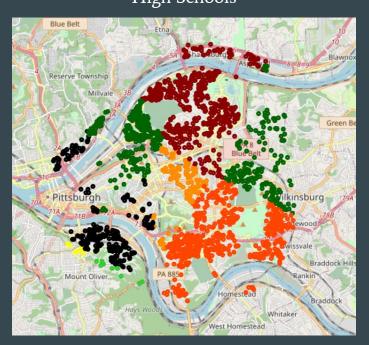


New Features - Local Schools

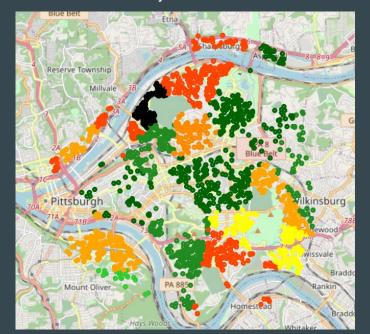
NCES National Center for Education Statistics

New Features - Local Schools

High Schools



Elementary/Middle Schools



Score

90-100	
80-90	
70-80	
60-70	
50-60	
40-50	
30-40	
20-30	
10-20	
0-10	

Features



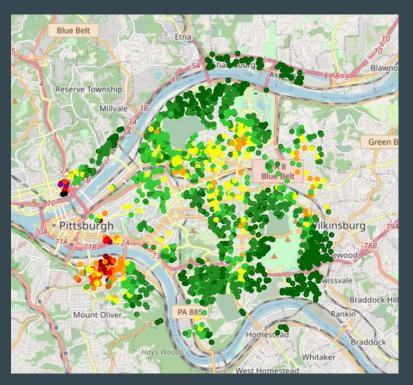




New Features - Crime



New Features - Crime



Score = Max(0, 1 - (SQRT(Distance/Max Radius)))

Score

0-10	
10-20	
20-30	
30-40	
40-50	
50-60	
60-70	
70-80	
80-90	
90-100	

Features









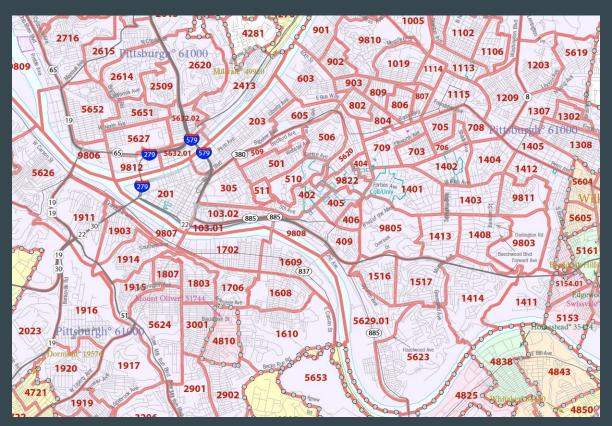
New Features - Census Data



American Community Survey

Detailed 5 Year Estimates

What is a Census Tract?



Example Census Features

B25109_001E housing_OwnerOccupiedMedianValue

B25111_001E renting_MedianRentValue

B15012_009E bachelors_STEM B19001_017E income_200KOrMore

B15003_025
Eeducation_DoctorateDegree

..... And more

Data Preparation

Data Preparation and Feature Engineering

R	S	Т	U
joinKey	age_Median	$housing_OwnerOccupiedMedianValue$	renting_MedianRentValue
42003090100	33.2	250000	1470
42003110600	42.7	322200	935
42003562300	54.4	79400	664
42003424000	43.1	78300	820
42003516200	37.5	216500	903
42003090100	33.2	250000	1470
42003140300	40.3	450800	1682
42003141300	33.2	275800	1116
42003140500	35.1	-66666666	1340
42003130700	36.6	43800	574
42003090200	37.1	250800	981

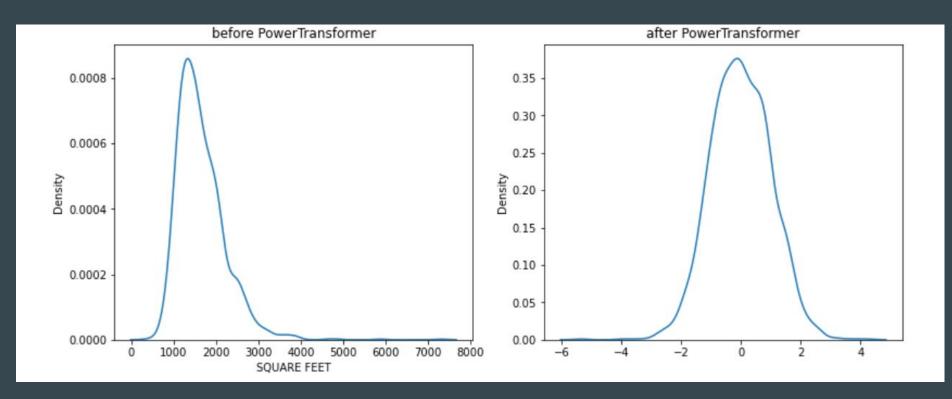
Remove Outliers: Census

% STEM Bachelor's Degrees =

of People with STEM Degrees

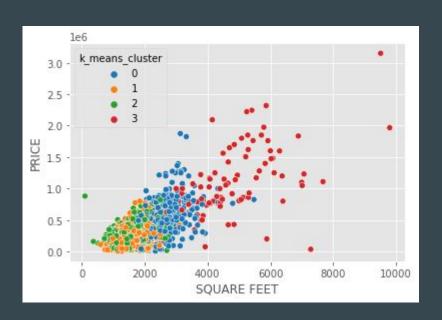
Total Bachelors Degrees

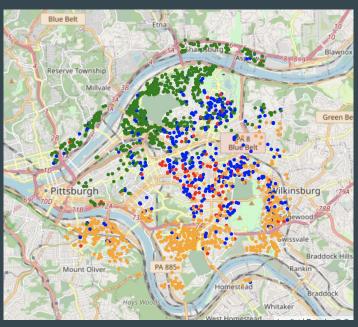
Data Preparation - Transform and Standardize



Modeling - ML

K-Means Experiment— Unsupervised EDA





Added: Latitude and Longitude Vars

Modeling Approach — Supervised





Regression Models with GridSearchCV

AutoML tool developed by Amazon

Target -> **Property Prices**

Modeling Approach

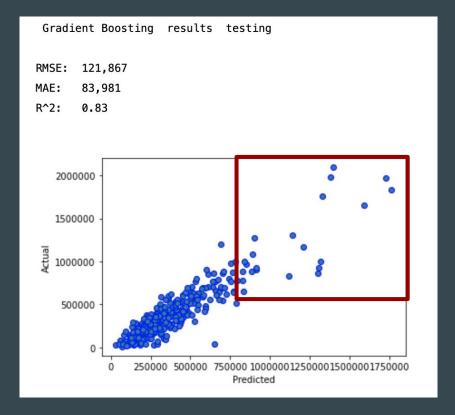


Models Evaluated:

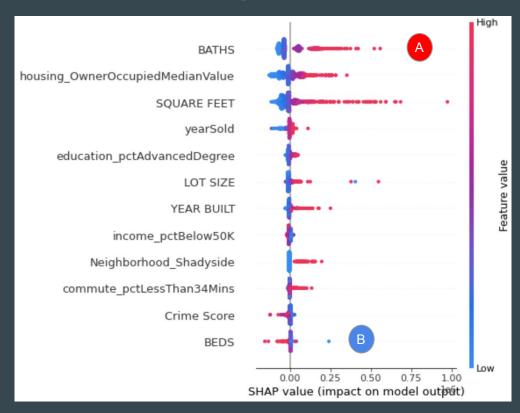
Lasso Ridge Elastic Net Kernel Ridge Bayesian Ridge Decision Tree Random Forest **Gradient Boosting** Multilayer Perceptron Stochastic Gradient Descent

Scikit Learn Champion Model

- Gradient Boosting Champion Model
- MAE and RMSE
- High leverage testing points



Scikit Learn Champion Model



A BATHS is most important feature

B High BEDS -> lowers home price

Modeling Approach

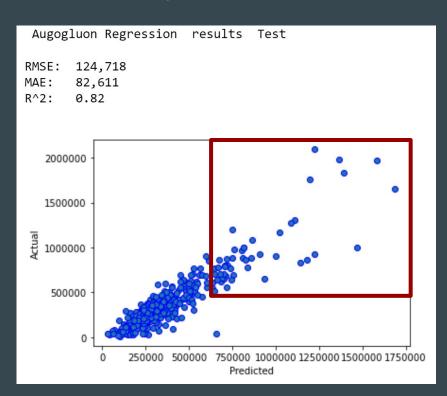


Models Evaluated:

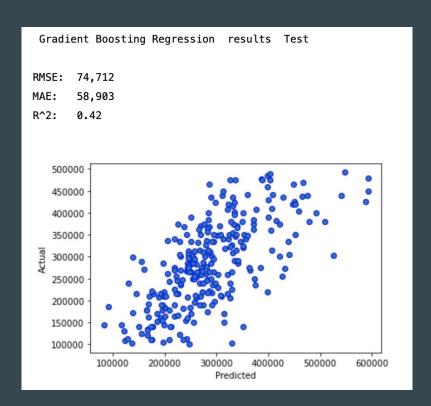
XGBoost CatBoost Extra Trees Light GBM K Neighbors Random Forest Neural Net Fast AI Light GBM Xtreme Weighted Ensemble

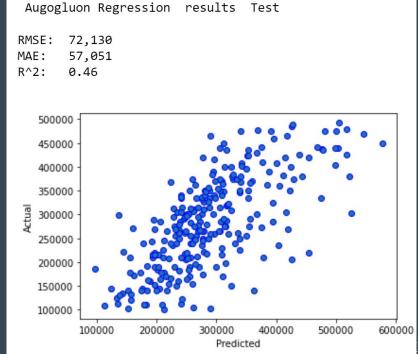
AutoGluon Champion Model (Weighted Ensemble)

Large residuals for properties priced over \$500,000



Limiting Results to Homes to \$100K - \$500K





Results Comparison

Solution Effectiveness

	Baseline Linear Reg	SK Learn GB Regression	AutoGluon Ensemble	
R Squared	0.74	0.83	0.82	1
MAE	\$93,381	\$83,981	\$82,611	1
RMSE	\$137,752	\$121,867	\$124,718	1

Next Steps

Next Steps

- Modeling
 - Computer Vision
 - NLP on Property Descriptions
- Business
 - Expansion to other cities
 - Property investment opportunities

Lesson Learned

- Real World Variability

- New Information is helpful

References

Redfin - https://www.redfin.com/

Pittsburgh School Data - https://nces.ed.gov/ccd/districtsearch/district_detail.asp?ID2=4219170

Pittsburgh Crime Data - https://data.wprdc.org/dataset/uniform-crime-reporting-data

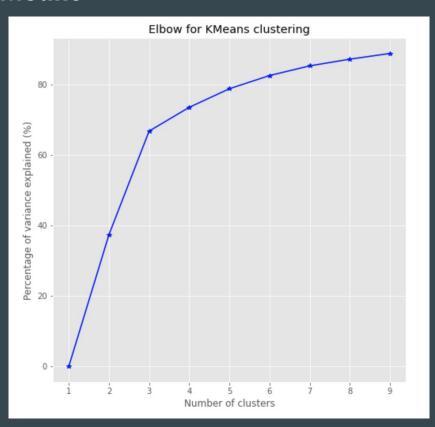
American Census Survey - https://www.census.gov/programs-surveys/acs

Pittsburgh Census Data - https://api.census.gov/data/

Redfin Description

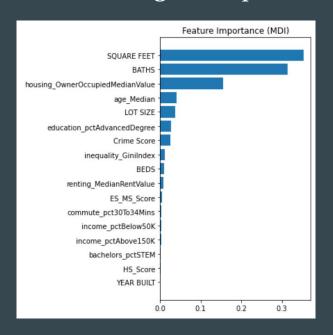
	PRICE	BEDS	BATHS	SQUARE FEET	LOT SIZE	YEAR BUILT	yearSold	monthSold
count	1.989000e+03	1989.000000	1989.000000	1989.000000	1.989000e+03	1989.000000	1989.000000	1989.000000
mean	3.634715e+05	3.356461	2.032931	1868.541981	8.697352e+04	1919.804424	2021.212670	6.885872
std	2.836188e+05	1.101095	0.952755	916.721625	3.706572e+06	28.070127	1.002271	3.052285
min	3.000000e+03	0.000000	0.500000	100.000000	4.300000e+01	1620.000000	2017.000000	1.000000
25%	1.990000e+05	3.000000	1.500000	1288.000000	1.742000e+03	1900.000000	2021.000000	5.000000
50%	2.950000e+05	3.000000	2.000000	1632.000000	2.857000e+03	1915.000000	2021.000000	7.000000
75%	4.420000e+05	4.000000	2.500000	2146.000000	4.356000e+03	1930.000000	2022.000000	9.000000
max	3.150000e+06	10.000000	7.500000	9800.000000	1.653102e+08	2022.000000	2022.000000	12.000000

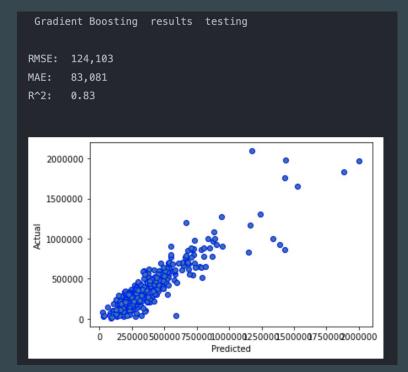
Elbow Plot for K-Means



Scikit Learn Champion Model

Gradient Boosting Champion Model





AutoML Model Summary

	model	score_test	score_val	pred_time_test	pred_time_val	fit_time	pred_time_test_marginal	pred_time_val_marginal
0	KNeighborsDist_BAG_L1	-0.009254	-94503.542167	0.081001	0.079997	0.007003	0.081001	0.079997
1	ExtraTreesMSE_BAG_L1	-32336.244507	-88013.193618	0.340000	0.103001	0.418531	0.340000	0.103001
2	RandomForestMSE_BAG_L1	-32655.529895	-88931.898728	0.323603	0.142521	0.588086	0.323603	0.142521
3	LightGBMLarge_BAG_L1	-35722.490630	-90949.892843	0.255069	0.055046	111.492148	0.255069	0.055046
4	XGBoost_BAG_L1	-48967.557468	-90132.450736	0.463506	0.063006	29.379372	0.463506	0.063006
5	WeightedEnsemble_L2	-50821.279852	-82663.896414	1.560961	0.514040	230.363301	0.010003	0.001000
6	CatBoost_BAG_L2	-54514.490200	-85647.385207	2.529183	0.850601	324.738806	0.046061	0.018027
7	ExtraTreesMSE_BAG_L2	-55107.740047	-86190.300607	2.721129	0.958577	279.030031	0.238007	0.126003
8	RandomForestMSE_BAG_L2	-56376.698633	-87558.457622	2.786123	0.965562	279.304029	0.303001	0.132987
9	WeightedEnsemble_L3	-56626.070952	-83862.584294	3.549666	1.301103	447.021861	0.007999	0.001000
10	XGBoost_BAG_L2	-56730.190265	-89000.715616	2.671115	0.902619	303.194270	0.187993	0.070045
11	LightGBMXT_BAG_L2	-57072.669427	-85215.750754	2.840119	0.924579	360.717721	0.356997	0.092004
12	LightGBM_BAG_L2	-60027.630535	-88874.699325	2.530123	0.851135	294.348327	0.047001	0.018560
13	NeuralNetFastAI_BAG_L2	-60871.639785	-86811.756196	2.900602	1.064069	318.197394	0.417480	0.231495
14	LightGBM_BAG_L1	-63967.901916	-87909.295392	0.062057	0.018015	18.406258	0.062057	0.018015
15	LightGBMXT_BAG_L1	-65497.239355	-86761.932689	0.121130	0.030996	18.518195	0.121130	0.030996
16	NeuralNetFastAl_BAG_L1	-67531.790104	-85544.692577	0.624768	0.226999	38.902772	0.624768	0.226999
17	CatBoost_BAG_L1	-75030.357181	-88919.960555	0.128991	0.017002	60.877663	0.128991	0.017002
18	KNeighborsUnif_BAG_L1	-77579.979509	-95760.004733	0.082997	0.095992	0.007006	0.082997	0.095992
4								

Variables Selected

```
B19001_001E -> income_Total
B01002_001E -> age_Median
B25109_001E -> housing_OwnerOccupiedMedianValue
                                                        B19001_002E -> income_LessThan10K
B25111_001E -> renting_MedianRentValue
                                                        B19001_003E -> income_10Kto15K
B08134_001E -> commute_Total
                                                        B19001_004E -> income_15Kto20K
B08134_007E -> commute_30to34mins
                                                        B19001_005E -> income_20Kto25K
B15012_001E -> bachelors_Total
                                                        B19001_006E -> income_25Kto30K
B15012_009E -> bachelors_STEM
                                                        B19001_007E -> income_30Kto35K
B15003_001E -> education_Total
                                                        B19001_008E -> income_35Kto40K
B15003_023E -> education_MasterDegree
                                                        B19001_009E -> income_40Kto45K
B15003_024E -> education_ProfessionalDegree
                                                        B19001_010E -> income_45Kto50K
B15003_025E -> education_DoctorateDegree
                                                        B19001_014E -> income_100Kto125K
B19083_001E -> inequality_GiniIndex
                                                        B19001_015E -> income_125Kto150K
                                                        B19001_016E -> income_150Kto200K
                                                        B19001_017E -> income_200KOrMore
```