

# **Multiple Linear Regression**



The project aims to help the real estate agencies and homeowners in making informed decisions about home selling and buying by utilizing the King County House Sales dataset. By analyzing and modeling the dataset, we can determine the influence of various factors on house prices, ultimately providing valuable insights to real estate agencies and homeowners regarding the potential change in the estimated value of their homes through different choices.

## **OBJECTIVES**

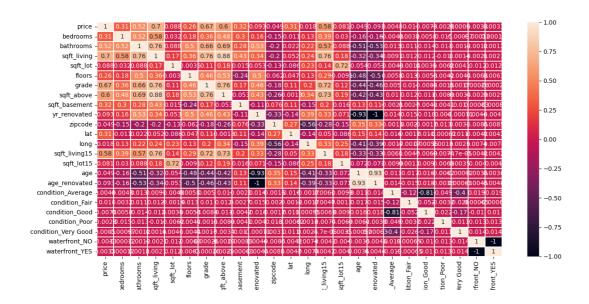
To understand which factors determines the price of a home. To understand how square feet living affect the value of a home. To explore how condition affect the price of a home. To explore features which decrease and increase value of the house.

## DATA PREPARATION AND CLEANING

Data was cleaned through the following steps:

- 1. Checking for missing values where we found that the view, waterfront and year renovated column had missing values. We decided to drop the view column and replace Nans with mode in the waterfront column.
- 2. Checking for duplicates and outliers
- 3. Feature engineering using the date column to create a new column named age which shows the age of the house.

## **EXPLORATORY DATA ANALYSIS**



According to this heatmap, there are some variables which are highly correlated which will be considered in linear regression

## **MODELLING**

Below is a list of all models built and general description of changes between each model:

#### 1. Model 1: Baseline model

Our first model has an adjusted r-squared of .660. All features with p\_values that are significant, let's check our residuals.

Dep. Variable:

Model: Method:	Least :	OLS Squares	Ad	lj. R-squared: statistic:	0.660 1964.			
Date:	Fri, 02 J		Prob (F-statistic):			0.00		
Time:	22	2:59:57	Log-Likelihood:			-2.9085e+05		
No. Observations:	21244		AIC:			5.818e+05		
Df Residuals:	21222		ΒI	C:	5.819e+05			
Df Model:		21						
Covariance Type:	noi	nrobust						
	coef	std	err	t	P> t	[0.025	0.975]	
const	-3.371e+07	4.13e	+06	-8.159	0.000	-4.18e+07	-2.56e+07	
bedrooms	-4.55e+04	2024.	056	-22.479	0.000	-4.95e+04	-4.15e+04	
bathrooms	4.745e+04	3497.	152	13.569	0.000	4.06e+04	5.43e+04	
sqft_living	109.1784	22.	653	4.820	0.000	64.777	153.580	
sqft_lot	0.1422	0.0	051	2.792	0.005	0.042	0.242	
floors	9096.6499	3867.		2.352	0.019	1515.728	1.67e+04	
grade	1.033e+05	2309.	367	44.711	0.000	9.87e+04	1.08e+05	
sqft_above	76.7000	22.	666	3.384	0.001	32.272	121.128	
sqft_basement	74.6117	22.		3.293	0.001	30.202	119.021	
yr_renovated	2.549e+04	3143.	506	8.108	0.000	1.93e+04	3.17e+04	
zipcode	-522.2306	34.	950	-14.942	0.000	-590.736	-453.725	
lat	5.477e+05	1.14e		48.031	0.000	5.25e+05	5.7e+05	
long	-2.482e+05	1.41e		-17.635	0.000	-2.76e+05	-2.21e+05	
sqft_living15	38.0384	3.0	657	10.401	0.000	30.870	45.207	
sqft_lot15	-0.3115	0.0	078	-3.992	0.000	-0.464	-0.159	
age	3854.6952	135.3		28.471	0.000	3589.321	4120.069	
age_renovated	2.487e+04	3144.		7.909	0.000	1.87e+04	3.1e+04	
condition_Average	-6.755e+06	8.26e		-8.176	0.000	-8.37e+06	-5.14e+06	
condition_Fair	-6.735e+06	8.26e		-8.150	0.000	-8.35e+06	-5.11e+06	
condition_Good	-6.757e+06	8.26e		-8.179	0.000	-8.38e+06	-5.14e+06	
condition_Poor	-6.703e+06			-8.102	0.000	-8.32e+06	-5.08e+06	
condition_Very Good		8.26e		-8.180	0.000	-8.38e+06	-5.14e+06	
waterfront_NO	-1.685e+07	2.07e		-8.159	0.000	-2.09e+07	-1.28e+07	
waterfront_YES	-1.685e+07	2.07e	+06	-8.159	0.000	-2.09e+07	-1.28e+07	
Omnibus:	19043.086 Durbin-Watson:					1.36		
Prob(Omnibus):	150	0.000		rque-Bera (JB):		1873733.100		
Skew:		3.914		ob(JB):		0.00		
Kurtosis:		48.338		nd. No.		6.88e+2		

price R-squared:

### 2. Model 2: with log transformed y variables

After log transformation of the dependent variables our residuals are much closer to a normal distribution.

## 3. Model 3: Dealing with Multicollinearity

Conclusion: There are several features that seem to have multicollinearity. Rather than just dropping some of these features, let's first look at the variance inflation factor to understand the severity of the multicollinearity.

## 4. Model 4: Dropping Insignificant Features

Conclusion: Our adjusted R squared still stays the same at .740 and all features are significant. Next, we will further refine our data by removing additional, potential outliers.



## 5. Model 5: Standardizing Features

Interpretation: Since the p-value (0.0024) is less than the significance level (e.g., 0.05), we can reject the null hypothesis. This suggests that there is significant evidence of heteroscedasticity in the data. It implies that the variance of the errors is not constant across the range of the predictors.

<sup>[1]</sup> Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 4.55e-28. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

In summary, F statistic and p-value, there is evidence of heteroscedasticity in the data, indicating that the assumption of constant error variance may not hold.

ULS Regression Results											
Date: Fri, 02 J Time: 2 No. Observations: Df Residuals: Df Model:		price OLS ast Squares 92 Jun 2023 23:00:29 21244 21230 13 nonrobust	A-squared: Adj. R-squared: F-statistic: Prob (F-statistic): Log-Likelihood: AIC: BIC:								
	coef	std err	t	P> t	[0.025	0.975]					
const bedrooms bathrooms sqft_living sqft_lot floors grade sqft_above zipcode lat long sqft_living15 age_renovated waterfront_ND waterfront_YES	-19.1124 -0.0198 0.0725 0.0002 4.287e-07 0.0657 0.1669 -5.477e-05 -0.0006 1.3575 -0.2469 0.0001 0.0037 -9.5608 -9.5516	2.512 0.003 5.77e-06 4.63e-08 0.005 0.005 5.75e-06 4.37e-05 0.014 0.017 4.57e-06 8.93e-05 1.256	-7.609 -7.819 16.586 35.087 9.256 13.593 55.785 -9.523 -12.865 9.525 -14.131 24.031 41.553 -7.614 -7.605	0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000	-24.036 -0.025 0.064 0.000 3.38e-07 0.056 0.155 -6.6e-05 -0.001 1.330 -0.281 0.000 0.004 -12.022 -12.013	-14.189 -0.015 0.081 0.000 5.19e-07 0.075 0.167 -4.35e-05 -0.000 1.385 -0.213 0.000 0.004 -7.099					
Omnibus: Prob(Omnibus): Skew: Kurtosis:		426.976 0.000 0.089 3.977	Prob(JB): 2.		1.143 373.336 28e-190 .00e+20						

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 2.6e-28. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

## Conclusion

Analyzing the models the following conclusion can be made: An increase with one bedroom decreases the house sale by \$ 0.002. An increase with one bathroom increases the house price by \$ 0.0725. An increase in Square footage of the home by one square foot increases the price of the house by \$ 0.0002. An increase in Square footage of the by one square feet decreases the house price by \$ 4.287e-07. An increase in floors by one increases price by \$0.0657. An increase in grade rating by one increases the price by \$ 0.1609. An increase in one square foot from basement decrease price by \$ -5.477e-05. An increase in Square footage of interior housing living space for the nearest 15 neighbors by one foot increase prices by \$ 0.0001. There is no significant increase/decrease in the house price with the condition of the house. Presence of waterfront decreases the house price by \$ -9.5516.

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### Languages

Jupyter Notebook 100.0%