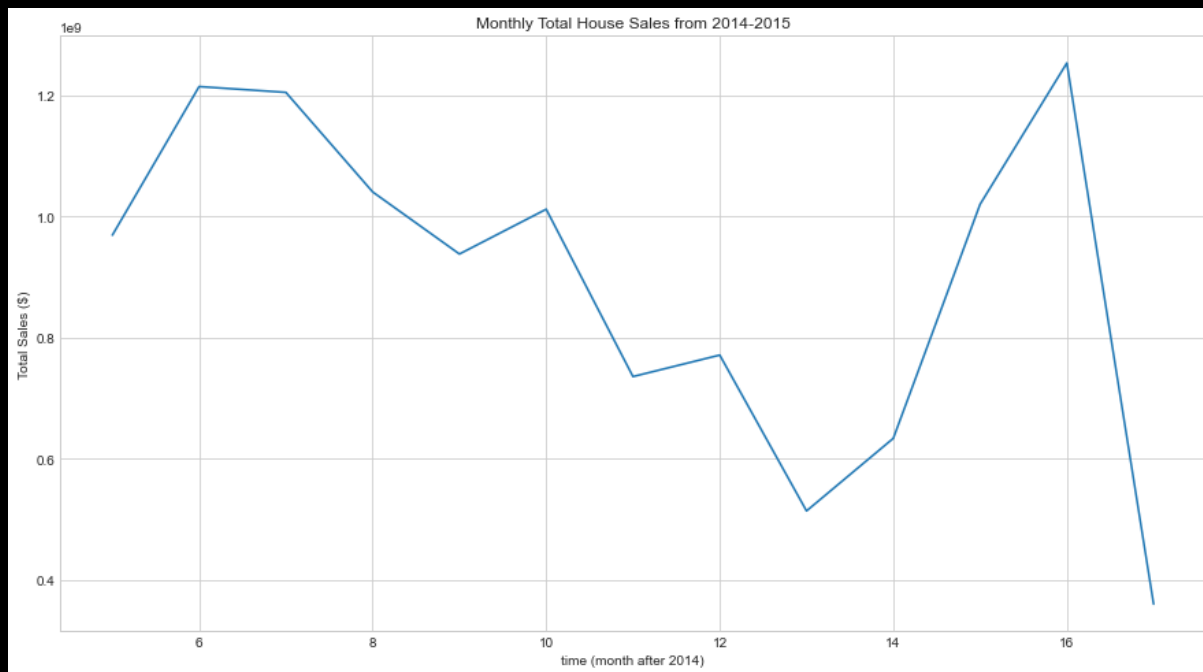


# How to hack house prices

Sung Bae

# Introduction



- House sale is a huge even during recessions (around \$1B each month)
- House prices differ depending on various factors (ex. location)



# Question 1

What factors affect the house prices the most in most interpretable and reasonable way?

# Model

1. Priority: interpretability
2. Reasonable predictors
3. May not result in highest  $r^2$  value

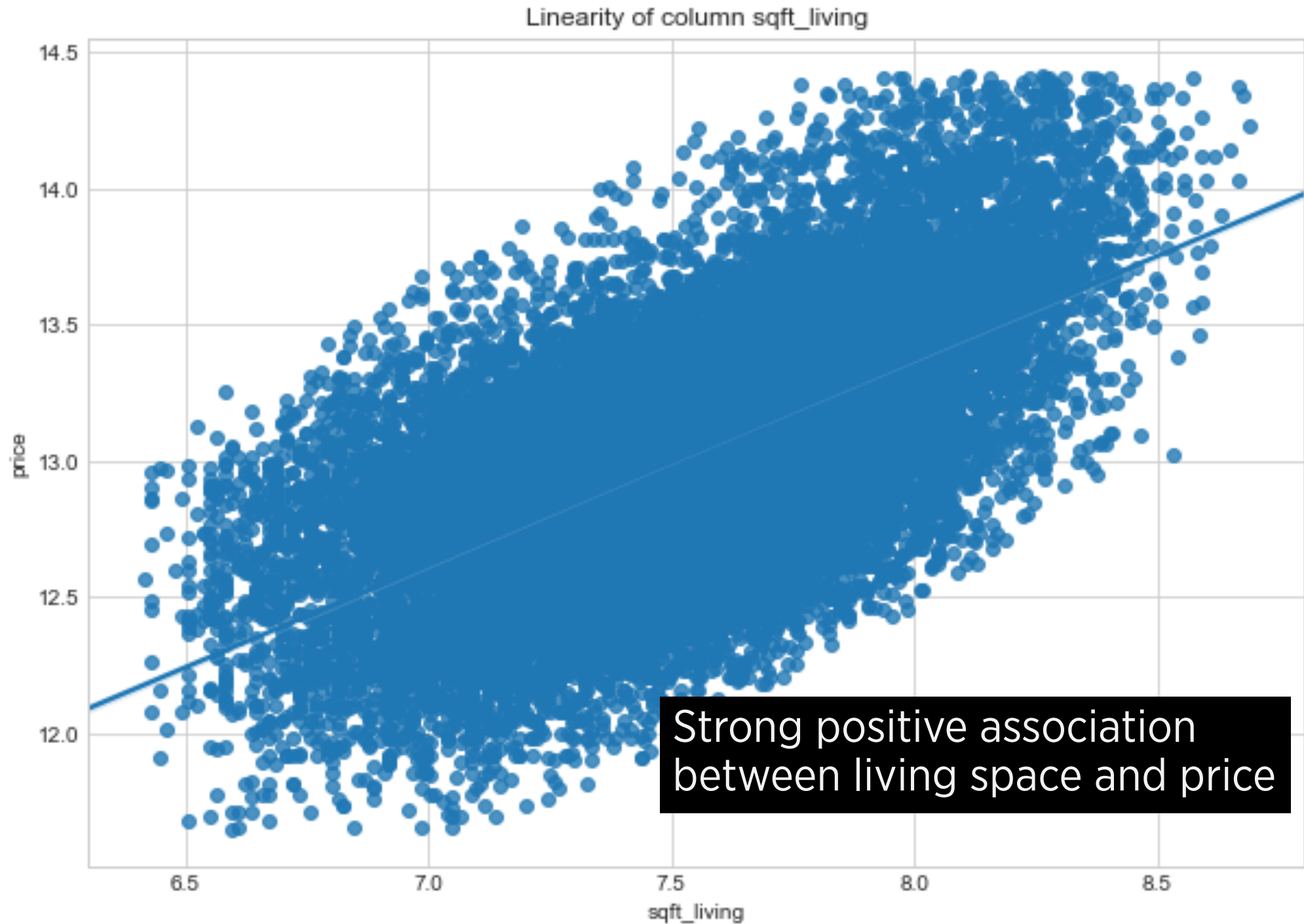
# Question 1: Factors that affect house prices

## Positive effectors:

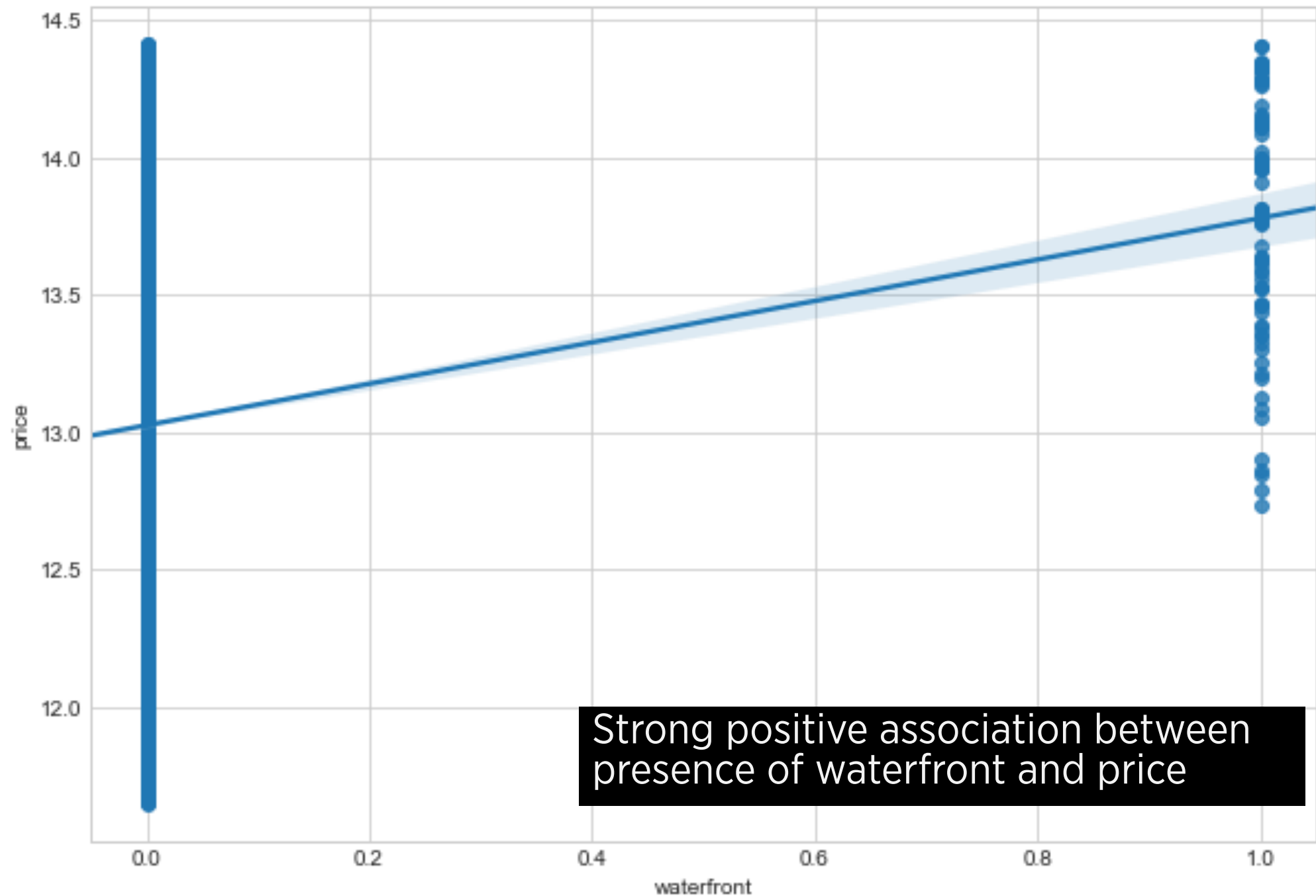
1. living area = more space means higher price
2. waterfront = having waterfront increases the value of the price
3. grade x bathroom = having great bathrooms count!
4. higher latitude = usually results in higher price

## Negative effectors:

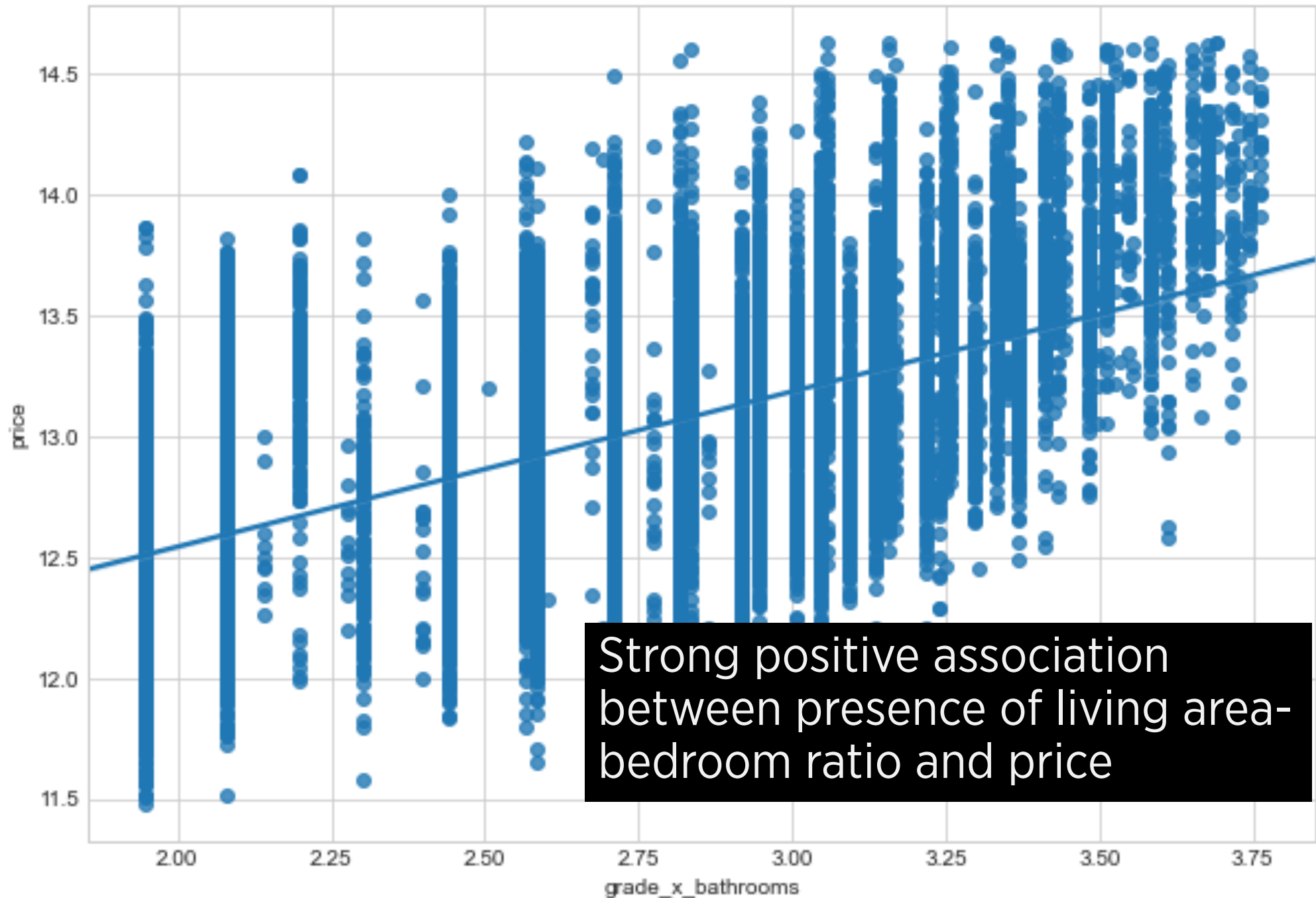
1. bath and bed= having too many of them decreases the price
2. longitude = higher longitude results in lower price



Linearity of column waterfront



Linearity of column grade\_x\_bathrooms





## Question 2

So what can be done to maximize house price by the homeowners?

# Actions that can be done:

## *Increase Living Area*

- second strongest factor
- Shows that people love having bigger independent open spaces

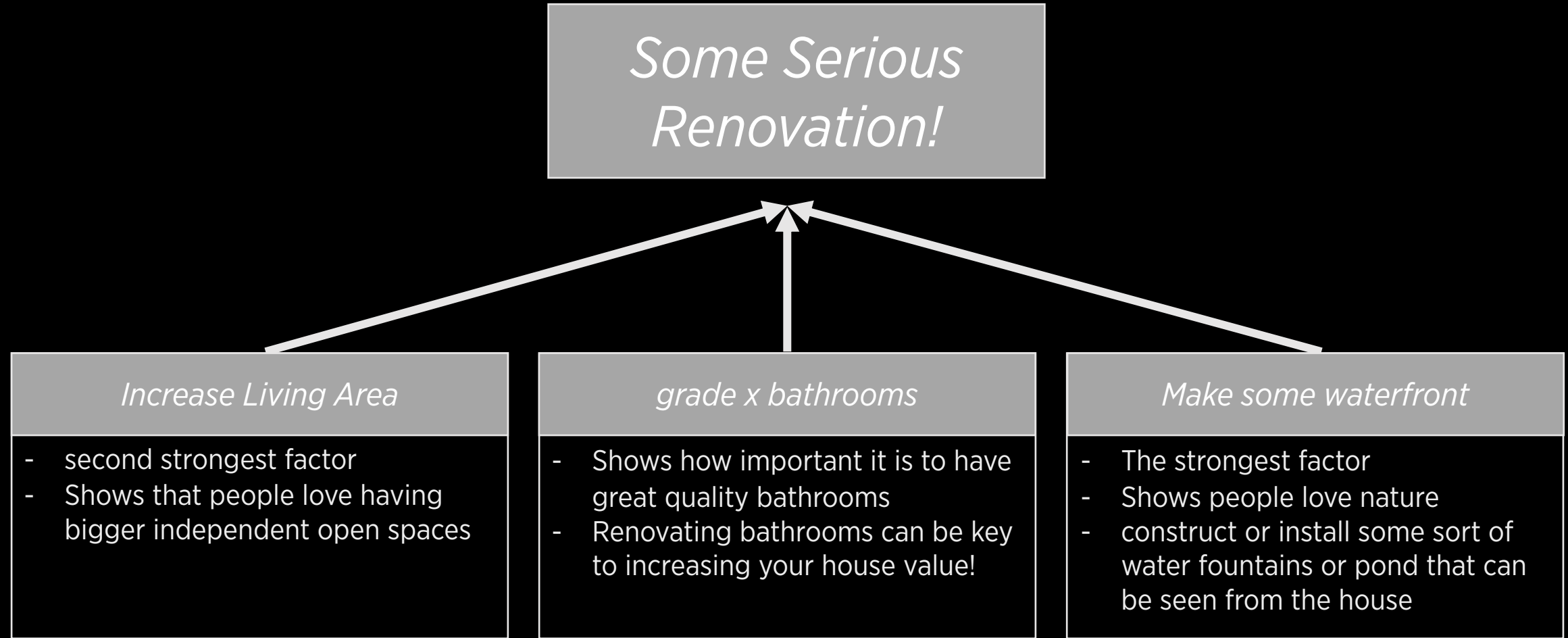
## *grade x bathrooms*

- Shows how important it is to have great quality bathrooms
- Renovating bathrooms can be key to increasing your house value!

## *Make some waterfront*

- The strongest factor
- Shows people love nature
- construct or install some sort of water fountains or pond that can be seen from the house

# Actions that can be done:



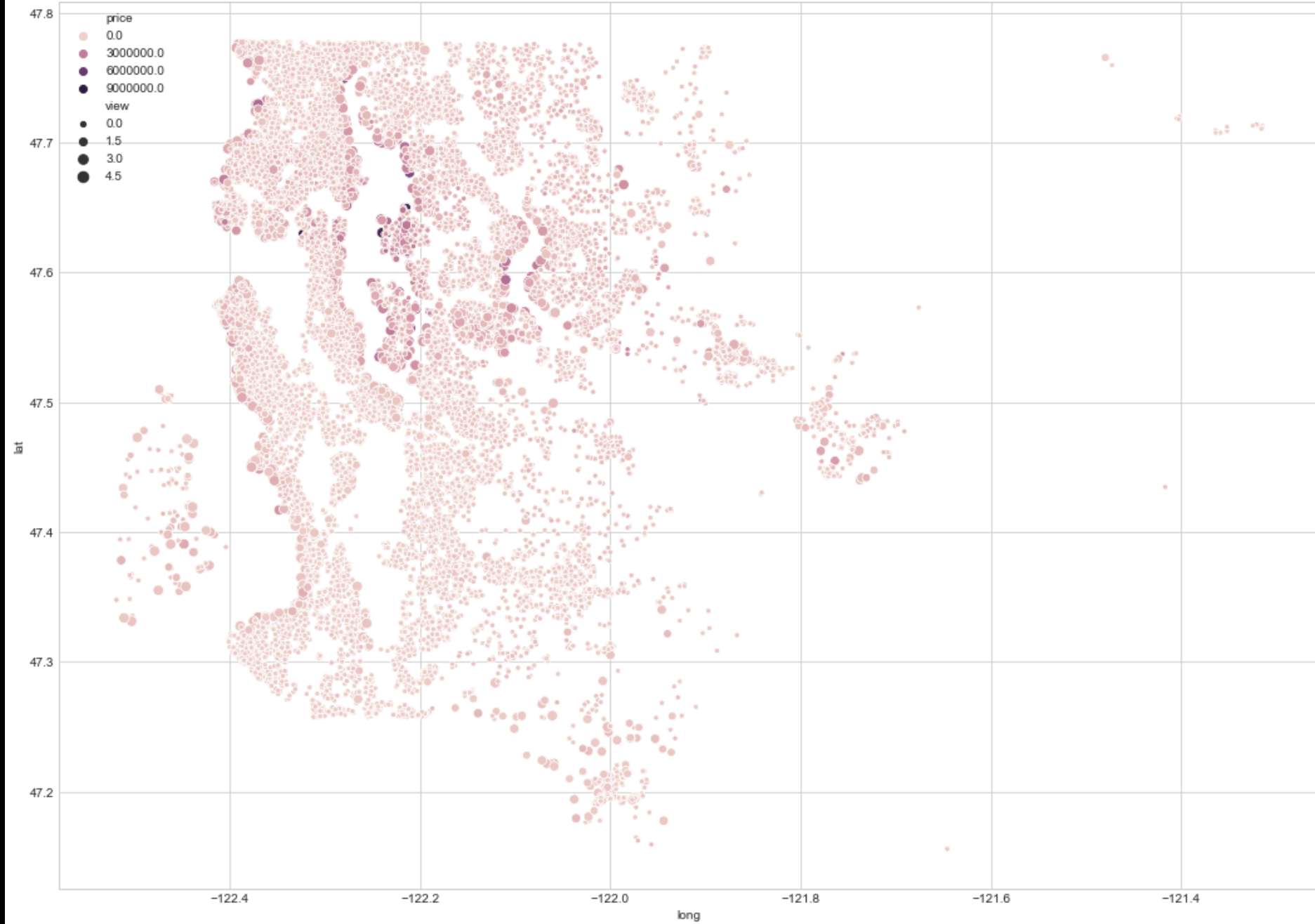
# Conclusion

- Model is limited
- However it can give us a good idea of what factors we can control and change to change the house price
  - Actionable changes
    - Renovate to
      - Increase open space
      - Waterfront presence
      - Better quality bathrooms
  - What NOT to do
    - increase number of bathrooms and bedrooms in total

Thank you for listening

# Appendix

House Prices Around King's County Area



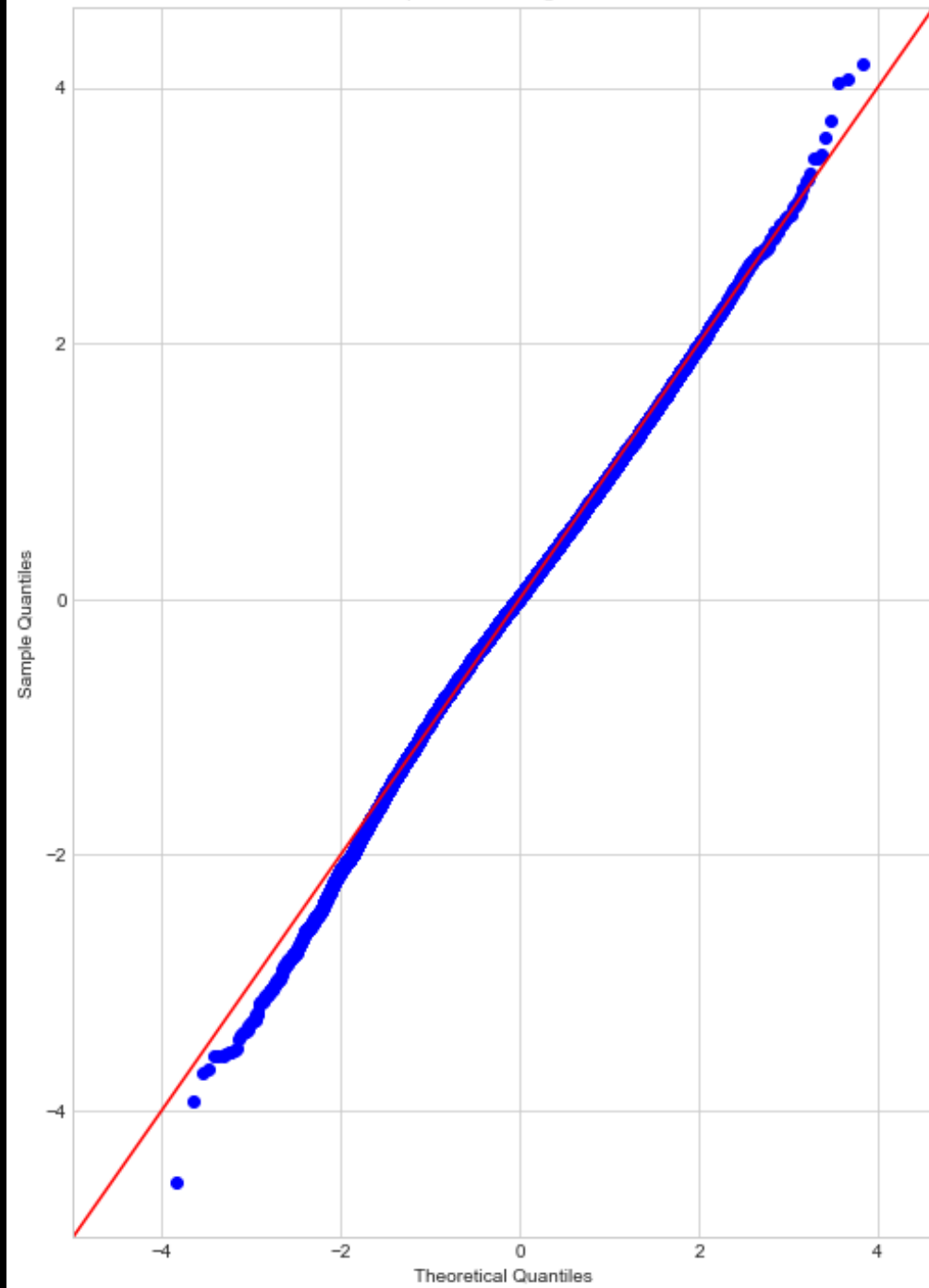
<b>Dep. Variable:</b>	price	<b>R-squared:</b>	0.653
<b>Model:</b>	OLS	<b>Adj. R-squared:</b>	0.653
<b>Method:</b>	Least Squares	<b>F-statistic:</b>	3230.
<b>Date:</b>	Thu, 17 Sep 2020	<b>Prob (F-statistic):</b>	0.00
<b>Time:</b>	18:43:41	<b>Log-Likelihood:</b>	-2665.6
<b>No. Observations:</b>	15459	<b>AIC:</b>	5351.
<b>Df Residuals:</b>	15449	<b>BIC:</b>	5428.
<b>Df Model:</b>	9		
<b>Covariance Type:</b>	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
<b>Intercept</b>	7.6598	0.058	132.387	0.000	7.546	7.773
<b>sqft_living</b>	0.7205	0.010	69.292	0.000	0.700	0.741
<b>bath_and_bed</b>	-0.5359	0.021	-25.865	0.000	-0.576	-0.495
<b>grade_x_bathrooms</b>	0.3316	0.011	30.751	0.000	0.310	0.353
<b>lat</b>	0.2097	0.002	90.303	0.000	0.205	0.214
<b>long</b>	-0.0329	0.003	-12.347	0.000	-0.038	-0.028
<b>waterfront_10</b>	0.6248	0.035	18.017	0.000	0.557	0.693
<b>yr_renovated_True</b>	0.1501	0.013	11.535	0.000	0.125	0.176
<b>grade_5</b>	-0.0957	0.053	-1.811	0.070	-0.199	0.008
<b>grade_6</b>	-0.0075	0.009	-0.819	0.413	-0.026	0.010

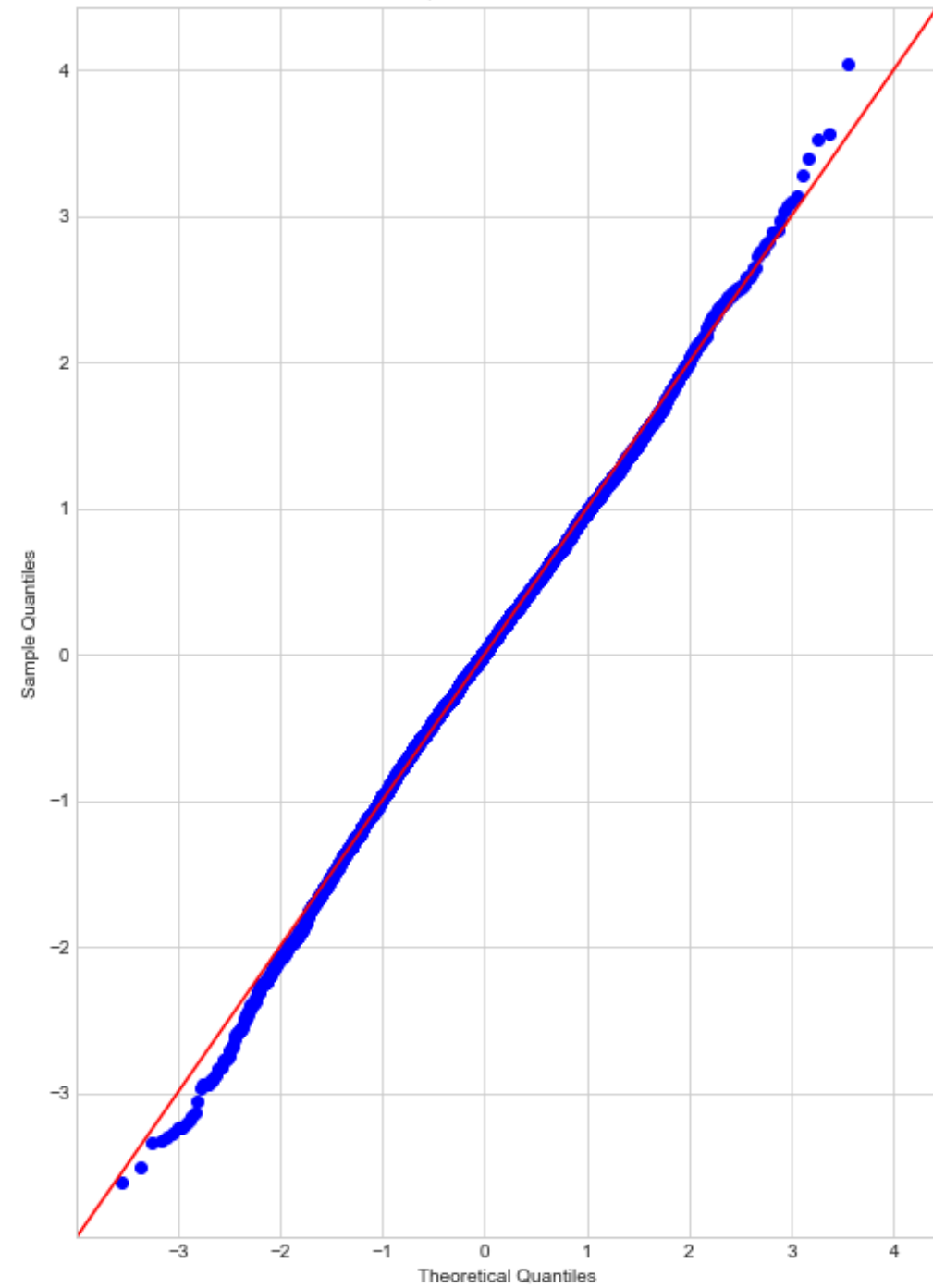
<b>Omnibus:</b>	237.270	<b>Durbin-Watson:</b>	1.988
<b>Prob(Omnibus):</b>	0.000	<b>Jarque-Bera (JB):</b>	294.416
<b>Skew:</b>	0.231	<b>Prob(JB):</b>	1.17e-64
<b>Kurtosis:</b>	3.494	<b>Cond. No.</b>	212.



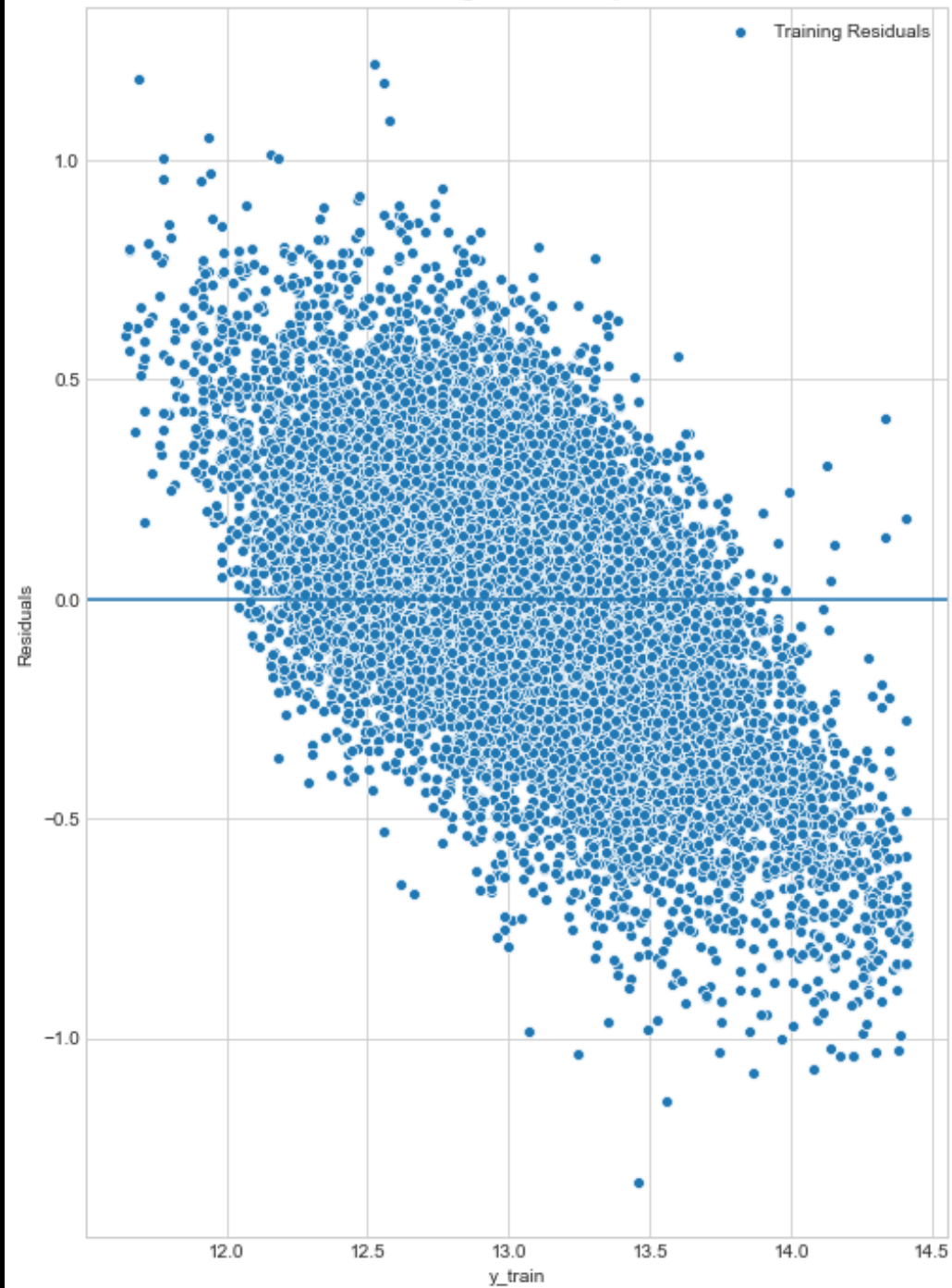
QQ plot for training data set



QQ plot for test data set



Training Residual Graph



Test Residual Graph

