House Price Regression Modelling Project

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Summary

The purpose of this regression model is to predict the house prices in King County by analysing the King County House Sales dataset.

Outline

- Business Problem
- Cleaning the Data
- Exploratory Data Analysis
- Models
- Conclusions

Business Problem

How can we predict the house price sales in King County?

In order to solve this problem, I intended to answer the below questions:

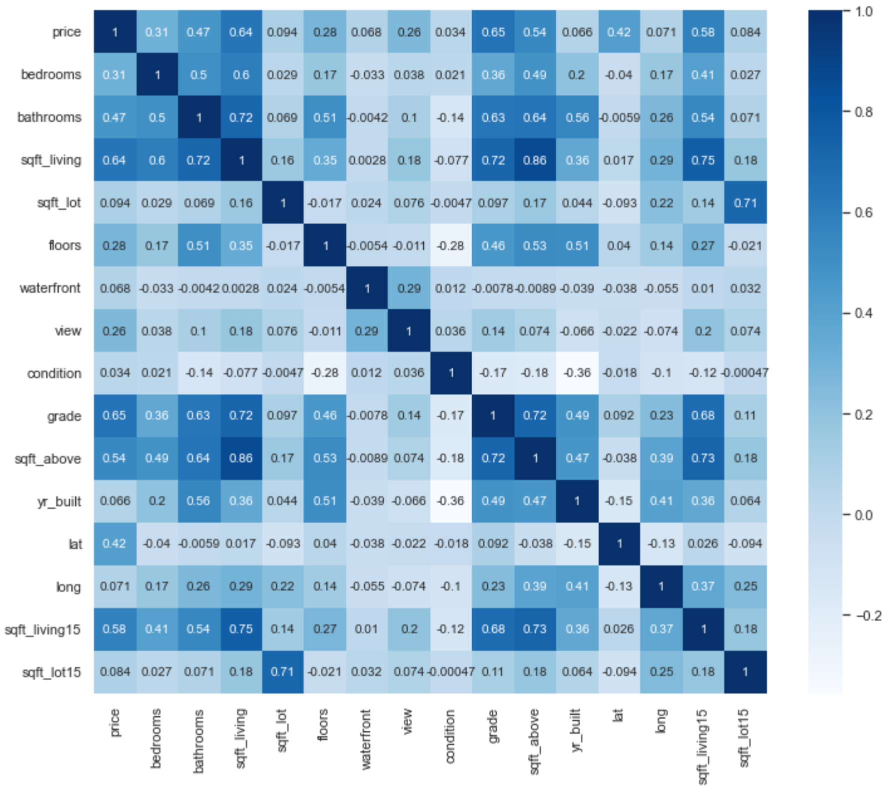
1. Does location impact sale price?
2. Does the size of the house impact sale price?
3. Does quality of the house impact sale price?

Cleaning the Data

- Dropped unnecessary data
- Replaced or removed null values
- Narrowed data to only included houses with <6 bedrooms
- Using the empirical formula I removed outliers
- Addressed multicollinearity
- Split data set between continuous and categorical data
- Binned Grade into Low, Average and High

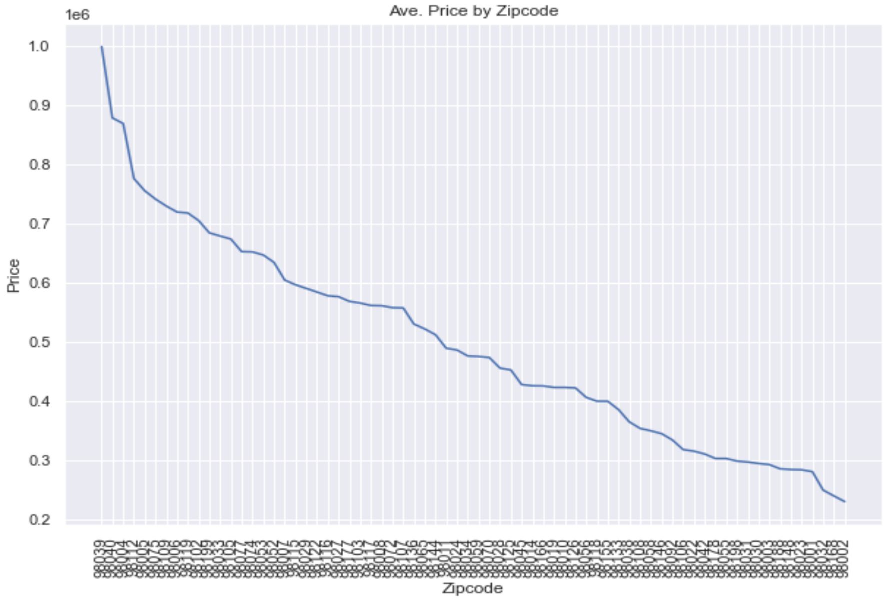
Exploratory Data Analysis

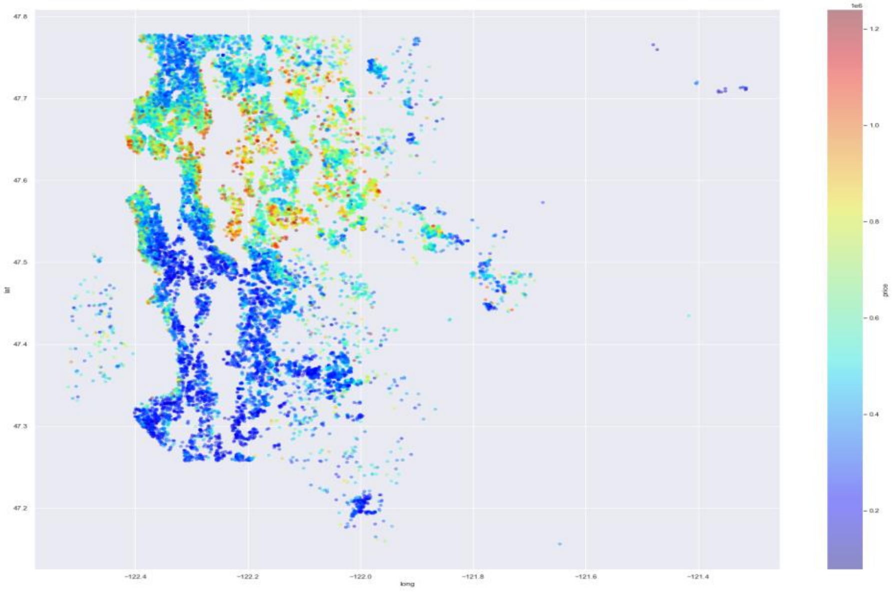
- Key Features include:
  - Bathrooms
  - Square Foot living space
  - Grade
  - Latitude
  - Square Foot Above
  - Square Foot Living 15 (neighbors)
- Notes:
  - Zip code excluded as data-type is a string
  - Latitude correlates with price more than Longitude



Exploratory Data Analysis

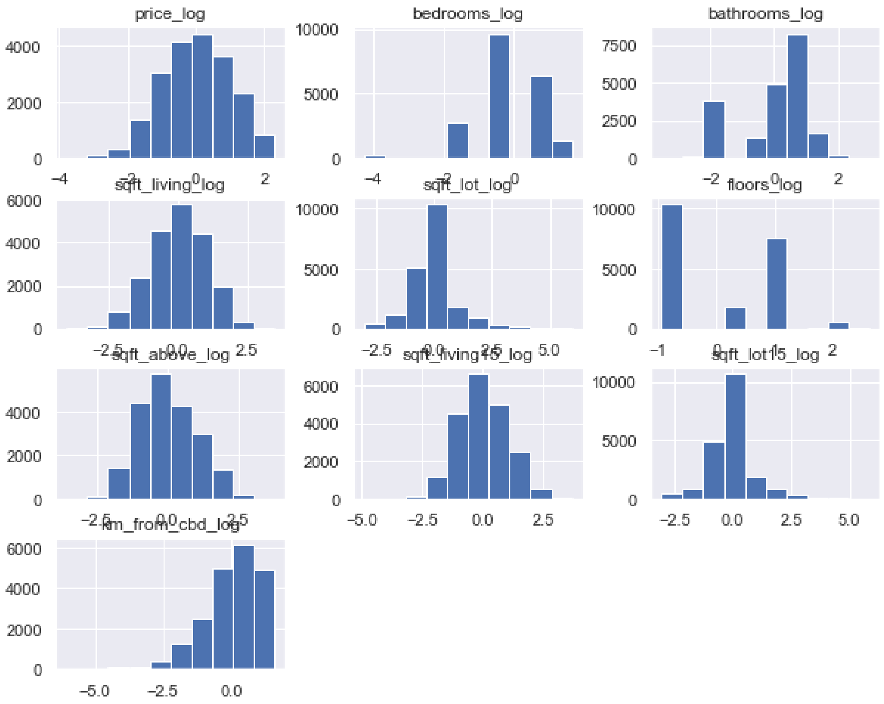
- Created price vs zip code graph to explore price distribution across zip codes and then plotted to a heatmap.
- Using these visualization I created a new variable – Distance from CBD





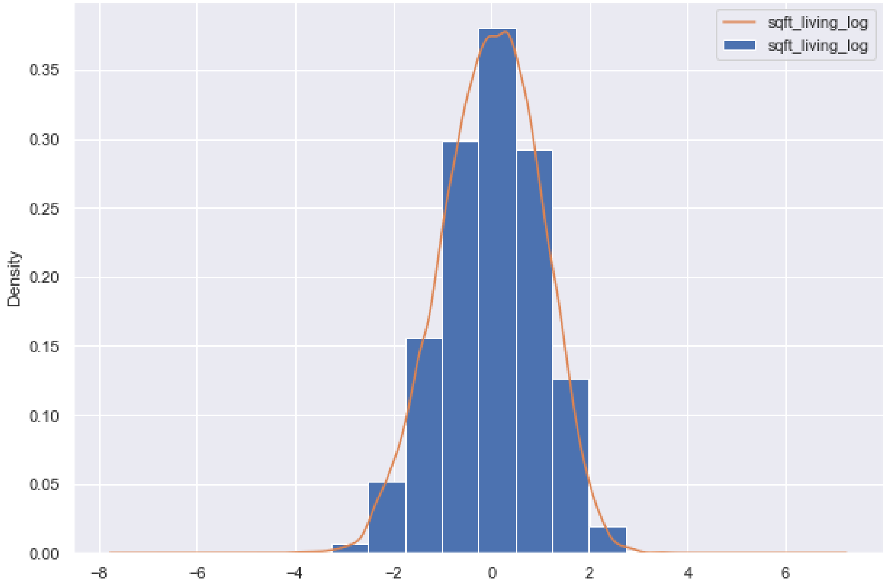
Exploratory Data Analysis

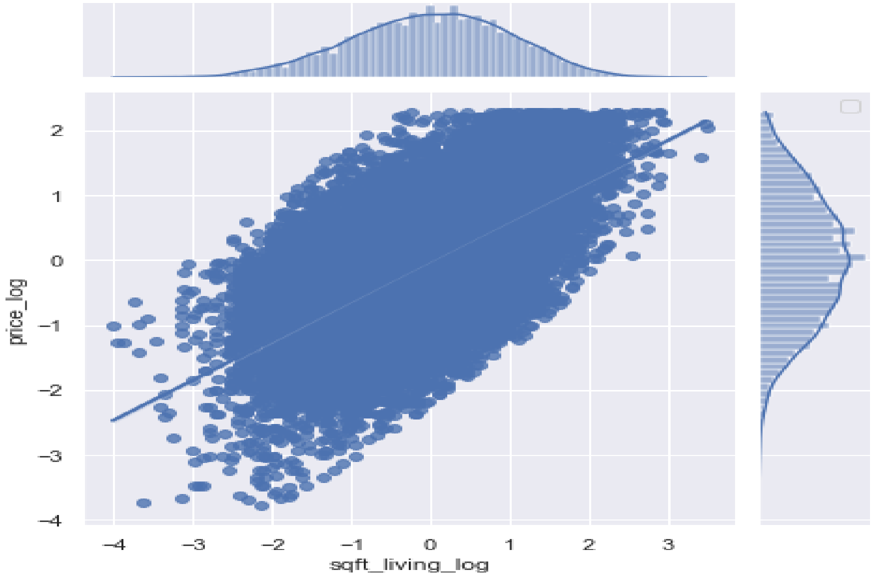
- Used mean normalization to standardise the data
- Sqft living, sqft lot, sqft above, sqft living 15, sqft lot 15 appear good
- Km from CBD is negatively skewed



Exploratory Data Analysis

- Used KDE plot and joint plot to explore data





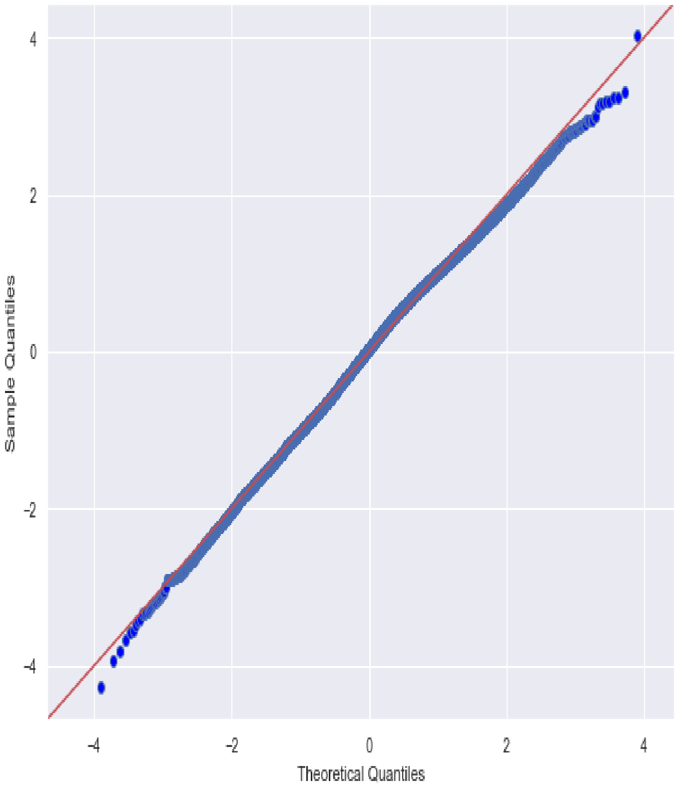
Model 1

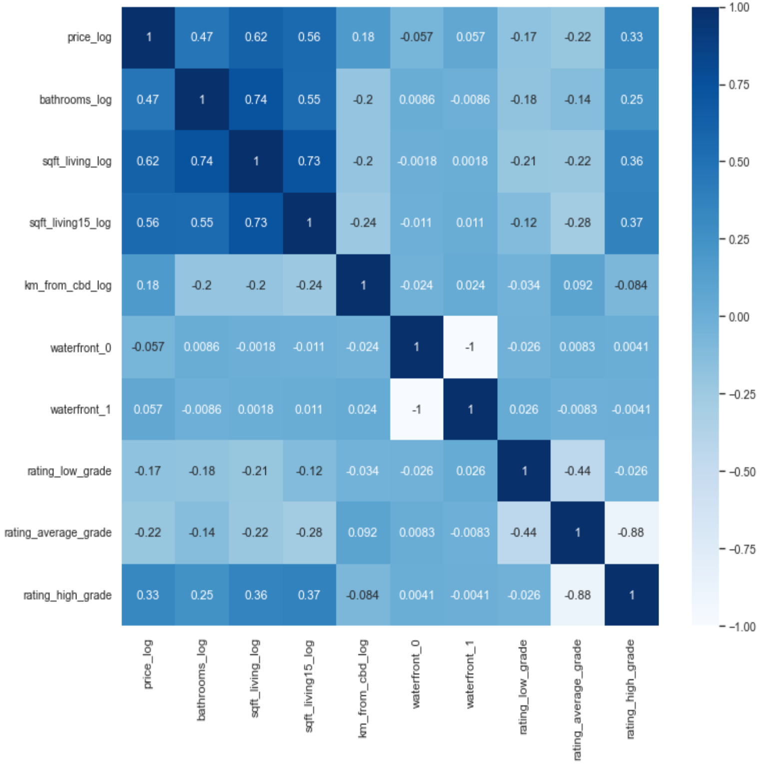
OLS Regression Results

Dep. Variable:	price_log	R-squared:	0.527
Model:	OLS	Adj. R-squared:	0.527
Method:	Least Squares	F-statistic:	3244.
Date:	Fri, 03 Jun 2022	Prob (F-statistic):	0.00
Time:	10:23:16	Log-Likelihood:	-21322.
No. Observations:	20407	AIC:	4.266e+04
Df Residuals:	20399	BIC:	4.272e+04
Df Model:	7		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0273	0.012	2.268	0.023	0.004	0.051
bathrooms_log	0.0632	0.007	8.810	0.000	0.049	0.077
sqft_living_log	0.3877	0.009	43.476	0.000	0.370	0.405
sqft_living15_log	0.2796	0.007	38.529	0.000	0.265	0.294
km_from_cbd_log	0.3396	0.005	67.982	0.000	0.330	0.349
waterfront_1	0.8624	0.089	9.685	0.000	0.688	1.037
rating_low_grade	-0.3423	0.034	-10.215	0.000	-0.408	-0.277
rating_average_grade	-0.0493	0.013	-3.929	0.000	-0.074	-0.025
rating_high_grade	0.4189	0.021	19.581	0.000	0.377	0.461

Omnibus:	92.698	Durbin-Watson:	1.990
Prob(Omnibus):	0.000	Jarque-Bera (JB):	90.193
Skew:	-0.144	Prob(JB):	2.60e-20
Kurtosis:	2.848	Cond. No.	7.34e+15





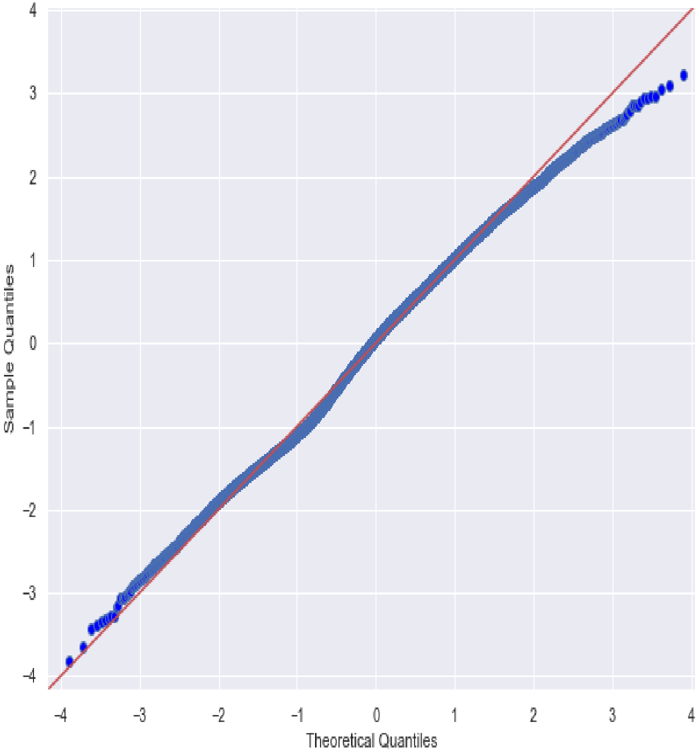
Model 2

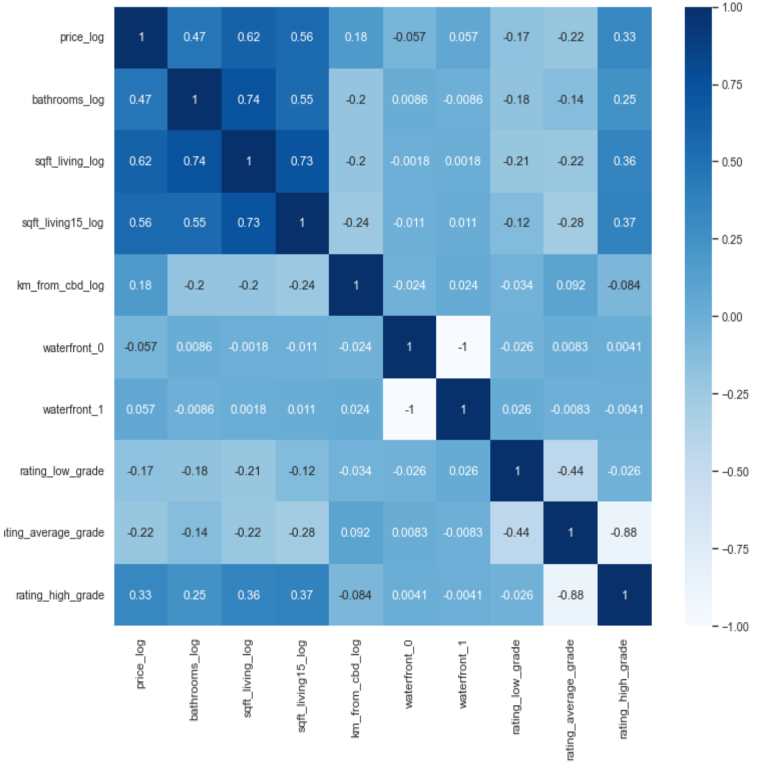
OLS Regression Results

Dep. Variable:	price_log	R-squared:	0.413
Model:	OLS	Adj. R-squared:	0.413
Method:	Least Squares	F-statistic:	3592.
Date:	Fri, 03 Jun 2022	Prob (F-statistic):	0.00
Time:	10:23:18	Log-Likelihood:	-23516.
No. Observations:	20407	AIC:	4.704e+04
Df Residuals:	20402	BIC:	4.708e+04
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-0.0235	0.006	-4.259	0.000	-0.034	-0.013
bathrooms_log	0.0280	0.008	3.521	0.000	0.012	0.044
sqft_living_log	0.4062	0.010	41.272	0.000	0.387	0.425
sqft_living15_log	0.2075	0.008	25.980	0.000	0.192	0.223
rating_high_grade	0.4723	0.027	17.611	0.000	0.420	0.525

Omnibus:	305.924	Durbin-Watson:	1.969
Prob(Omnibus):	0.000	Jarque-Bera (JB):	187.564
Skew:	-0.072	Prob(JB):	1.87e-41
Kurtosis:	2.553	Cond. No.	7.71





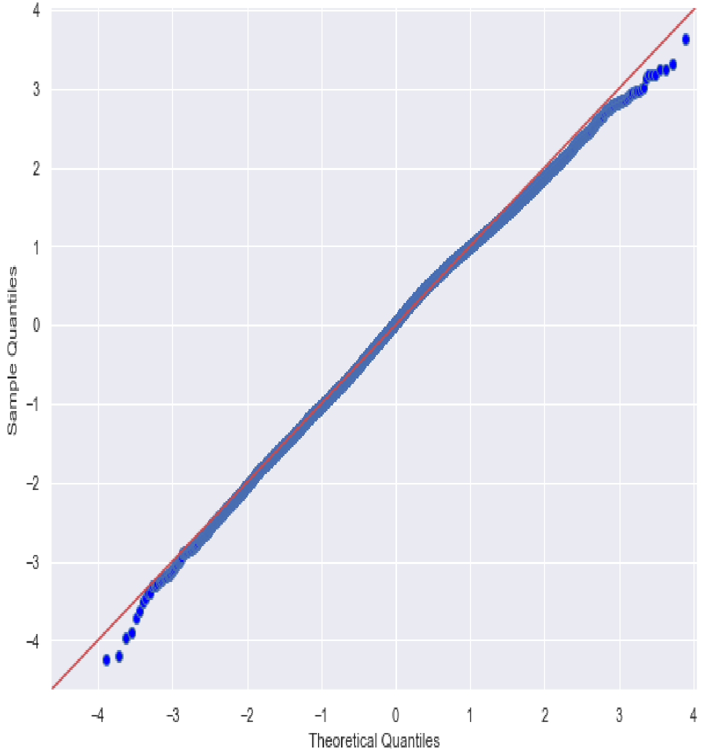
Model 3

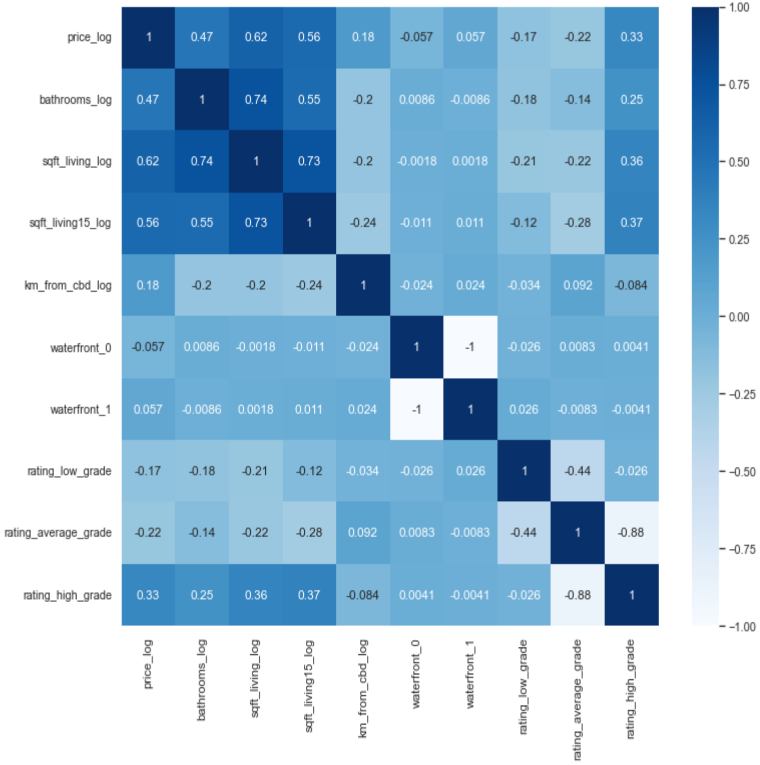
OLS Regression Results

Dep. Variable:	price_log	R-squared:	0.524
Model:	OLS	Adj. R-squared:	0.524
Method:	Least Squares	F-statistic:	4485.
Date:	Fri, 03 Jun 2022	Prob (F-statistic):	0.00
Time:	10:23:18	Log-Likelihood:	-21390.
No. Observations:	20407	AIC:	4.279e+04
Df Residuals:	20401	BIC:	4.284e+04
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.0229	0.005	-4.593	0.000	-0.033	-0.013
sqft_living15_log	0.2791	0.007	38.373	0.000	0.265	0.293
sqft_living_log	0.3956	0.009	44.604	0.000	0.378	0.413
km_from_cbd_log	0.3434	0.005	68.749	0.000	0.334	0.353
rating_high_grade	0.4590	0.024	18.991	0.000	0.412	0.506
bathrooms_log	0.0645	0.007	8.973	0.000	0.050	0.079

Omnibus:	92.684	Durbin-Watson:	1.993
Prob(Omnibus):	0.000	Jarque-Bera (JB):	91.160
Skew:	-0.149	Prob(JB):	1.60e-20
Kurtosis:	2.863	Cond. No.	7.86

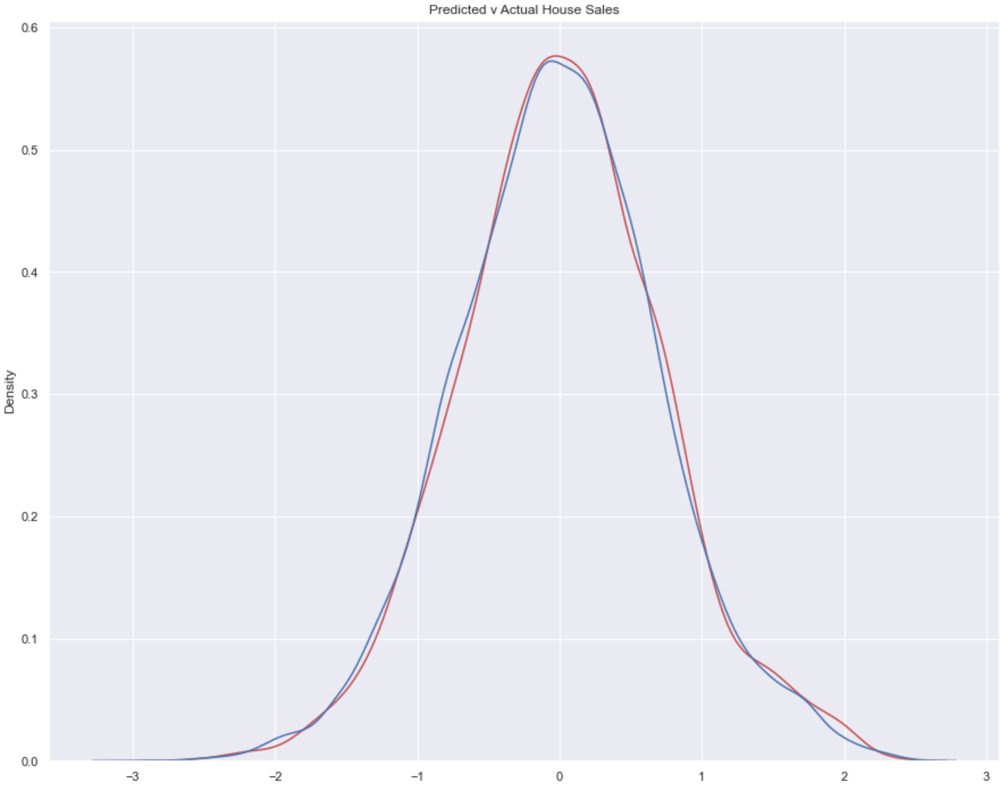




	price_log	bathrooms_log	sqft_living_log	sqft_living15_log	km_from_cbd_log	waterfront_0	waterfront_1	rating_low_grade	rating_average_grade	rating_high_grade
price_log	1	0.47	0.62	0.56	0.18	-0.057	0.057	-0.17	-0.22	0.33
bathrooms_log	0.47	1	0.74	0.55	-0.2	0.0086	-0.0086	-0.18	-0.14	0.25
sqft_living_log	0.62	0.74	1	0.73	-0.2	-0.0018	0.0018	-0.21	-0.22	0.36
sqft_living15_log	0.56	0.55	0.73	1	-0.24	-0.011	0.011	-0.12	-0.28	0.37
km_from_cbd_log	0.18	-0.2	-0.2	-0.24	1	-0.024	0.024	-0.034	0.092	-0.084
waterfront_0	-0.057	0.0086	-0.0018	-0.011	-0.024	1	-1	-0.026	0.0083	0.0041
waterfront_1	0.057	-0.0086	0.0018	0.011	0.024	-1	1	0.026	-0.0083	-0.0041
rating_low_grade	-0.17	-0.18	-0.21	-0.12	-0.034	-0.026	0.026	1	-0.44	-0.026
rating_average_grade	-0.22	-0.14	-0.22	-0.28	0.092	0.0083	-0.0083	-0.44	1	-0.88
rating_high_grade	0.33	0.25	0.36	0.37	-0.084	0.0041	-0.0041	-0.026	-0.88	1

Conclusions

- Model 3 provided most reliable result with R^ of 0.524
- Selected features all statistically significant with p-value <0.05
- sqft living15 coef – 0.2791
- sqft living coef – 0.3956
- distance from CBD coef - 0.3434
- Bathrooms coef – 0.0645
- high grade rating coef– 0.4590
- These Coef figures mean for unit increase in any one of these variables there was in increase in price by ~0.3 units.



Thank You!

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