King County Real Estate Analysis

Our findings, our narrative, our *future*

Our questions:

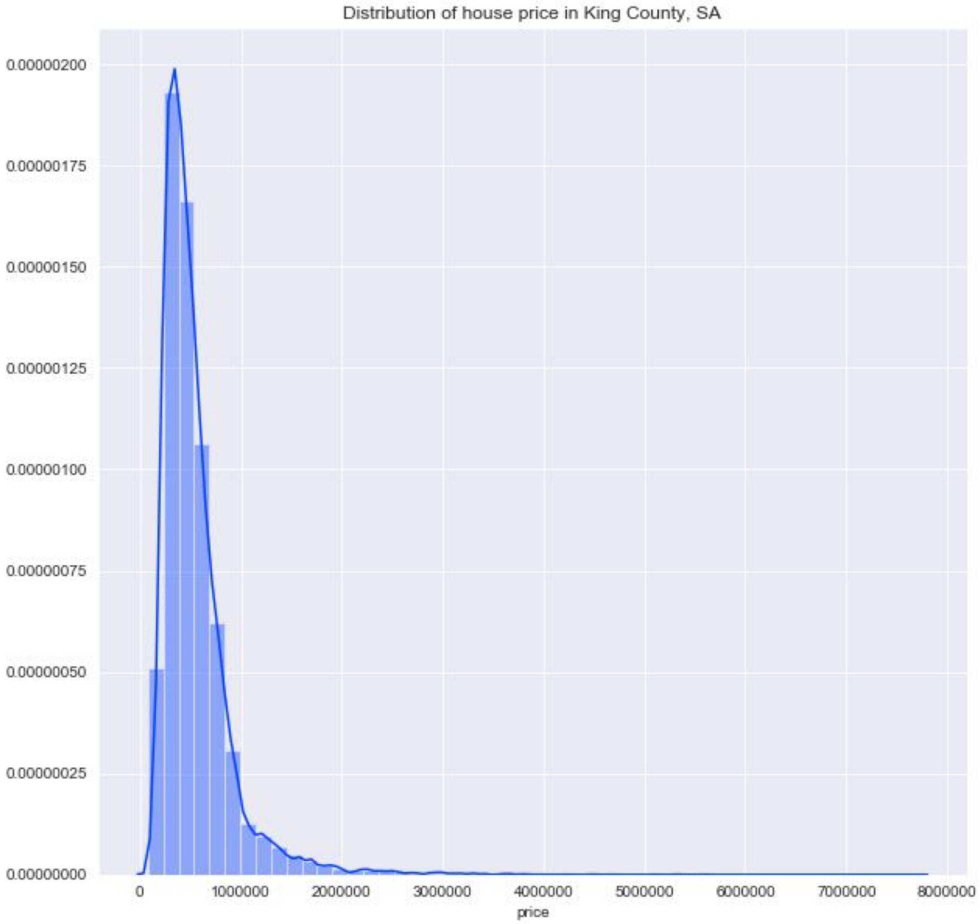
1. How accurate a predictor is the amount of square feet of living space?
2. Do more recently modified houses have higher prices?
3. Are there any clear geographical trends in price?

Stakeholder Overview

Real Estate Companies	Housing Development Firms
Focus on maximising: Sales, Profits	Focussed on maximising sale price after spending on renovations or extensions
Focussed on efficiency in: Costs related to marketing and sales	Minimising cost when investing in house developments

Adjusting the data

- Non-normal distribution
- Data heavily skewed by outliers
- Took the logarithm of our price for final models



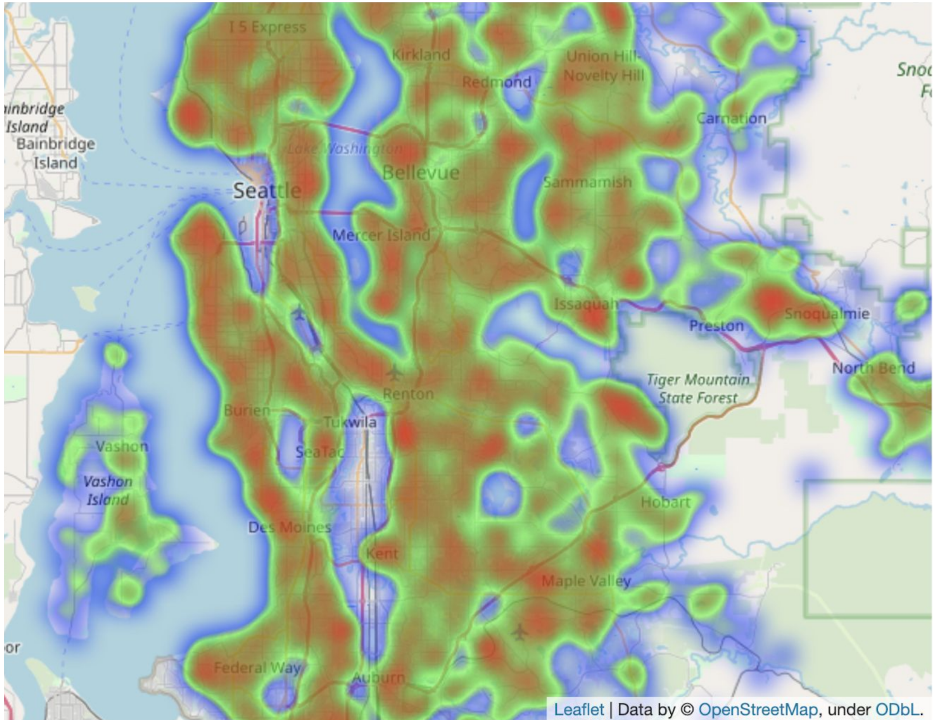
Size: An Efficient Price Predictor?

Living Space of a property Vs Price

- Initial data exploration showed a high correlation between living space and price
- Non-normality of price distribution led us to take the log
- Further regression analysis showed it to be the strongest predictor of house price, out of all variables included in our model

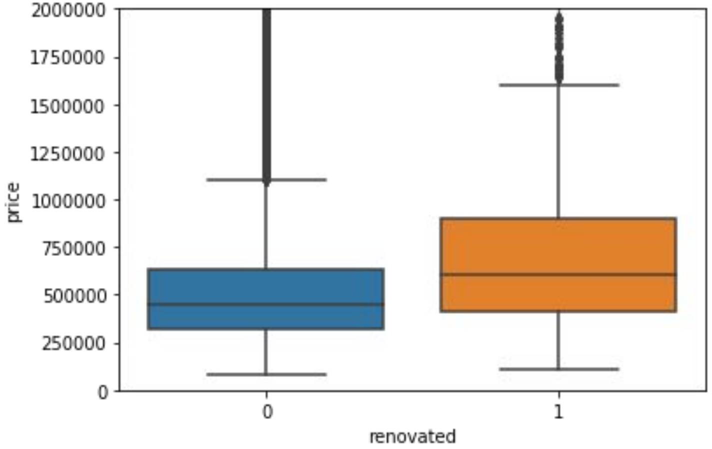
Location, location, location ...

- We spotted clusters of high prices around specific locational points
- Locational price data impacts both of our stakeholders:
    - Enabling real estate companies to appropriately price their properties
    - Calculation for a housing development profit margin, based on maximum cost per square foot of building houses or extensions
- This led us into further analysis and mapping



- Our initial visualisation suggested a cluster of high price points around a central area
- Mapping on price per square foot subsets the data, while removing variation based on total property size
- This sets a benchmark ceiling of spending on cost per square foot in various areas, for a housing development firm to profit after a build
- However, more in depth mapping showed there were actually multiple clusters of high priced areas across the dataset
- Key:
    - Blue: $231.5 / sqft or less
    - Green: $231.5 - $270 /sqft
    - Red: : $405/sqft +

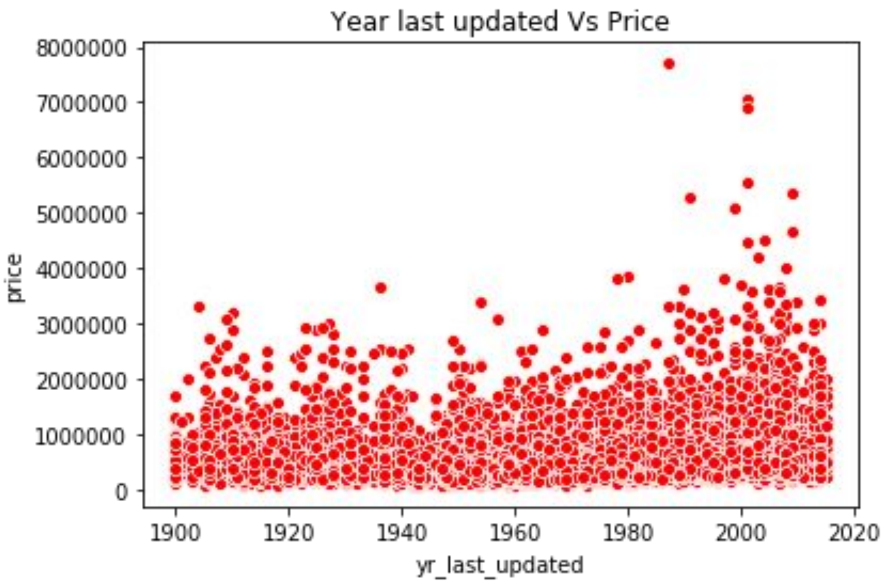
To renovate or not to renovate



Does Renovation affect house price?

- Initial data exploration and visualization showed that the subset of houses that had been renovated in the past were on average a higher price at point of sale
- This led us to include it in our predictive model, which proved less useful
- In conclusion: house renovations on average increase the price, however did not yield useful predictive qualities at a later stage

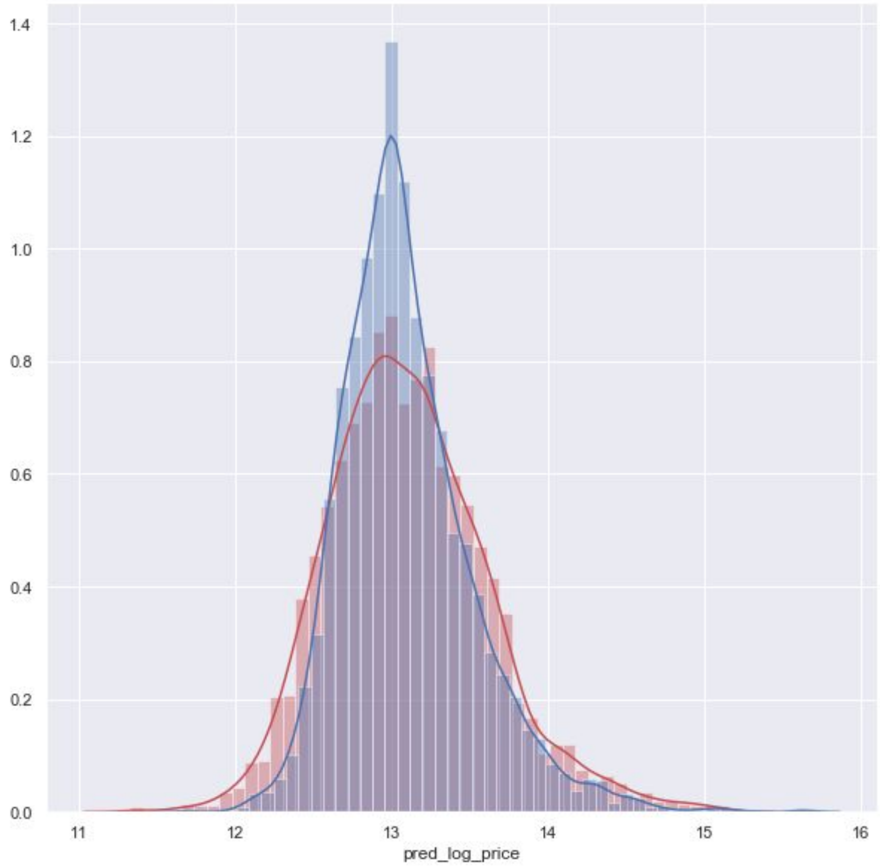
Further exploration around renovations



- Our previous slide led us to further analysis around renovations, and building age
- We created a new variable to test our hypothesis that buildings that had been recently updated (either through initial build or renovation) would be a higher price
- If this was the case, it would be useful to include in our predictive model
- While the scatter plot showed a potential positive correlation, it was very weak

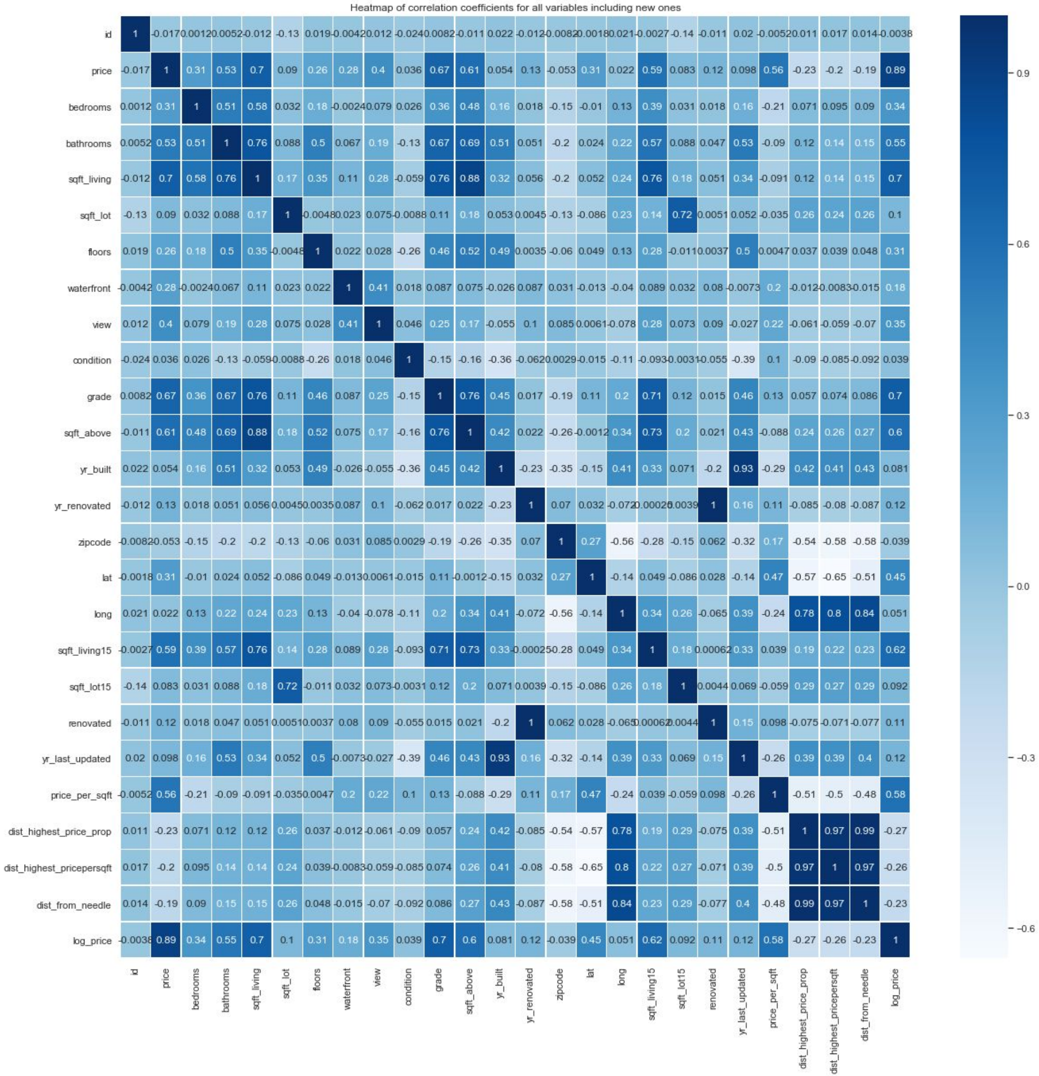
Price Prediction Model

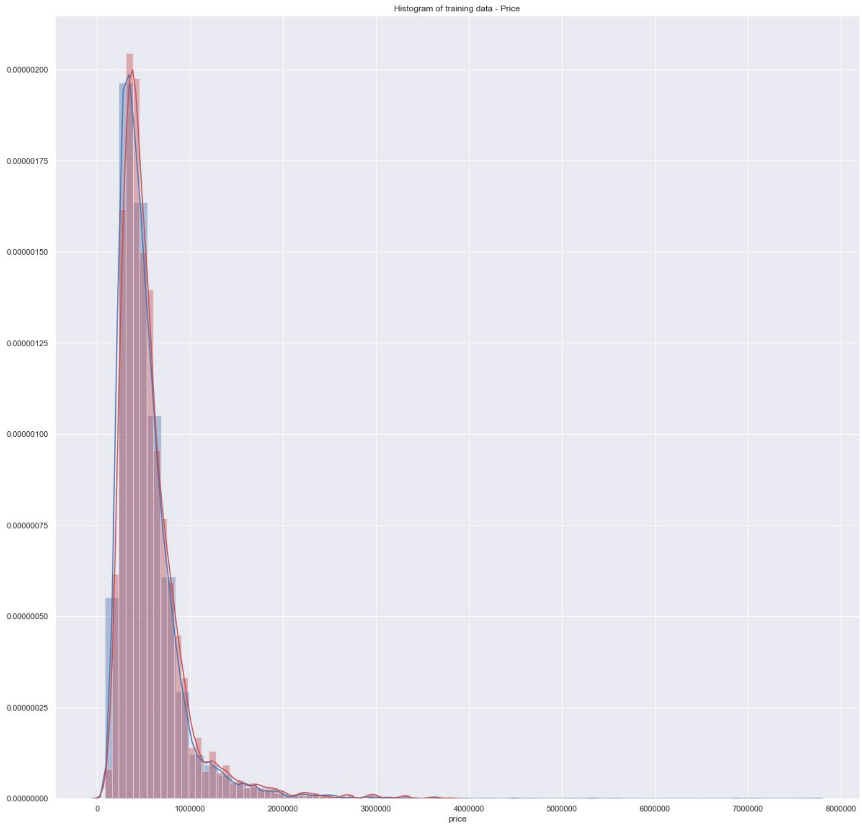
1. Both absolute price and cost per square foot are dependent on location
   a. Average $264/sqft across whole dataset
   b. This relationship is not focussed around a central point
2. Doubling square footage from 1500 to 3000 results in 82.2% increase in price
3. Renovation increases price of 40-year old house by 0.8%; a 90-year old house by 1.8%.
4. We are quite confident in our results, however would have achieved similar using purely square footage - other variables have a limited impact
5. Separate model for **housing development**

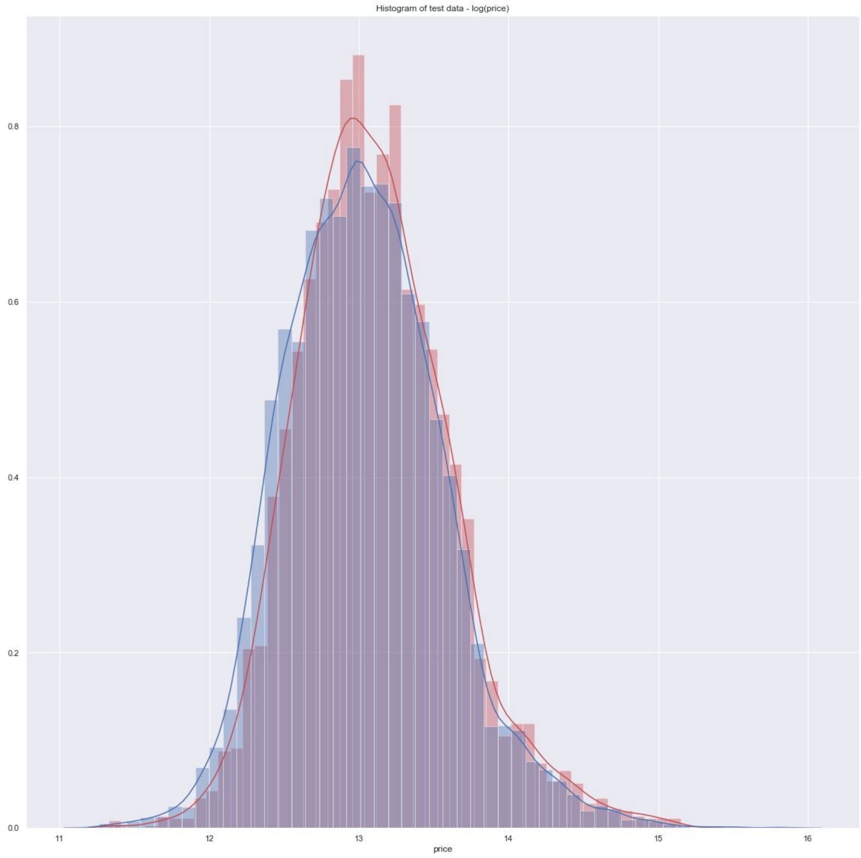


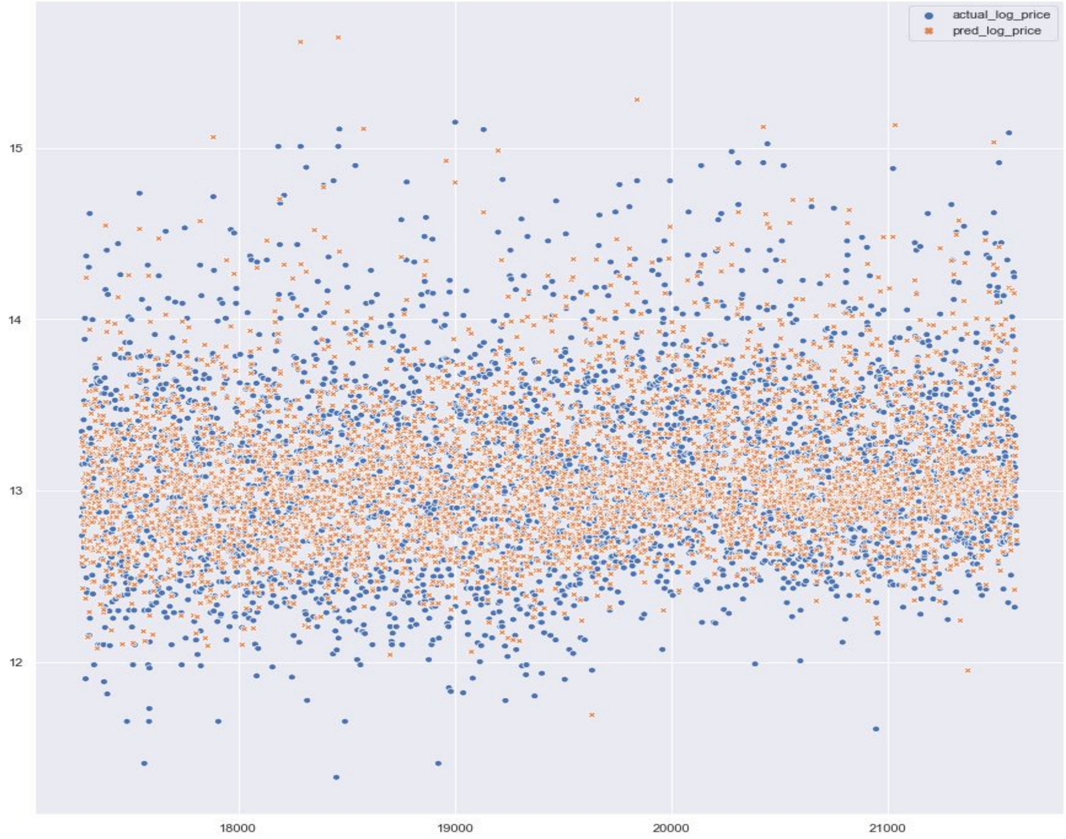
Thank you

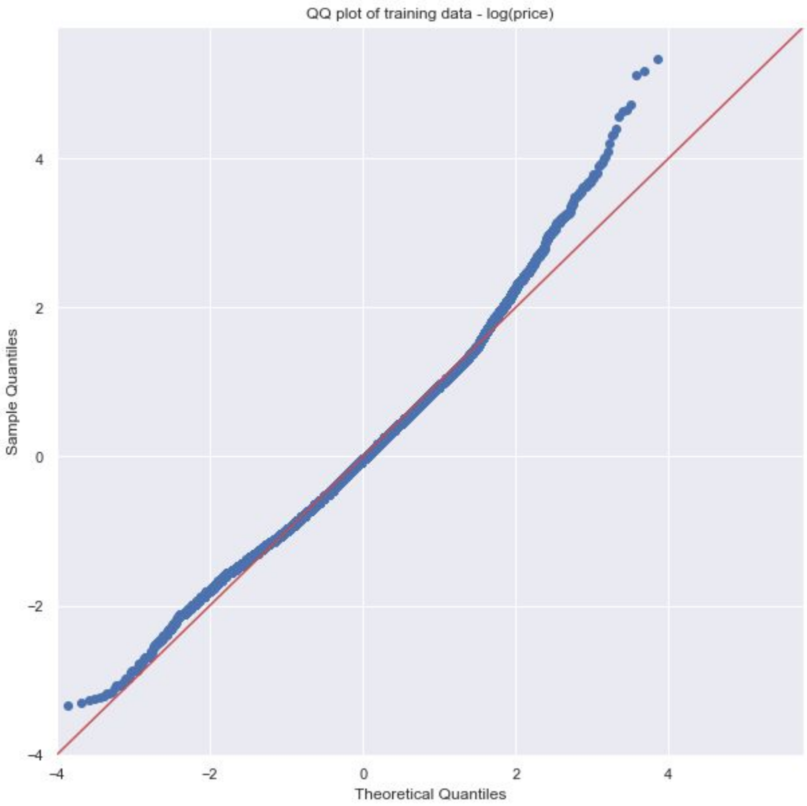
Questions, please

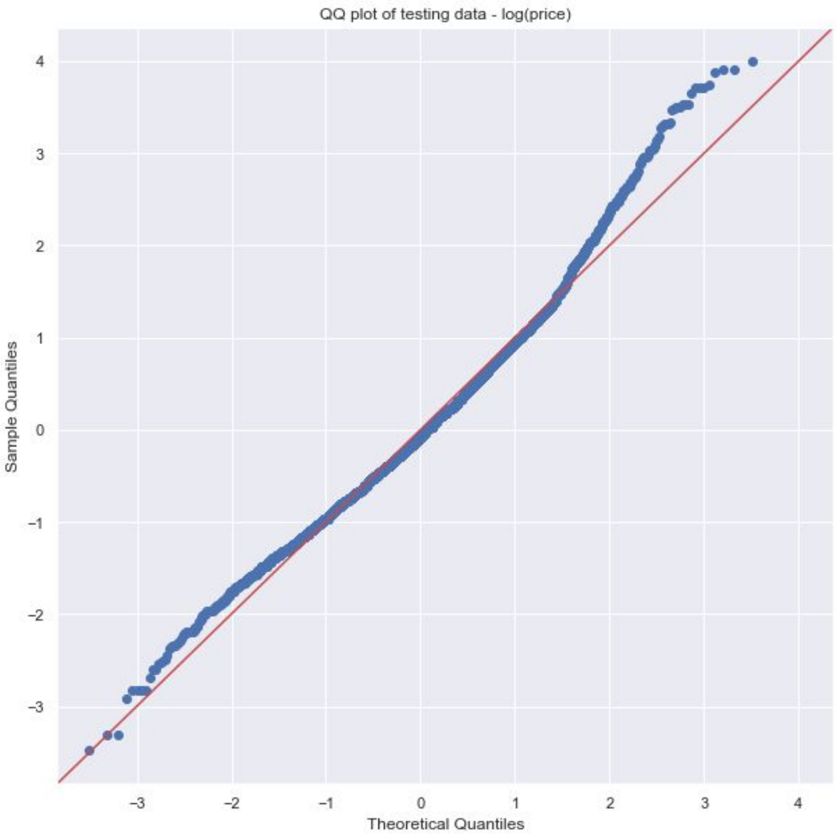

Heatmap of correlation coefficients for all variables including new ones
id
price
bedrooms
bathrooms
sqft_living
sqft_lot
floors
waterfront
view
condition
grade
sqft_above
yr_built
yr_renovated
zipcode
lat
long
sqft_living15
sqft_lot15
renovated
yr_last_updated
price_per_sqft
dist_highest_price_prop
dist_highest_pricepersqft
dist_from_needle
log_price
0.9
0.6
0.3
0.0
−0.3
−0.6


Histogram of training data - Price
0.00000200
0.00000175
0.00000150
0.00000125
0.00000100
0.00000075
0.00000050
0.00000025
0.00000000
0
1000000
2000000
3000000
4000000
5000000
6000000
7000000
8000000
price


Histogram of test data - log(price)
0.8
0.6
0.4
0.2
0.0
11
12
13
14
15
16
price


actual_log_price
pred_log_price
15
14
13
12
18000
19000
20000
21000


QQ plot of training data - log(price)
Sample Quantiles
Theoretical Quantiles
4
2
0
−2
−4
−4
−2
0
2
4


QQ plot of testing data - log(price)
Sample Quantiles
Theoretical Quantiles
4
3
2
1
0
−1
−2
−3
−3
−2
−1
0
1
2
3
4

Multivariate model summary

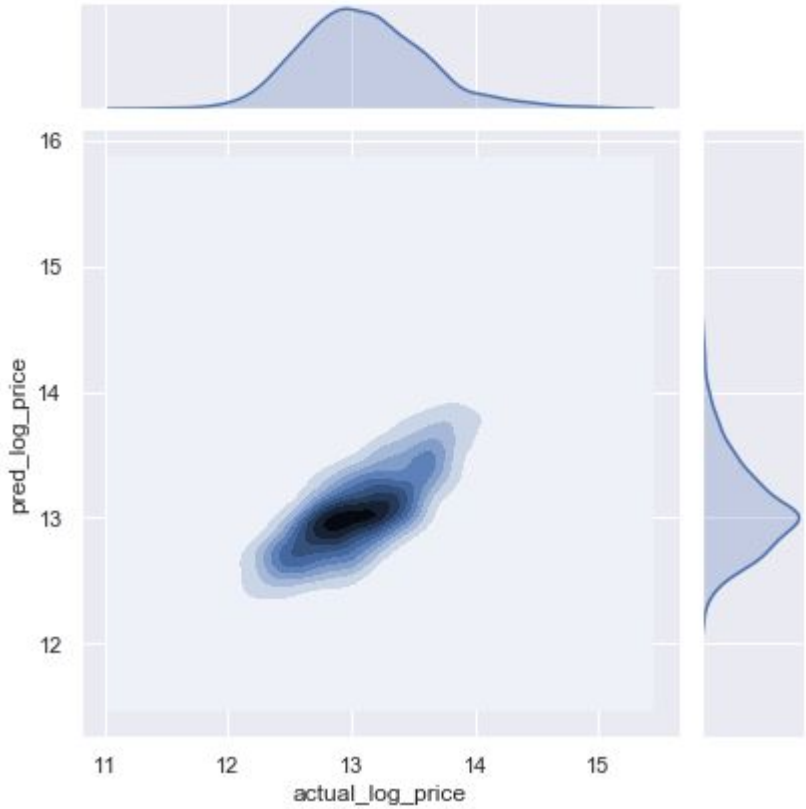
Dep. Variable:	price	**R-squared:**	0.610
Model:	OLS	**Adj. R-squared:**	0.610
Method:	Least Squares	**F-statistic:**	9019.
Date:	Wed, 23 Oct 2019	**Prob (F-statistic):**	0.00
Time:	14:26:01	**Log-Likelihood:**	-5372.8
No. Observations:	17276	**AIC:**	1.075e+04
Df Residuals:	17272	**BIC:**	1.078e+04
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	12.0262	0.207	58.151	0.000	11.621	12.432
sqft_living	0.0004	2.97e-06	144.129	0.000	0.000	0.000
dist_highest_pricepersqft	-1.3372	0.019	-70.648	0.000	-1.374	-1.300
yr_last_updated	0.0002	0.000	2.212	0.027	2.69e-05	0.000

Omnibus:	220.331	**Durbin-Watson:**	1.995
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	390.197
Skew:	-0.055	**Prob(JB):**	1.86e-85
Kurtosis:	3.728	**Cond. No.**	2.41e+05

Measures of dispersion for model on test data

	actual_log_price	pred_log_price	error
count	4321.000000	4321.000000	4321.000000
mean	13.104645	13.093593	0.244508
std	0.512552	0.419085	0.185173
min	11.326596	11.690549	0.000230
25%	12.751300	12.814923	0.105758
50%	13.071070	13.031974	0.209871
75%	13.415033	13.310939	0.339736
max	15.150512	15.645168	1.423324



16
15
14
13
12
pred_log_price
11
12
13
14
15
actual_log_price

Multivariate model (log(sqft_living) summary

Dep. Variable:	price	**R-squared:**	0.594
Model:	OLS	**Adj. R-squared:**	0.594
Method:	Least Squares	**F-statistic:**	1.262e+04
Date:	Wed, 23 Oct 2019	**Prob (F-statistic):**	0.00
Time:	14:26:02	**Log-Likelihood:**	-5734.0
No. Observations:	17276	**AIC:**	1.147e+04
Df Residuals:	17273	**BIC:**	1.150e+04
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	6.5085	0.046	141.241	0.000	6.418	6.599
log_sqft_living	0.9112	0.006	147.999	0.000	0.899	0.923
dist_highest_pricepersqft	-1.3670	0.018	-77.939	0.000	-1.401	-1.333

Omnibus:	48.480	**Durbin-Watson:**	2.001
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	49.760
Skew:	0.116	**Prob(JB):**	1.57e-11
Kurtosis:	3.124	**Cond. No.**	138.