Data Housing Project

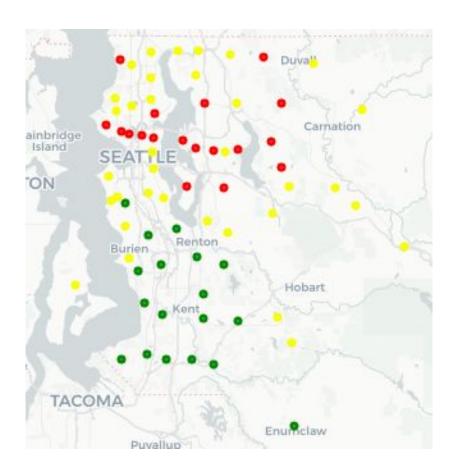
Mod 1 Project

1. Data Cleaning

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
id
                 21597 non-null int64
                21597 non-null object
date
                21597 non-null float64
price
bedrooms
                21597 non-null int64
bathrooms
               21597 non-null float64
sqft living
               21597 non-null int64
sqft lot
                21597 non-null int64
floors
                21597 non-null float64
waterfront
                 19221 non-null float64
view
                21534 non-null float64
condition
                21597 non-null int64
                21597 non-null int64
grade
sqft above
                21597 non-null int64
sgft basement 21597 non-null object
yr built
                21597 non-null int64
yr renovated
                17755 non-null float64
zipcode
                21597 non-null int64
lat
                21597 non-null float64
                21597 non-null float64
long
sqft living15 21597 non-null int64
sqft lot15
                21597 non-null int64
dtypes: float64(8), int64(11), object(2)
memory usage: 3.5+ MB
```

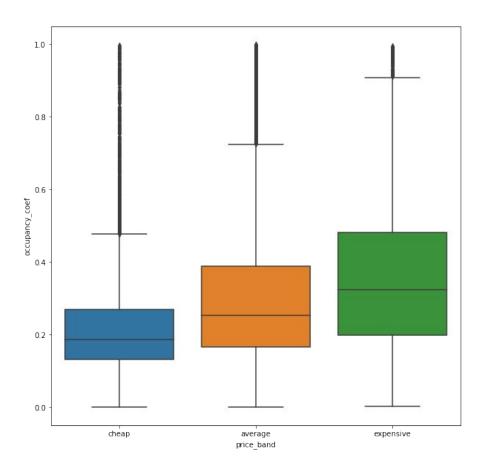
- a. Data import
- b. Checking data types
- c. Resolving missing values
- d. Removing outliers

2. Exploratory Data Analysis



a. How does location have an impact on price?

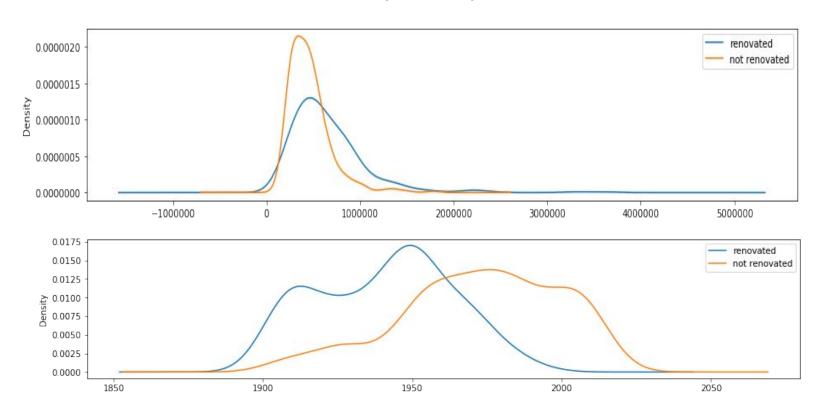
2. Exploratory Data Analysis



b. How does living density have an impact on price?

2. Exploratory Data Analysis

c. How does renovation have an impact on price?



3. Modeling

	correlation		
price	1.000000		
sqft_living	0.701554		
grade	0.668262		
sqft_above	0.605510		
sqft_living15	ing15 0.585597		
bathrooms	0.524823		
view	0.395640		
sqft_basement	0.319199		
bedrooms	0.315193		
lat	0.308032		

a. Adding predictors to the model

3. Modeling

el:		100000		incentered):	0.862
•	OLS	Adj. R-sq	uared (u	incentered):	0.862
od: Least	Squares			F-statistic:	2.248e+04
te: Tue, 22	Oct 2019		Prob	(F-statistic):	0.00
ne:	13:46:08		Log	-Likelihood:	-2.9744e+0
ns:	21529			AIC:	5.949e+0
ls:	21523			BIC:	5.949e+0
el:	6				
oe: n	onrobust				
coef	std err	t	P> t	[0.025	0.975]
285.7753	2.338	122.205	0.000	281.192	290.359
7.198e+04	2433.015	29.586	0.000	6.72e+04	7.68e+04
-5.067e+04	2281.429	-22.208	0.000	-5.51e+04	-4.62e+04
1935.5536	133.999	14.445	0.000	1672.906	2198.201
5.533e+05	2.19e+04	25.304	0.000	5.1e+05	5.96e+05
61.1899	4.552	13.443	0.000	52.268	70.112
12922.614	Durbir	n-Watson:		1.981	
0.000	Jarque-	Bera (JB):	41839	7.294	
2.347		Prob(JB):		0.00	
	ne: ns: ls: el: coef 285.7753 7.198e+04 -5.067e+04 1935.5536 5.533e+05 61.1899 12922.614 0.000	ne: 13:46:08 ns: 21529 ls: 21523 el: 6 nonrobust coef std err 285.7753 2.338 7.198e+04 2433.015 -5.067e+04 2281.429 1935.5536 133.999 5.533e+05 2.19e+04 61.1899 4.552 12922.614 Durbin 0.000 Jarque-1 2.347	ne: 13:46:08 ns: 21529 ls: 21523 el: 6 nonrobust coef std err t 285.7753 2.338 122.205 7.198e+04 2433.015 29.586 -5.067e+04 2281.429 -22.208 1935.5536 133.999 14.445 5.533e+05 2.19e+04 25.304 61.1899 4.552 13.443 12922.614 Durbin-Watson: 0.000 Jarque-Bera (JB): 2.347 Prob(JB):	ne: 13:46:08 Log ns: 21529 ls: 21523 el: 6 nonrobust coef std err t P> t 285.7753 2.338 122.205 0.000 7.198e+04 2433.015 29.586 0.000 7.198e+04 2281.429 -22.208 0.000 1935.5536 133.999 14.445 0.000 5.533e+05 2.19e+04 25.304 0.000 61.1899 4.552 13.443 0.000 12922.614 Durbin-Watson: 0.000 Jarque-Bera (JB): 41839 2.347 Prob(JB):	ne: 13:46:08 Log-Likelihood: ns: 21529 AIC: ls: 21523 BIC: el: 6 For: 6 oe: nonrobust 7.18 [0.025] 285.7753 2.338 122.205 0.000 281.192 7.198e+04 2433.015 29.586 0.000 6.72e+04 5.067e+04 2281.429 -22.208 0.000 -5.51e+04 1935.5536 133.999 14.445 0.000 1672.906 5.533e+05 2.19e+04 25.304 0.000 5.1e+05 61.1899 4.552 13.443 0.000 52.268 12922.614 Durbin-Watson: 1.981 0.000 Jarque-Bera (JB): 418397.294 2.347 Prob(JB): 0.00

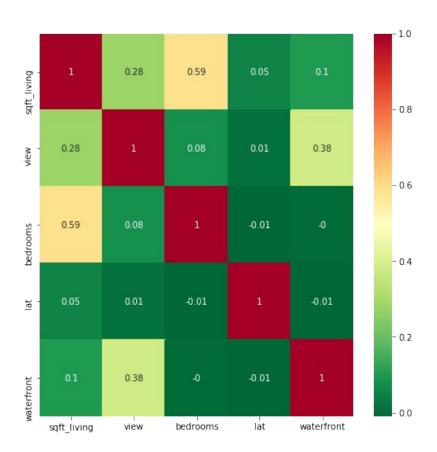
a. Evaluating the coefficients

3. Modeling

	correlation
sqft_living	1.000000
sqft_above	0.945416
sqft_living_per_bed	0.786544
grade	0.782506
bathrooms	0.777182
sqft_living15	0.772939

c. Checking for collinearity between predictors

4. Possible extensions



a. Reducing collinearity using feature engineering

4. Possible extensions

- b. Using feature scaling to scale model coefficients
- c. Splitting the data into training and test sets
- d. Checking for normality of predictors