Final Project Report

Problem Selection:

House Price Prediction of King county the most populous county in Washington.

Useful for prediction of real-estate prices which fluctuate every year. Our Aim would be to create a regression model to predict the house prices of King County based on the feature-set and estimate the price of a house based on its location using clustering techniques.

Data-Selection:

The dataset can be found in Kaggle under the name **House sales on king county.**

Ref: https://www.kaggle.com/harlfoxem/housesalesprediction

Number of Features**: 21**

Number of observations: **21600**

Description of dataset:

S.No.	Attribute	Description
1	id	A notation for a house
2	date	Date house was sold
3	price	Price is prediction target
4	bedrooms	Number of Bedrooms/House
5	sqft_living	Square footage of the home
6	sqft_lot	Square footage of the lot

7	floors	Total floors (levels) in house
8	waterfront	House which has a view to a waterfront
9	view	Has been viewed
10	condition	How good the condition is (Overall)
11	grade	overall grade given to the housing unit, based on King County grading system
12	sqft_above	square footage of house apart from basement
13	sqft_basement	square footage of the basement
14	yr_built	Built Year
15	yr_renovated	Year when house was renovated
16	zip-code	zip
17	lat	Latitude coordinate
18	long	Longitude coordinate
19	sqft_living15	Living room area in 2015(implies-- some renovations) This might or might not have affected the lot-size area
20	lot-size area	sqft_lot15
21	sqft_lot15	lot-size area in 2015(implies-- some renovations)

Data-Preparation:

1. Trimmed the date format to year (Dirty Data):
   Ex: 20141013T000000 to 2014

2. Explore Missing values:
   - id 21613 non-null int64
   - date 21613 non-null object
   - price 21613 non-null float64
   - bedrooms 21613 non-null int64
   - bathrooms 21613 non-null float64
   - sqft_living 21613 non-null int64
   - sqft_lot 21613 non-null int64
   - floors 21613 non-null float64
   - waterfront 21613 non-null int64
   - view 21613 non-null int64
   - condition 21613 non-null int64
   - grade 21613 non-null int64
   - sqft_above 21613 non-null int64
   - sqft_basement 21613 non-null int64
   - yr_built 21613 non-null int64
   - yr_renovated 21613 non-null int64
   - zipcode 21613 non-null int64
   - lat 21613 non-null float64
   - long 21613 non-null float64
   - sqft_living15 21613 non-null int64
   - sqft_lot15 21613 non-null int64

   The dataset does not contain any missing values

3. Created a dummy variable for year with 2014 as 0 and 2015 as 1.

4. Removed outlier.
   - During Exploratory data-analysis we found that there was a house with 33 rooms for just 100000. Clearly that was an outlier, so we removed it.

Exploratory Data-Analysis:

1. Ran Select K Best function on all the features.

	Features	Scores	P-values
0	bedrooms	2270.655234	0.000000e+00
1	bathrooms	8228.943228	0.000000e+00
2	sqft_living	21001.909641	0.000000e+00
3	sqft_lot	175.140305	7.972505e-40
4	floors	1525.706143	1.581010e-322
5	waterfront	1650.463036	0.000000e+00
6	view	4050.458981	0.000000e+00
7	condition	28.611455	8.935654e-08
8	grade	17360.635441	0.000000e+00
9	sqft_above	12514.060897	0.000000e+00
10	sqft_basement	2531.506326	0.000000e+00
11	yr_built	63.229048	1.929873e-15
12	yr_renovated	351.074838	1.021348e-77
13	zipcode	61.344518	5.011050e-15
14	lat	2248.814652	0.000000e+00
15	long	10.112071	1.475092e-03
16	sqft_living15	11265.864580	0.000000e+00
17	sqft_lot15	147.906887	6.417560e-34
18	date_2015	0.276366	5.990981e-01

Clearly from the above table all the scores are statistically significant **except date_2015** taking **alpha = 0.01** Hence selecting the features with high scores, we get.

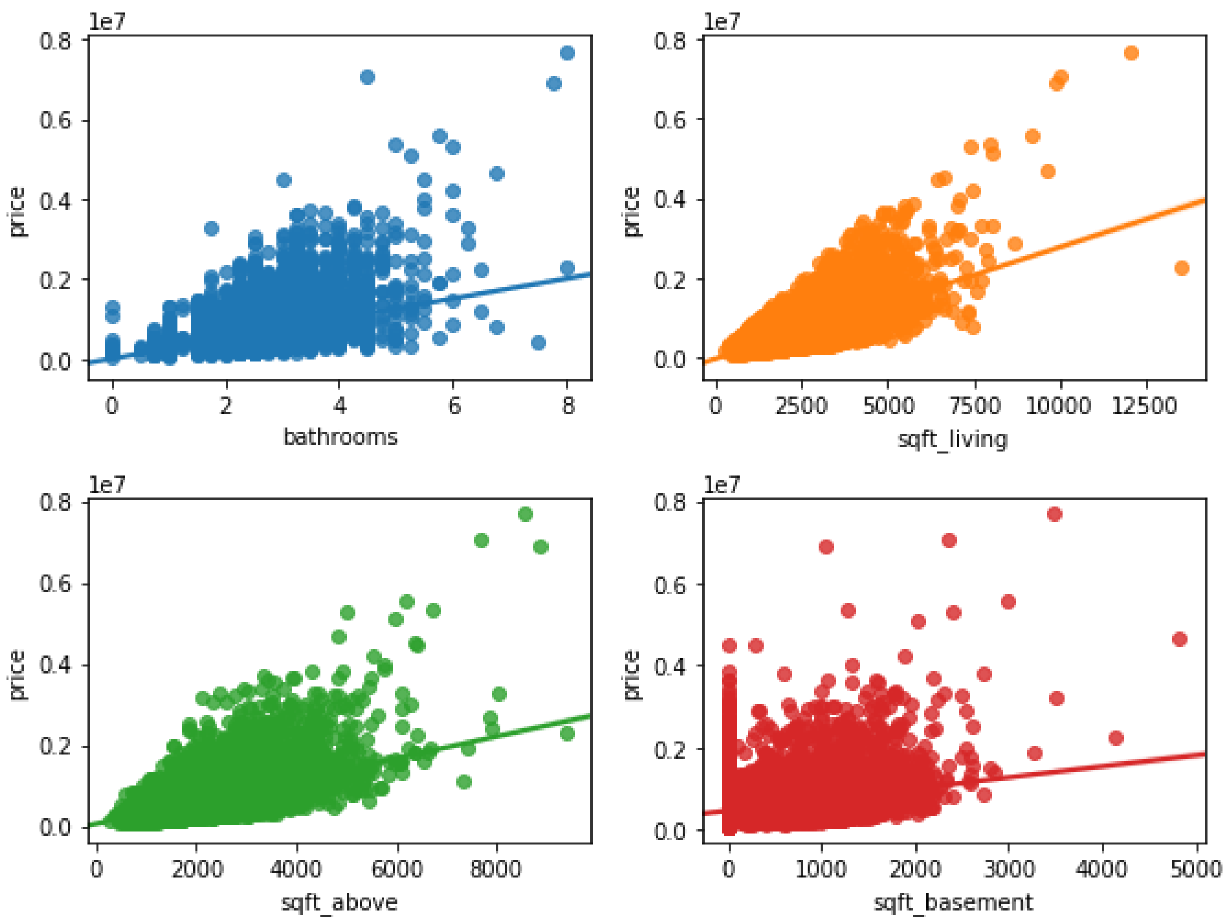
List of Important Features:

['bedrooms', 'bathrooms', 'sqft_living', 'floors', 'waterfront', 'view', 'grade','sqft_above', 'sqft_basement', 'yr_renovated', 'lat', 'sqft_living15']

2. **Price Info:**

```
count    2.161300e+04
mean     5.400881e+05
std      3.671272e+05
min      7.500000e+04
25%      3.219500e+05
50%      4.500000e+05
75%      6.450000e+05
max      7.700000e+06
```

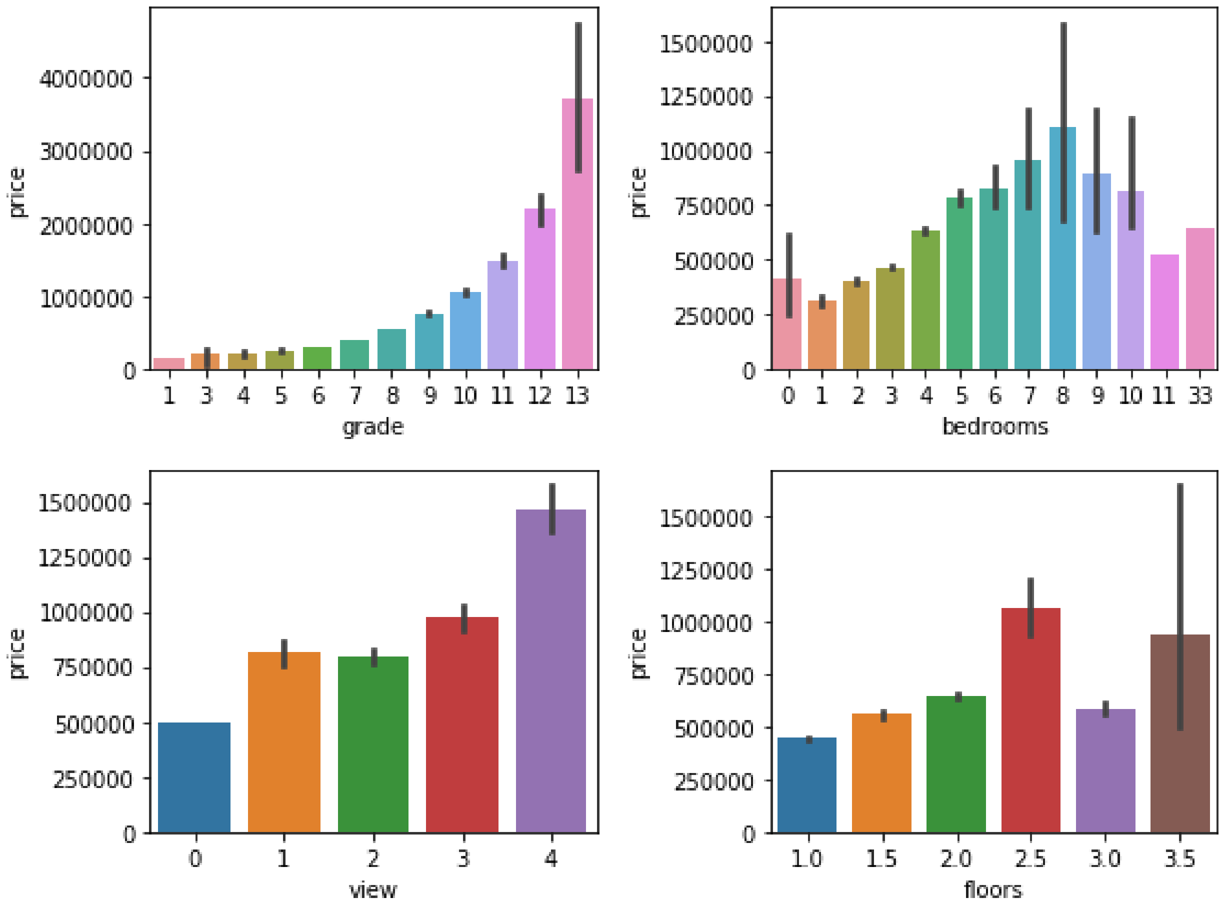
3. **Plots (Linear Regression)**



The above figure shows that the price of the houses is linearly dependent on the above numerical features and they fit the data well.

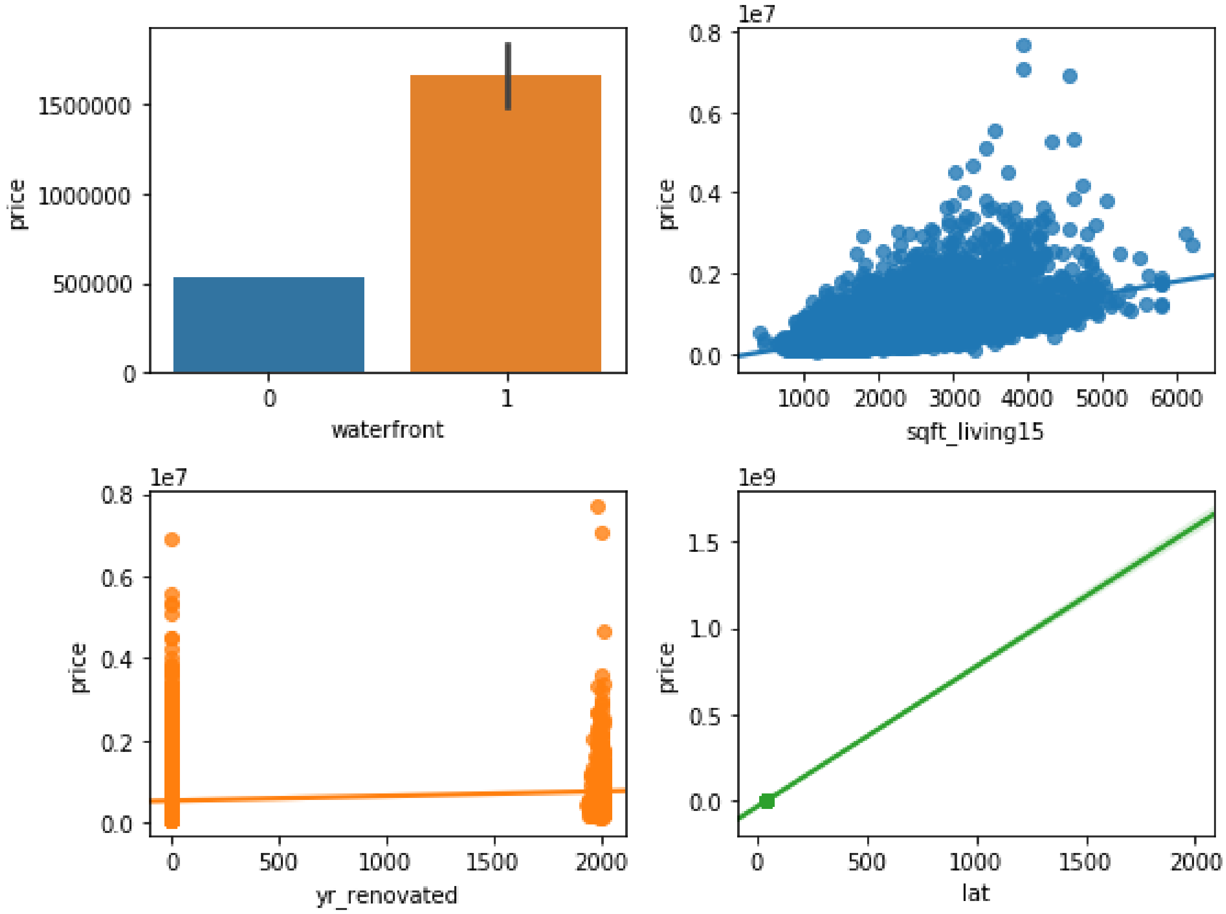
- The price of house increases with the increase in values of all features above.

4. **Categorical (Barplots)**



- The above shows average price of houses for different categorical features.
- The average price of house increases with increase in **grade** of the house.
- The average price of house with 8 **bedrooms** is the highest as there is a house with 33 rooms with very less price which suggests that that observation is an **outlier.**
- The average price of the house increases with the number of **views** present in the house
- The average price of houses with 2.5 **floors** is highest which can also imply that the dataset contains more houses with 2.5 floors

5. **Mixed Plots**



The above figure gives a mix of numerical and categorical regression and barplots of the remaining important features

- The average price increases with in presence of **waterfront**.
- The price linearly increases with increase in **living space.**
- The houses are located in the same **latitude** and hence the figure above.

Data Modelling:

- Divided the dataset into **train, test and validation sets.**
- **Used Standard Scaler** to fit the training set and transformed the train test and validation sets such that all the feature data have a **mean of zero and standard deviation of 1.**

Regression Models: (To predict house prices based on important features)

R_squared values on **Validation set** with **Important features**

Regressor Model	R_squared and Adj_R_Squared
Lasso	0.683640999182128 0.6826337537563347
KNN	0.7648410447043974 0.7640923295376298
Decision Tree	0.6021665304362689 0.6008998810240204
Multiple Regressor	0.6836439383426598 0.682636702274767
Random Forrest	**0.8049827440112232** **0.8043618347324051**

R_squared values on **Test set** with **Important features**

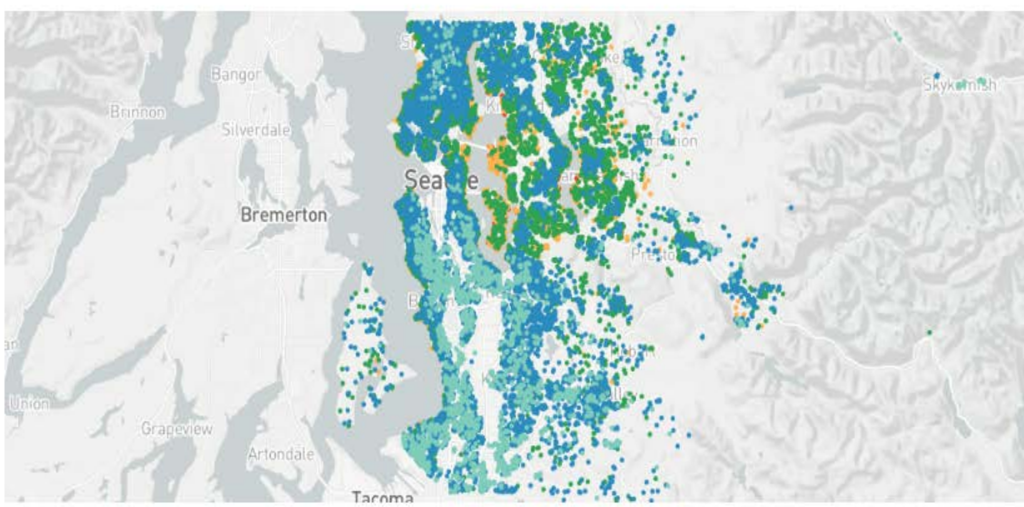
Regressor Model	R_squared and Adj_R_Squared
KNN	0.7398236661213362 0.7389952989134445
Random Forrest	**0.7820402618949703** **0.7813463067723223**

Clearly from above table we got highest adjusted R squared value on the test dataset using **Random Forrest Regressor.**

Clustering Models:

I. **Custom Cluster:** Using **longitude, latitude and price** of the house we gave color labels to **6 clusters** as following:
   - **a.** Price < 250000 – Light Blue
   - **b.** 250000<price<500000 – Dark Blue
   - **c.** 500000<price<1000000 – Green
   - **d.** 1000000<price<3000000 – Yellow
   - **e.** 3000000<price<5000000 – Light Red
   - **f.** Price>5000000 – Dark Red

House prices in King County (Custom Price Clustering)

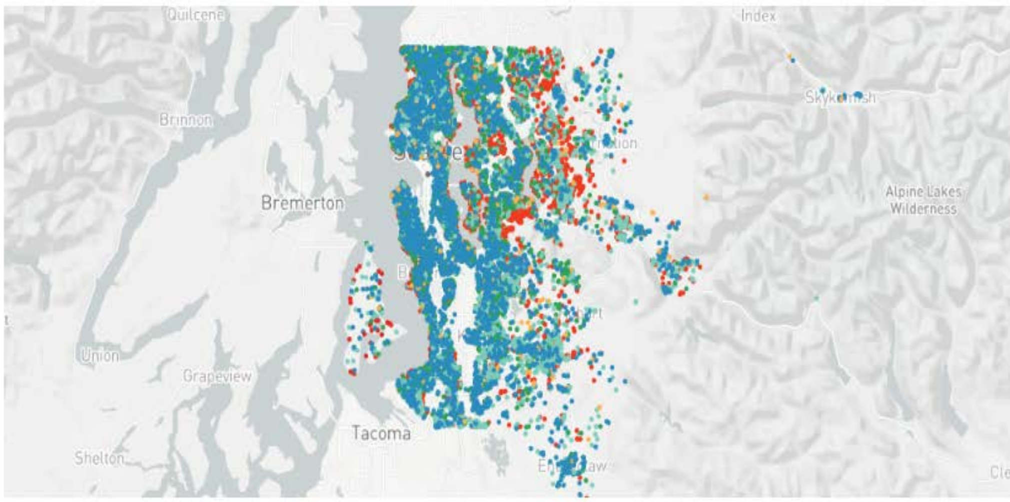


Clearly The pricier houses lie at the center and least expensive houses lie on the south side.

(See Jupyter Code map for a **zoomed** in view)

II. **K-Means Cluster:** Created 6 Clusters using K-means clustering on the important features. Below is the clustering figure.

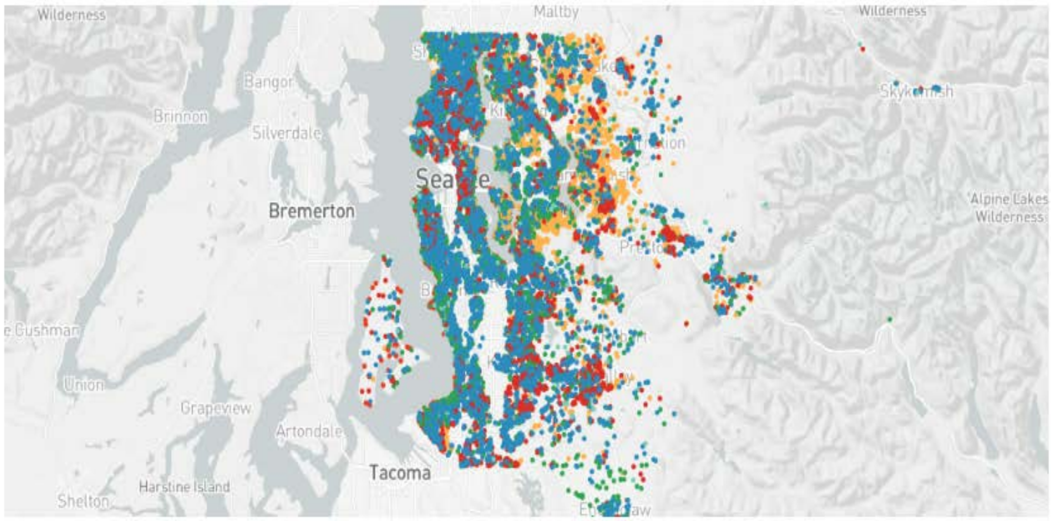
House prices in King County (K-Means) Clsutering



Clearly the clusters are different from the custom clusters and clusters regions randomly

III. **Ward's Linkage:** Created 6 Clusters using Ward's Linkage clustering on the important features. Below is the clustering figure.

House prices in King County (K-Means) Clsutering



Clearly ward's linkage also forms clusters randomly with respect to the desired clusters.