



AAI 500: Final Project

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Project Overview

Data set: Redfin data about house sales

Our goal



Predict the price of a house using
multiple linear regression





Data Set Overview

Data Set Size: 300 rows, 27 columns

Data Types

Categorical: Zip Code, City, Location, Property Type, State

Numerical: Price, Beds, Baths, Square Feet, Lot Size, Year Built



Data Set Details

Data Set Size: 300 rows, 27 columns

Categoricals	
Zip	5 zips: 92037, 92127, 91942, 92122, 92067
City	5 cities: La Jolla, San Diego, La Mesa, Rancho Santa Fe, Rancho Bernardo
Location	Provided by two columns: longitude and latitude
Property Type	5 types: Single Family, Condo, Townhouse, Vacant Land, Multi-Family
State	All in California



Data Set Details

Data Set Size: 300 rows, 27 columns

Numericals				
Category	Mean	Min	Max	Std Deviation
Price	\$3,237,747	\$369,000	\$45,000,000	\$4,735,400
Sq Feet	2806.9	432	22,897	2410.73
Beds	3.49	0	10	1.62
Baths	3.2	1	12.5	1.85
Year Built	1984	1920	2022	23.16

Data Cleaning





Dropping Data

- Drop columns with data that is irrelevant to the price (eg. time of next open house, state)
- Drop columns missing information (eg. Sold Date)
- Drop columns that have redundant information (eg. Address, since location is the same information, and easier to work with)
- Drop instances of vacant land, as it is a different type of asset. All other properties include a dwelling.



Data Cleaning

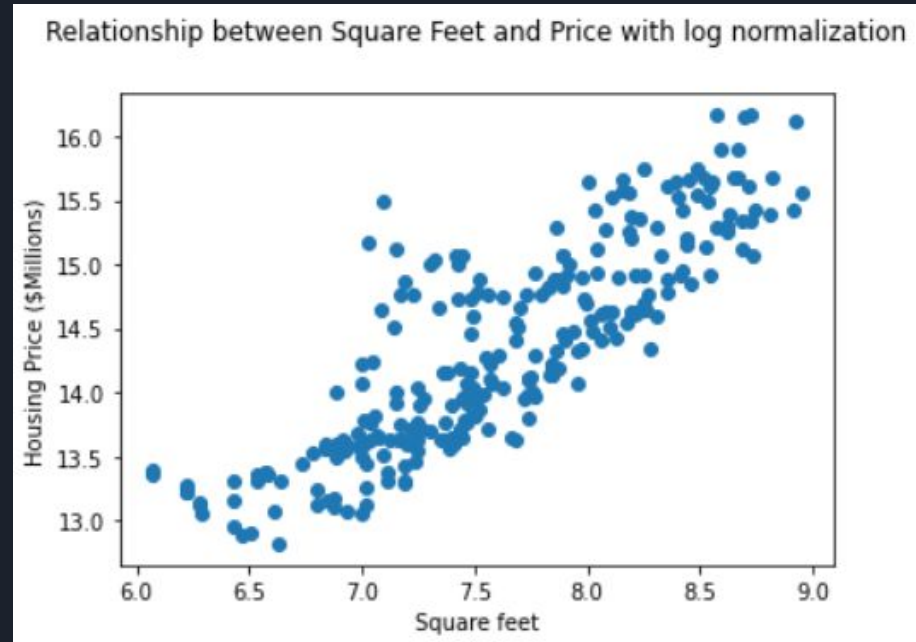
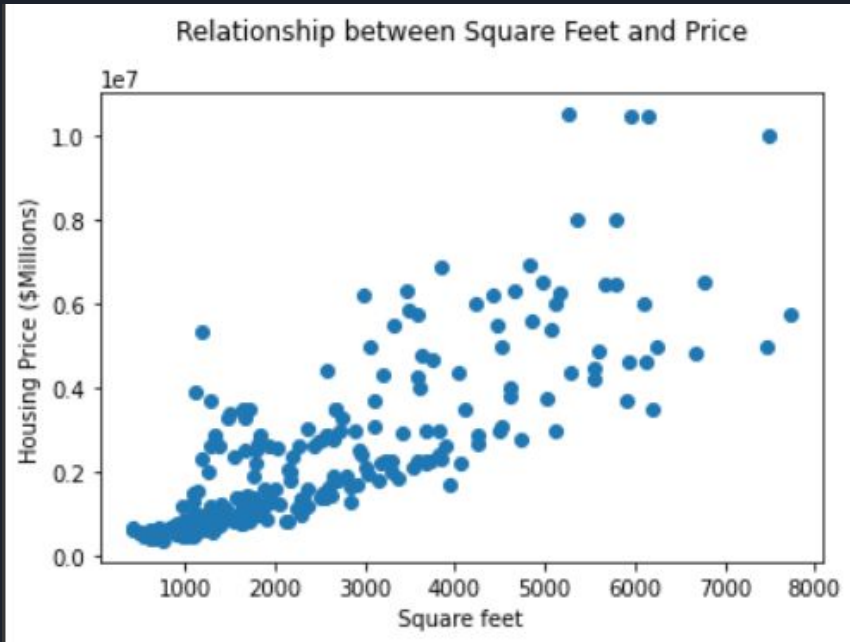
Removing outliers

In order to account for outliers we removed all observations where the value was greater than 2.5 standard deviations from the mean

Normalizing data

We normalized the price and square feet columns by using Numpy log function

Square Feet vs Price





Data Set Details After Cleaning

Data Set Size: 300 rows, 27 columns

Numericals				
Category	Mean	Min	Max	Std Deviation
Price	\$2,338,521	\$369,000	\$10,500,000	\$2,006,316
Sq Feet	2473.64	432	7,722	1604.33
Beds	3.41	0	7	1.39
Baths	3	1	7.5	1.47
Home Age	36.71	0	90	22.82

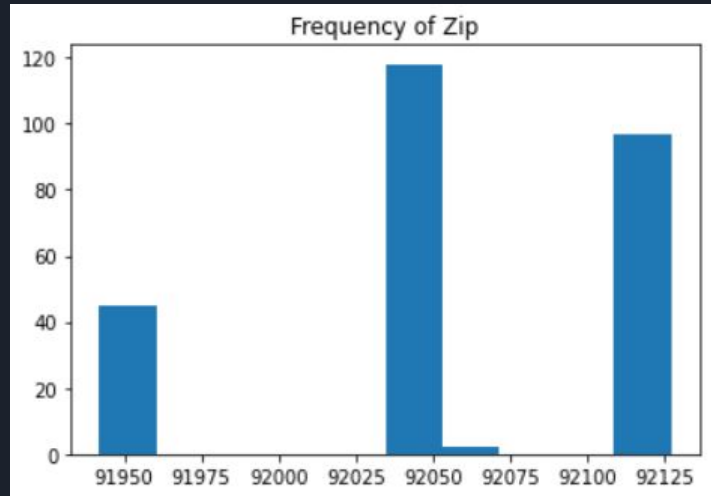
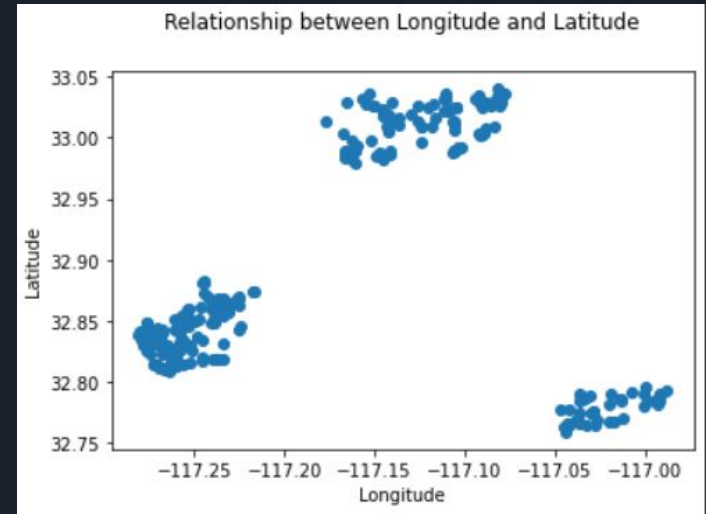
Data Cleaning

Variable Transformations:

-Transform year built into house age by subtracting the value from 2022.

-Create dummy categorical variable for house age → New houses and old houses.

-Create dummy categorical variable for longitude and latitude → 3 categories

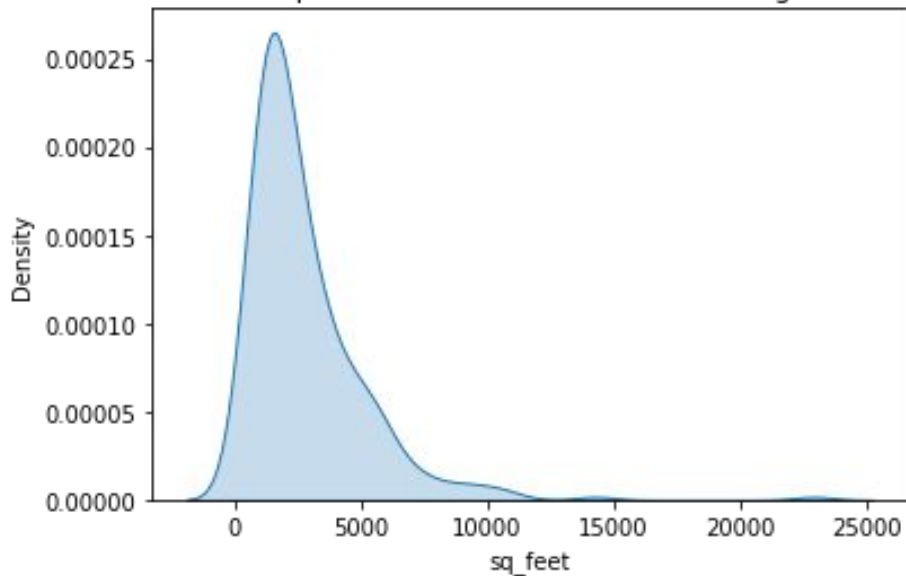


DESCRIPTIVE DATA

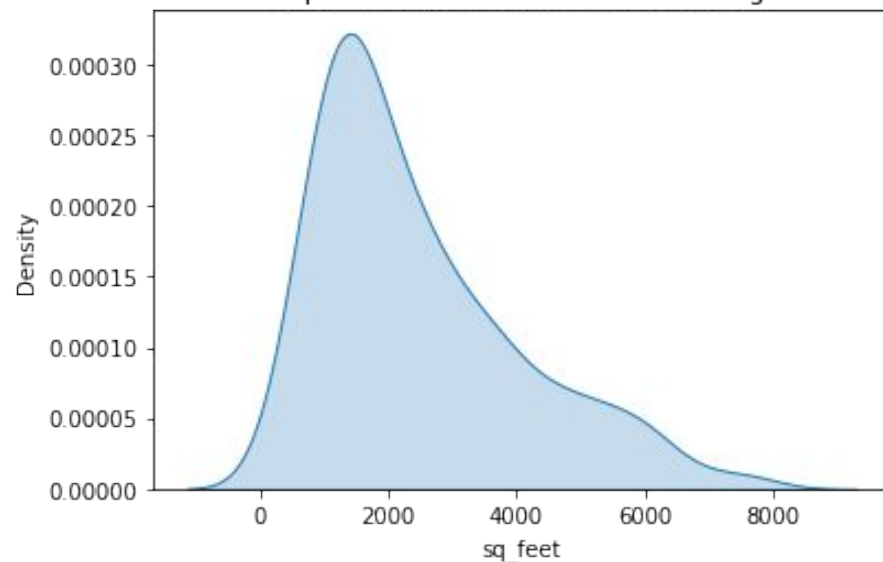


Square Feet

Square Feet PDF Before Data Cleaning

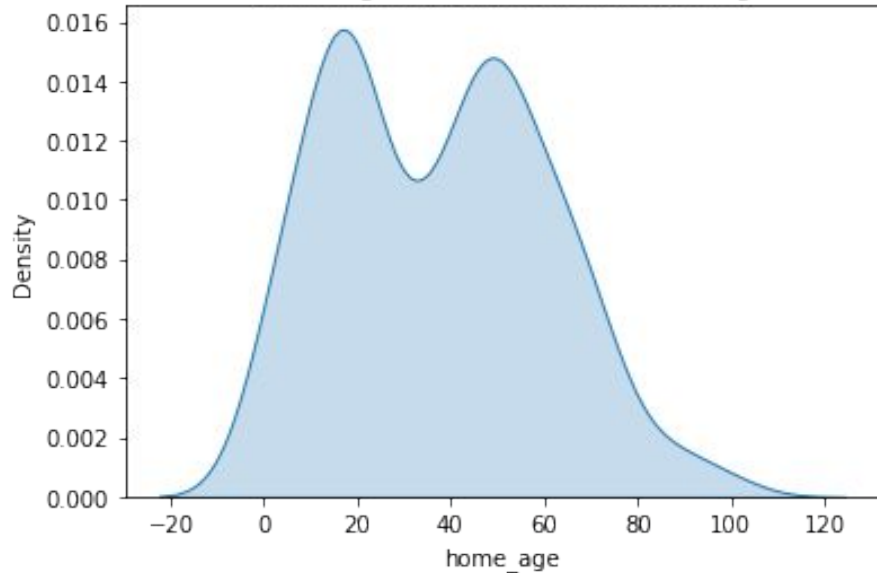


Square Feet PDF After Data Cleaning

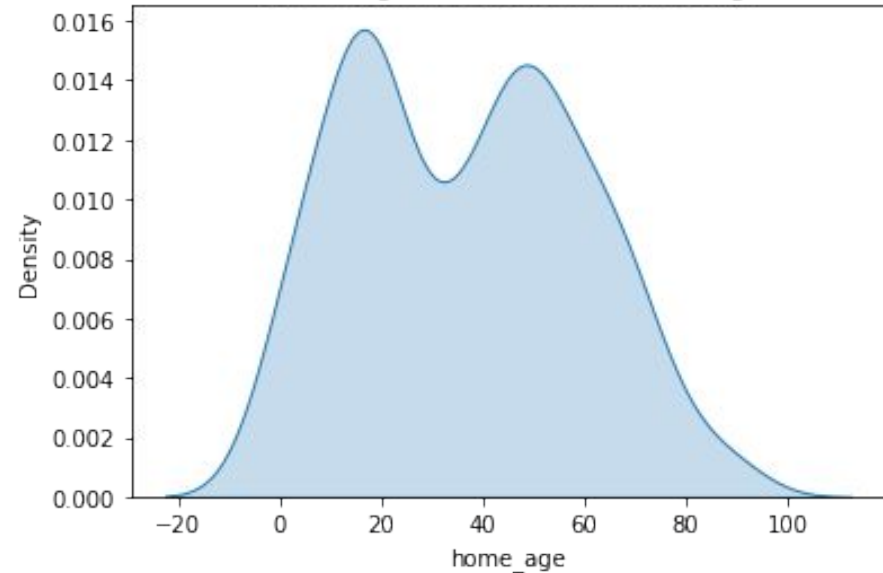


Home Age

Home Age PDF Before Data Cleaning

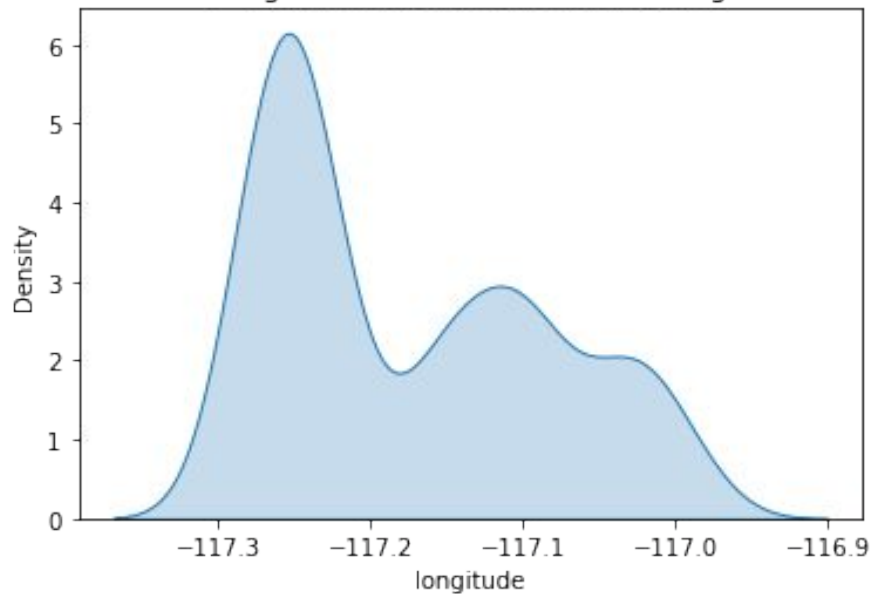


Home Age PDF After Data Cleaning

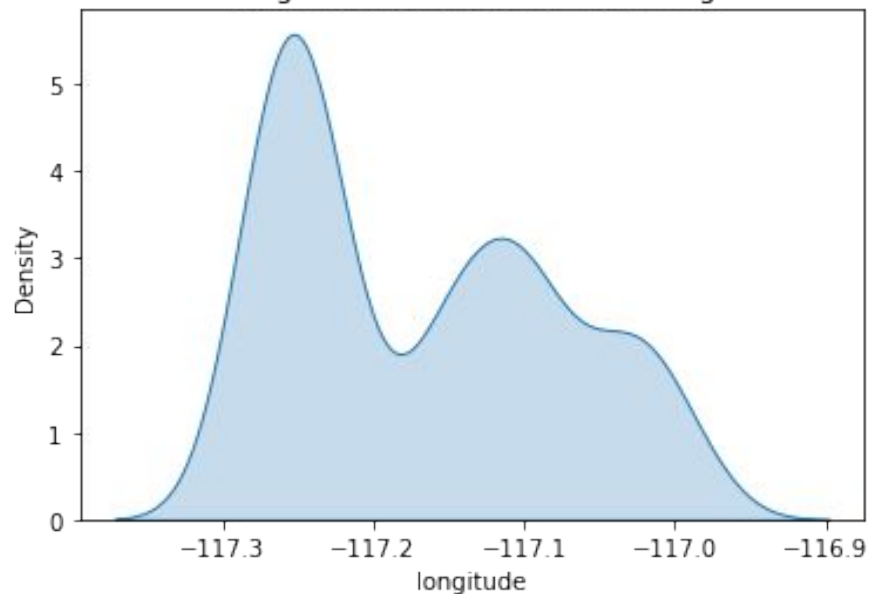


Longitude

Longitude PDF Before Data Cleaning

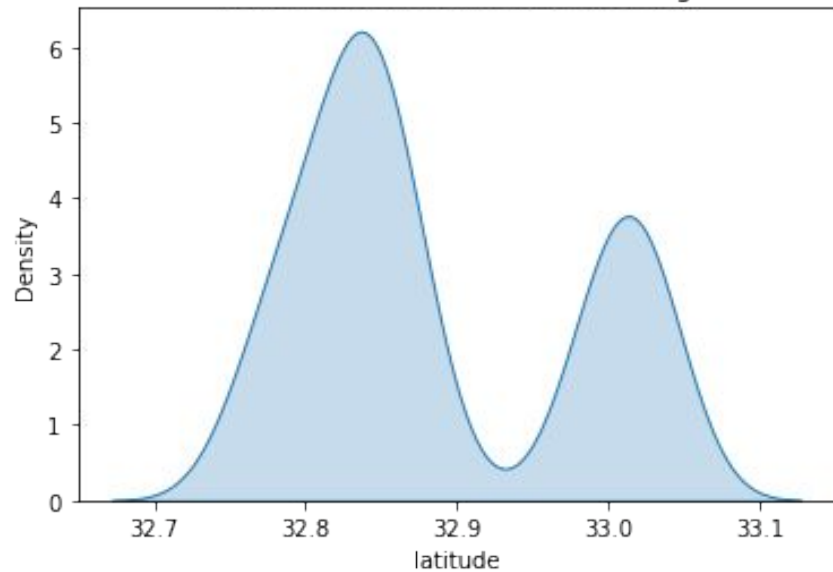


Longitude PDF After Data Cleaning

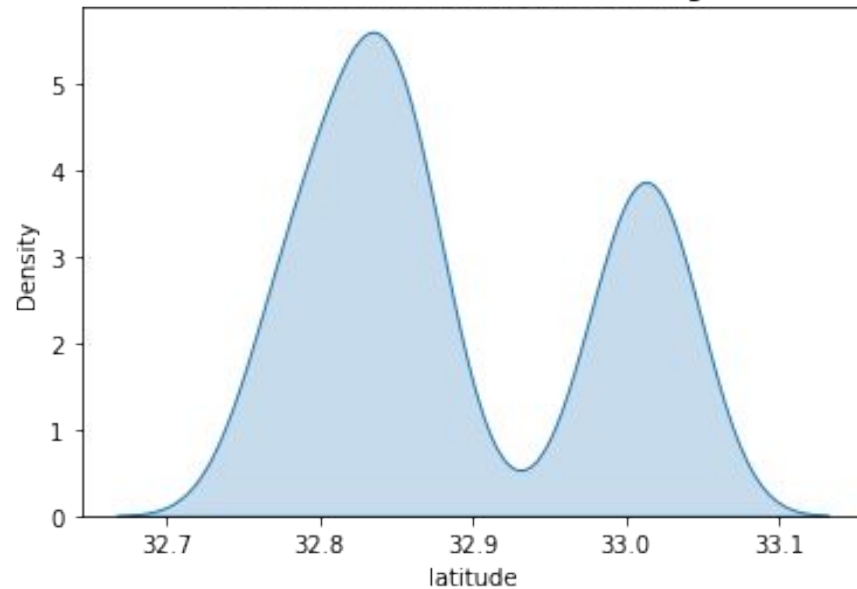


Latitude

Latitude PDF Before Data Cleaning

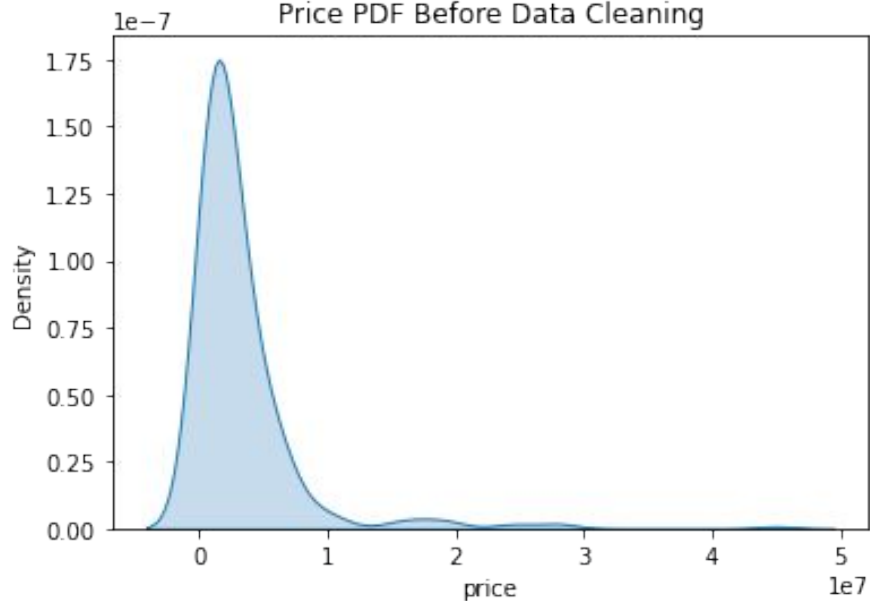


Latitude PDF After Data Cleaning

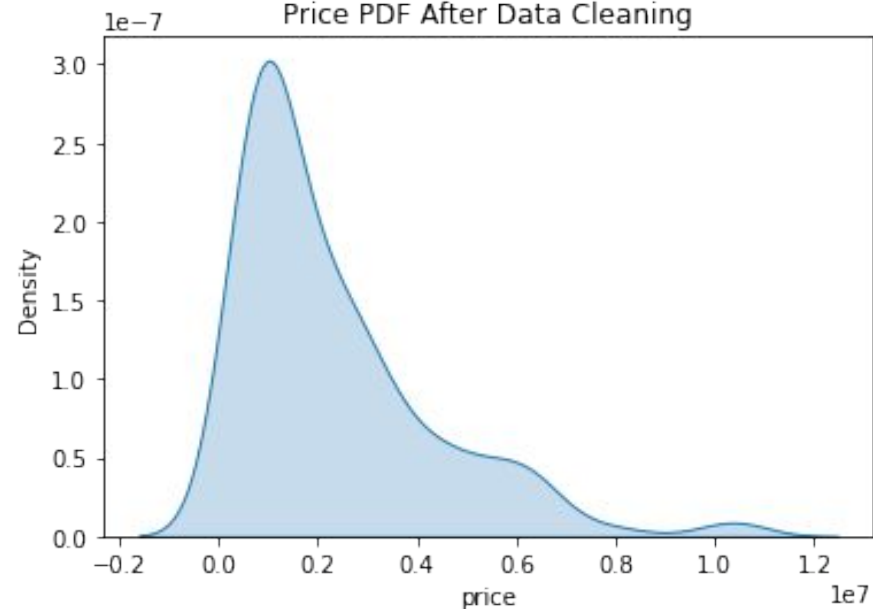


House Price

Price PDF Before Data Cleaning



Price PDF After Data Cleaning





Type of Distributions

Multimodal:

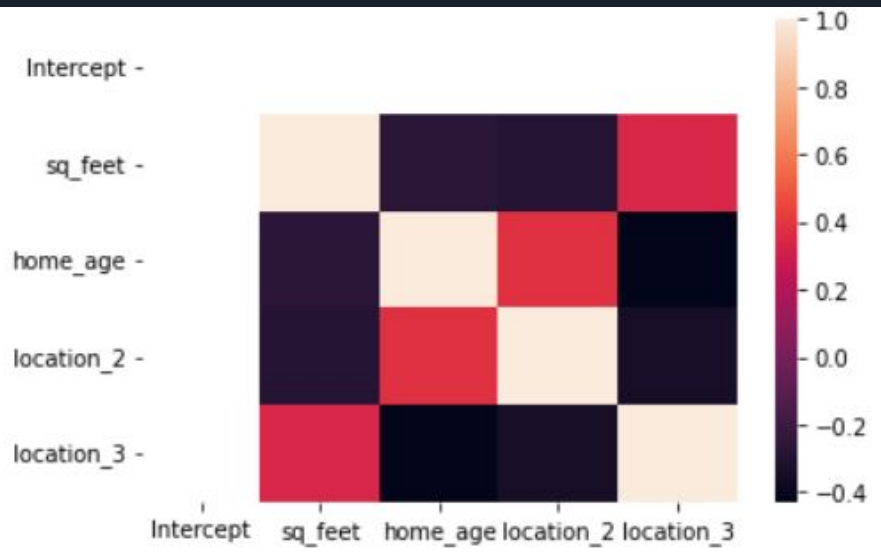
- Home Age (Bimodal),
- Longitude
- Latitude (Bimodal)

Log-Normal:

- Square Feet
- Price

Variable Relationships

Correlation Heat-Map



VIF Scores

	VIF	variable
0	157.620893	Intercept
1	1.189228	sq_feet
2	1.340798	home_age
3	1.259221	location_2
4	1.356345	location_3

Based on these results we can conclude that there is little multicollinearity and that the independent variables have a relationship to the dependent variable for our final model.

Model Results



Model Summary

OLS Regression Results

```
=====
Dep. Variable:          price    R-squared:                0.868
Model:                  OLS      Adj. R-squared:            0.865
Method:                 Least Squares    F-statistic:          334.5
Date:                  Sun, 23 Oct 2022    Prob (F-statistic):    2.26e-88
Time:                  05:36:51    Log-Likelihood:       -39.368
No. Observations:      209        AIC:                  88.74
Df Residuals:          204        BIC:                  105.4
Df Model:               4
Covariance Type:       nonrobust
=====
```

```
=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
const          6.5647      0.257      25.566      0.000       6.058       7.071
sq_feet        1.0569      0.034      31.463      0.000       0.991       1.123
home_age_50.0   0.1484      0.050       2.967      0.003       0.050       0.247
location_2.0   -0.7354      0.059     -12.483      0.000      -0.852      -0.619
location_3.0   -0.5243      0.050     -10.424      0.000      -0.623      -0.425
=====
```

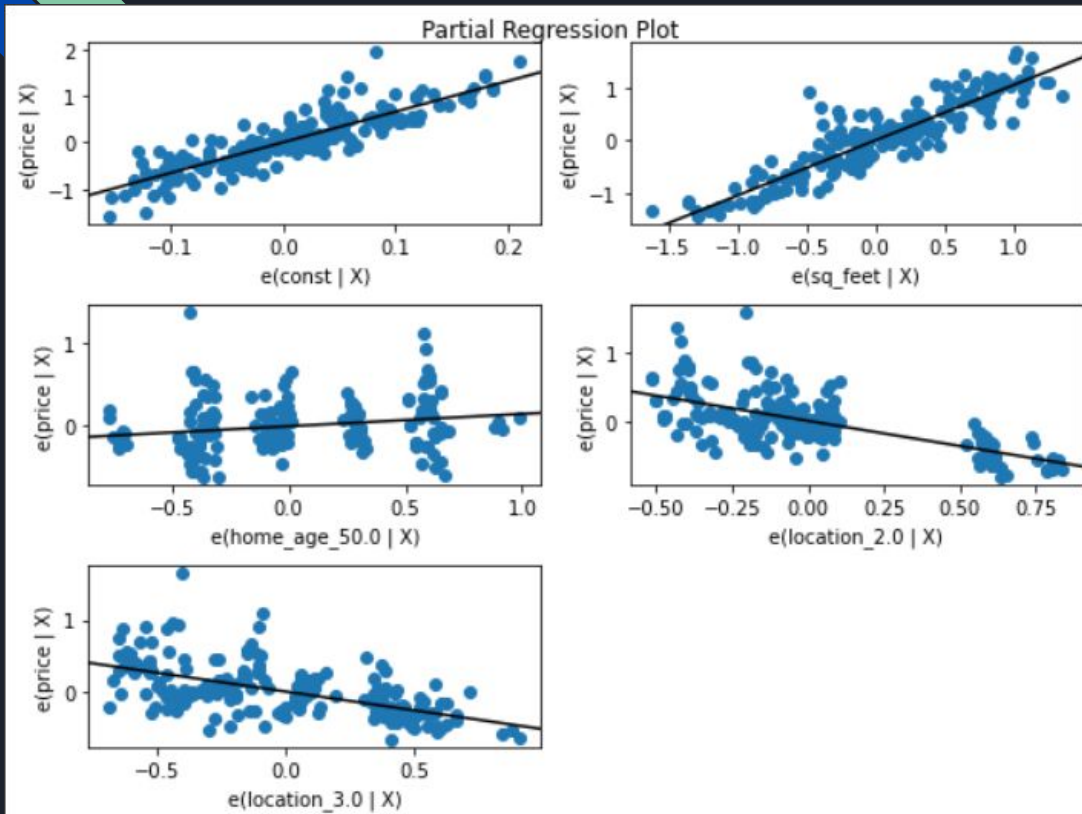
```
=====
Omnibus:          48.556    Durbin-Watson:           1.815
Prob(Omnibus):    0.000    Jarque-Bera (JB):        111.105
Skew:             1.058    Prob(JB):                7.48e-25
Kurtosis:         5.877    Cond. No.                 97.6
=====
```

- $R^2 = 0.868$
- P-values are less than 0.05 for all variables

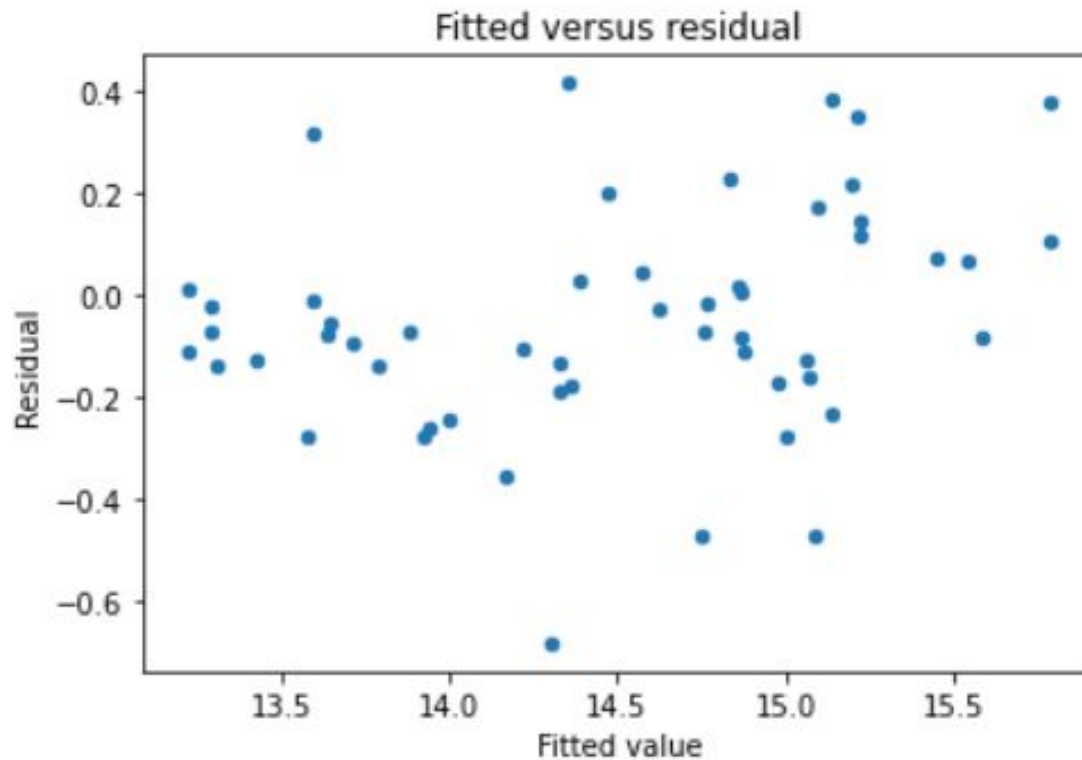
Equation:

$$y = X_1 1.0569 + X_2 0.1484 - X_3 0.7354 - X_4 0.5243 + 6.5647$$

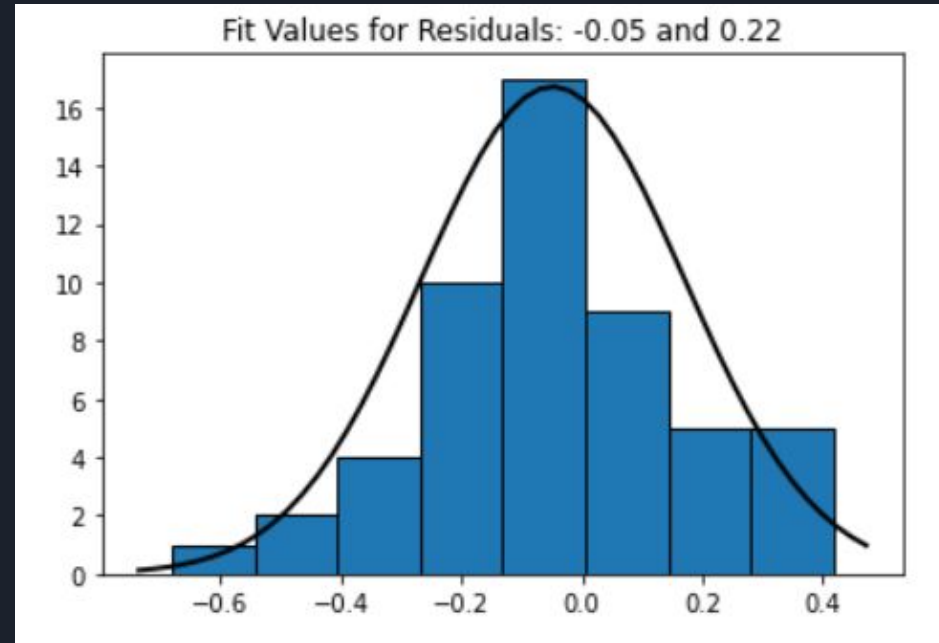
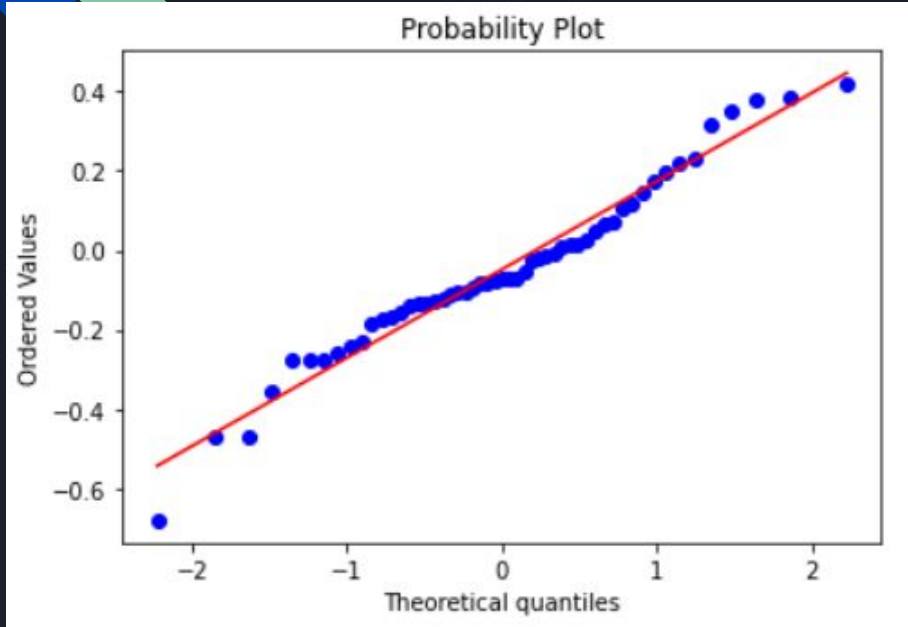
Partial Regression Graph



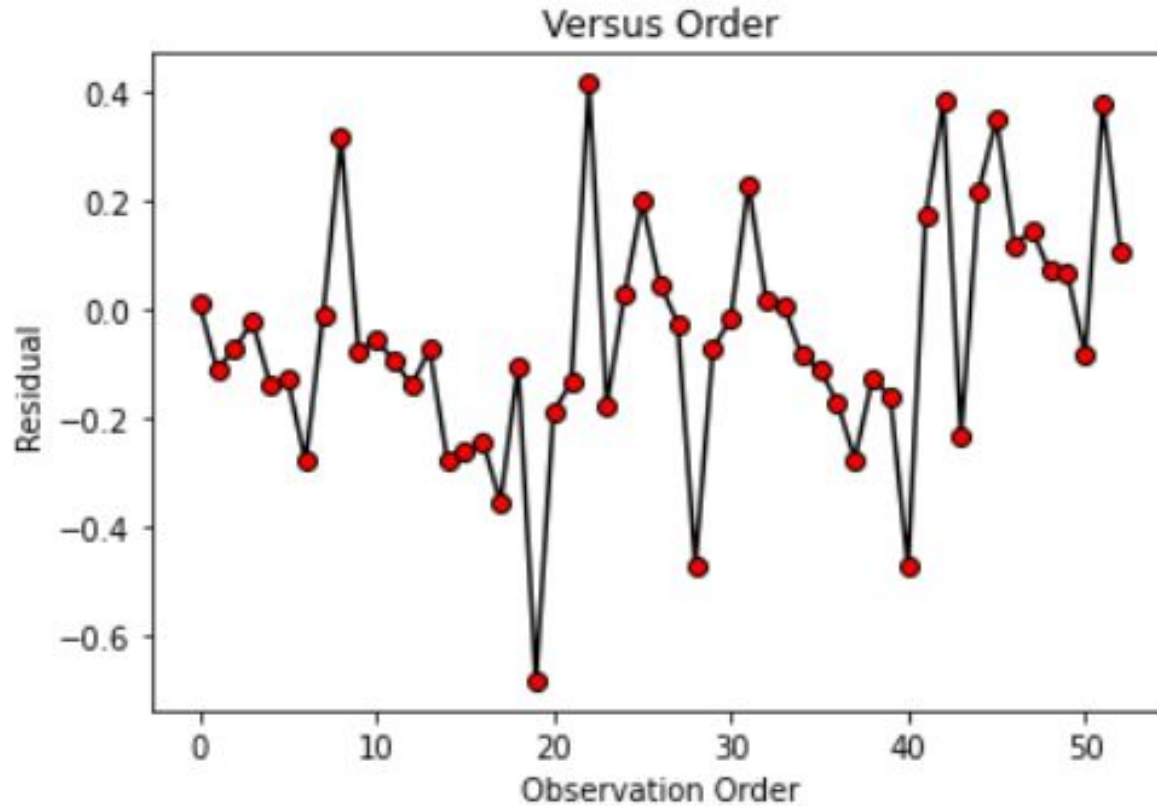
Model Residuals



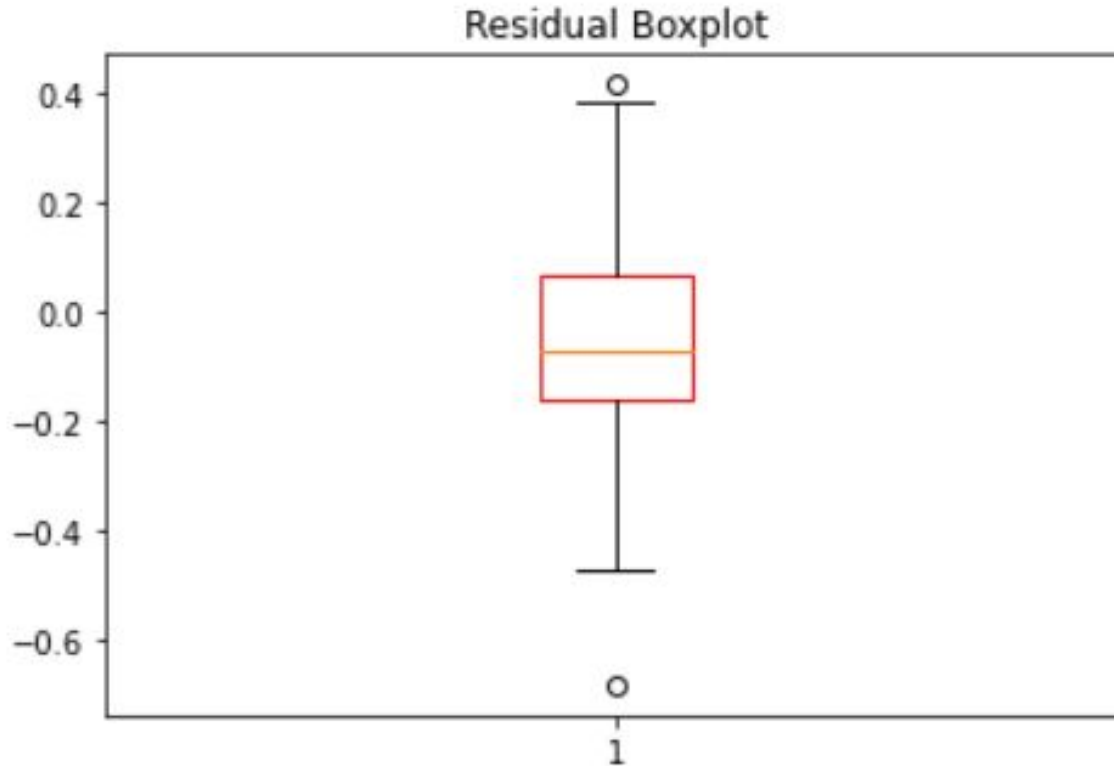
Model Residuals



Model Residuals



Model Residuals



Conclusion





Interpretation

- Overall the high R^2 and the low p-values indicate the statistical significance of the model.
- However outliers evident in the residual plots have decreased the predictive power of the model in some situations.



Improvements

- In order to improve this model there needs to be a closer examination of outliers and our filtering of those extreme values
- Analyzing for leverage on certain variables could help reduce outliers since these values could have a negative impact on our model
- One type of predictor that would have been valuable is economic data (eg. inflation rates), this would help improve accuracy overtime because changing economic conditions can affect house prices.

Thank You For Listening!

