Final Project - House Price Prediction of King county

In [11]:
```
# Load Libraries
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression,Lasso,Ridge,ElasticNet
from sklearn.neighbors import KNeighborsRegressor , KNeighborsClassifier
from sklearn.tree import DecisionTreeRegressor , DecisionTreeClassifier
from sklearn.ensemble import RandomForestRegressor, RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.cluster import KMeans, DBSCAN, AgglomerativeClustering
from scipy.cluster.hierarchy import linkage, fcluster
from sklearn import metrics
from sklearn.feature_selection import RFE,SelectKBest,f_regression
import warnings
warnings.filterwarnings('ignore')
```

Data Collection

In [12]:
```
# Read Dataset
kc_data = pd.read_csv('kc_house_data.csv')
```

In [13]:
```
kc_data.head()
```

Out[13]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade
0	7129300520	20141013T000000	221900.0	3	1.00	1180	5650	1.0	0	0	...	7
1	6414100192	20141209T000000	538000.0	3	2.25	2570	7242	2.0	0	0	...	7
2	5631500400	20150225T000000	180000.0	2	1.00	770	10000	1.0	0	0	...	6
3	2487200875	20141209T000000	604000.0	4	3.00	1960	5000	1.0	0	0	...	7
4	1954400510	20150218T000000	510000.0	3	2.00	1680	8080	1.0	0	0	...	8

5 rows × 21 columns

Data Preprocessing

In [14]:
```
# (noise) Change the date format to just the year
kc_data['date'] = kc_data['date'].str.slice(0,4)
```

In [15]:
```
kc_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21613 entries, 0 to 21612
Data columns (total 21 columns):
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
dtypes: float64(5), int64(15), object(1)
memory usage: 3.5+ MB
```

In [16]:
```
# (missing data) The dataset contains No Null Values with 5-float,15-int and 1-Object(string) featur
es.
```

In [17]:
```
# (creating dummy variable) Change categorical data to numerical data
kc_data = pd.get_dummies(kc_data,drop_first=True)
```

In [18]:
```
kc_data.shape
```

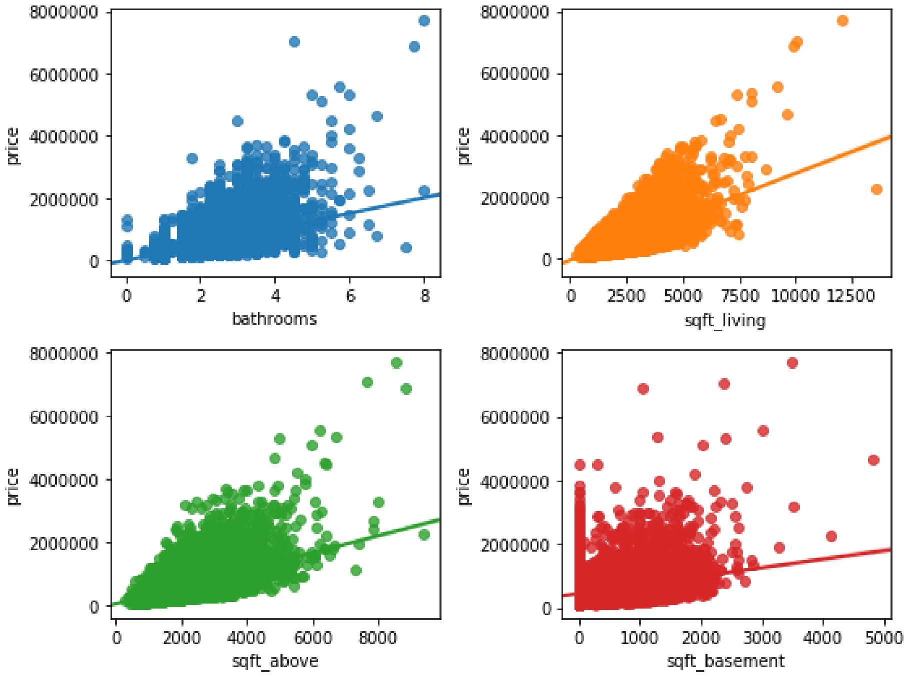
Out[18]:
```
(21613, 21)
```

Data Exploration

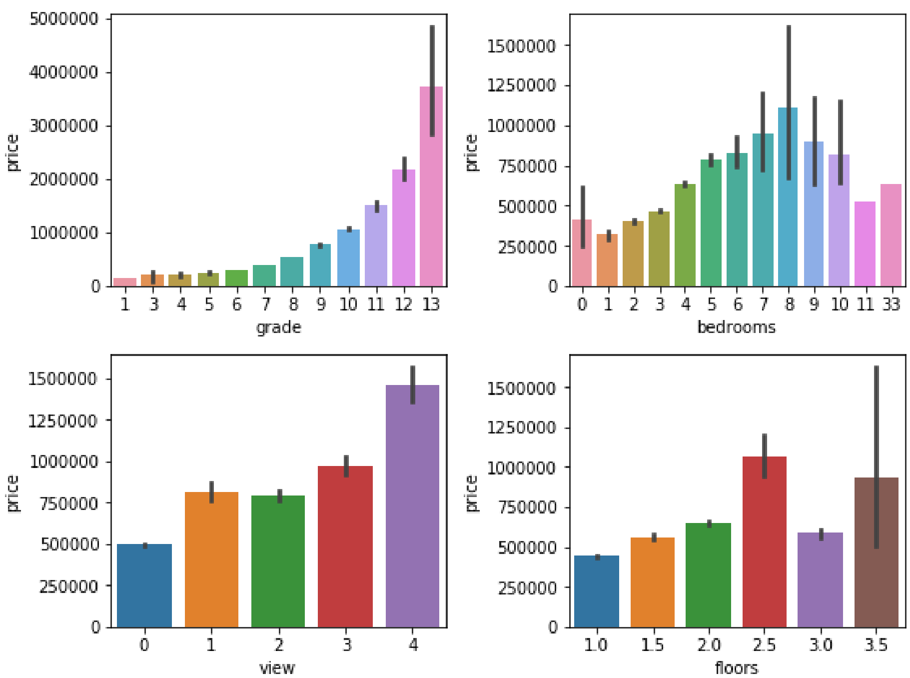
In [19]:
```
# Price Statistics
kc_data['price'].describe()
```

Out[19]:
```
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
Name: price, dtype: float64
```

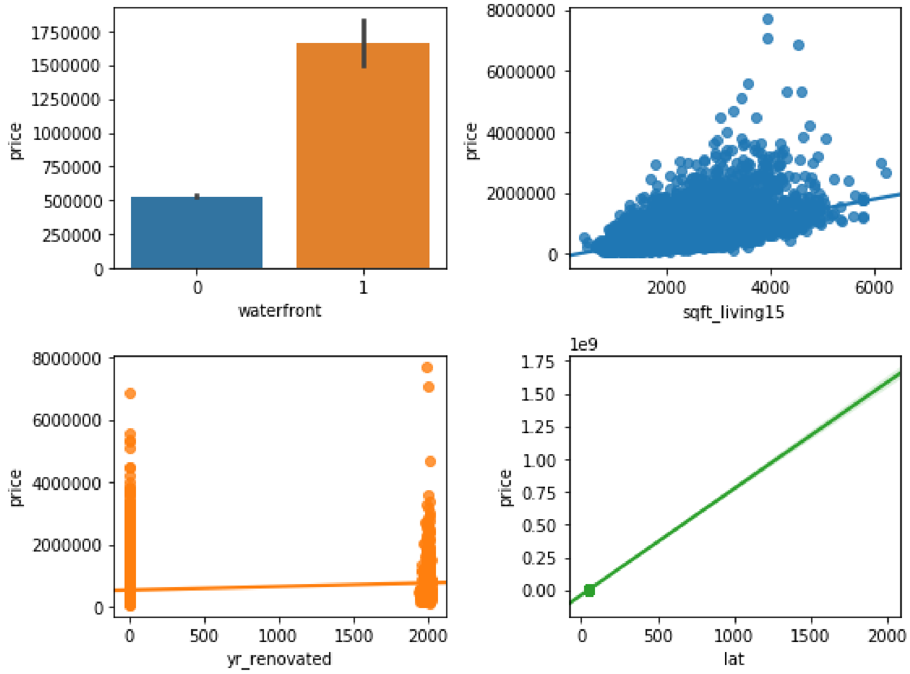
In [20]:
```python
# Comparing price with numerical features
fig, axs = plt.subplots(ncols=2,nrows=2,figsize=(8,6))
sns.regplot(kc_data['bathrooms'],kc_data['price'],ax=axs[0,0])
sns.regplot(kc_data['sqft_living'],kc_data['price'],ax=axs[0,1])
sns.regplot(kc_data['sqft_above'],kc_data['price'],ax=axs[1,0])
sns.regplot(kc_data['sqft_basement'],kc_data['price'],ax=axs[1,1])
plt.tight_layout()
```



In [21]:
```python
# Comparing price with categorical features
fig, axs = plt.subplots(ncols=2,nrows=2,figsize=(8,6))
sns.barplot(kc_data['grade'],kc_data['price'],ax=axs[0,0])
sns.barplot(kc_data['bedrooms'],kc_data['price'],ax=axs[0,1])
sns.barplot(kc_data['view'],kc_data['price'],ax=axs[1,0])
sns.barplot(kc_data['floors'],kc_data['price'],ax=axs[1,1])
plt.tight_layout()
```



In [22]:
```
# Comparing price with other important features
fig, axs = plt.subplots(ncols=2,nrows=2,figsize=(8,6))
sns.barplot(kc_data['waterfront'],kc_data['price'],ax=axs[0,0])
sns.regplot(kc_data['sqft_living15'],kc_data['price'],ax=axs[0,1])
sns.regplot(kc_data['yr_renovated'],kc_data['price'],ax=axs[1,0])
sns.regplot(kc_data['lat'],kc_data['price'],ax=axs[1,1])
plt.tight_layout()
```



Removing Outlier (found during EDA)

In [23]:
```
kc_data[kc_data['bedrooms']==33]
```

Out[23]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	...	sqft_above
15870	2402100895	640000.0	33	1.75	1620	6000	1.0	0	0	5	...	1040

1 rows × 21 columns

In [24]:
```
kc_data.drop(15870,inplace=True)
```

In [25]:
```
kc_features_data =  kc_data.iloc[:,2::]
```

Using Select K Best - Feature Selection

In [26]:
```
selector = SelectKBest(f_regression,k='all').fit(kc_features_data,kc_data['price'])
print('----------------------Feature Scores-------------------------')
print(selector.scores_)
print("-----------------Feature Scores' P-values--------------------")
print(selector.pvalues_)
```

```
----------------------Feature Scores-------------------------
[2.38792459e+03 8.22897741e+03 2.10023042e+04 1.75144105e+02
 1.52585113e+03 1.65040802e+03 4.05040206e+03 2.85696576e+01
 1.73610520e+04 1.25150392e+04 2.53131111e+03 6.32524672e+01
 3.51075477e+02 6.13561555e+01 2.24862897e+03 1.01217607e+01
 1.12668362e+04 1.47914597e+02 2.77706642e-01]
-----------------Feature Scores' P-values--------------------
[0.00000000e+000 0.00000000e+000 0.00000000e+000 7.95753908e-040
 1.48219694e-322 0.00000000e+000 0.00000000e+000 9.13037752e-008
 0.00000000e+000 0.00000000e+000 0.00000000e+000 1.90713406e-015
 1.02109197e-077 4.98161365e-015 0.00000000e+000 1.46736107e-003
 0.00000000e+000 6.39294519e-034 5.98213729e-001]
```

In [27]:
```
feature_scores = list(selector.scores_)
kc_features_data.head()
```

Out[27]:

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	yr_bui
0	3	1.00	1180	5650	1.0	0	0	3	7	1180	0	195
1	3	2.25	2570	7242	2.0	0	0	3	7	2170	400	195
2	2	1.00	770	10000	1.0	0	0	3	6	770	0	193
3	4	3.00	1960	5000	1.0	0	0	5	7	1050	910	196
4	3	2.00	1680	8080	1.0	0	0	3	8	1680	0	198

In [28]:
```
# features with corresponding scores
feature_names = list(kc_features_data.columns.values)
feature_score_dict = dict(zip(feature_names,feature_scores))
feature_score_dict
```

Out[28]:
```
{'bedrooms': 2387.9245920333806,
 'bathrooms': 8228.977408041797,
 'sqft_living': 21002.304161979228,
 'sqft_lot': 175.14410514581112,
 'floors': 1525.8511320891844,
 'waterfront': 1650.4080187000768,
 'view': 4050.402063130254,
 'condition': 28.569657602904442,
 'grade': 17361.05198133765,
 'sqft_above': 12515.039203719882,
 'sqft_basement': 2531.3111052778845,
 'yr_built': 63.252467228971014,
 'yr_renovated': 351.0754774238385,
 'zipcode': 61.35615545226101,
 'lat': 2248.6289720518616,
 'long': 10.121760712055881,
 'sqft_living15': 11266.83617592883,
 'sqft_lot15': 147.91459734591243,
 'date_2015': 0.27770664203842776}
```

In [29]:
```
# Using Standard Scaler
scaler = StandardScaler()
```

Train, Test and Validation sets

In [30]:
```
# Train and Test Set
x_train,x_test,y_train,y_test = train_test_split(kc_features_data,kc_data['price'],test_size=0.3, ra
ndom_state = 0)
```

In [31]:
```
# Train and Validataion Set
x_train,x_val,y_train,y_val = train_test_split(x_train,y_train,test_size=0.25,random_state=0)
```

Scaling Data

In [32]:
```
scaled_x_train = scaler.fit_transform(x_train)
scaled_x_val = scaler.transform(x_val)
scaled_x_test = scaler.transform(x_test)
```

Regression Models

Ridge Regression using all features

In [33]:
```
model = Ridge(alpha = 1).fit(X=scaled_x_train,y =y_train)
print(model.coef_)
print(model.intercept_)
```

```
[-31280.81795927  31702.00883315  76276.42856332   9683.79880041
   4235.9649007   41121.40020234  44296.11224133  17828.81449154
 118893.96791186  72282.24285923  23384.27604742 -76433.47749067
   6662.56516818 -31285.45197727  86285.90246499 -31031.47766046
  14509.18793544 -13477.71697338  15841.33869649]
538807.9664198802
```

In [34]:
```
score_train = model.score(X=scaled_x_train,y=y_train) # R squared (training)
score_val =model.score(X=scaled_x_val,y=y_val) # R squared (validation)
score_test = model.score(X =scaled_x_test, y = y_test) # R squared (test)
adj_r_squared = 1-(((1-score_val)*(len(x_val)-1))/(len(x_val)-x_val.shape[1]-1)) #adjusted R squared
(validation)
print([score_train, score_val, score_test])
print(adj_r_squared)
```

```
[0.6996290899404481, 0.7187317388523007, 0.6929334347955567]
0.7173111920788274
```

Lasso Regression using all features

In [35]:
```
model = Lasso(alpha = 1,random_state=0).fit(X=scaled_x_train,y =y_train)
print(model.coef_)
print(model.intercept_)
```

```
[-31289.54632804  31697.79323667 253778.55641706   9682.27070882
   4232.61220164  41123.50953083  44296.51779865  17825.19290496
 118918.07953281 -87516.81627851 -61585.81718966 -76449.1733656
   6657.76210594 -31293.88296766  86290.4750918  -31031.26442046
  14485.17047851 -13478.92660311  15842.13590976]
538807.9664198802
```

In [36]:
```
score_train = model.score(X=scaled_x_train,y=y_train) # R squared (training)
score_val =model.score(X=scaled_x_val,y=y_val) # R squared (validation)
score_test = model.score(X =scaled_x_test, y = y_test) # R squared (test)
adj_r_squared = 1-(((1-score_val)*(len(x_val)-1))/(len(x_val)-x_val.shape[1]-1)) #adjusted R squared
(validation)
print([score_train, score_val, score_test])
print(adj_r_squared)
```

```
[0.6996290938003702, 0.71873083153697, 0.692936296474021]
0.7173102801810962
```

ElasticNet using all features

In [37]:
```
model = ElasticNet(alpha = 1, l1_ratio = 0.5).fit(X=scaled_x_train,y =y_train)
print(model.coef_)
print(model.intercept_)
```

```
[ -4534.60755585  28340.66130067  57746.21335836   4918.5744192
   9821.8630233   30689.46558435  40379.86055044  16841.60322015
  72337.39719656  51310.80553586  24118.88512266 -35764.85352089
  12176.84775305  -6538.91993591  60908.27327012 -19333.99646958
  38434.65689743  -3171.53441616   9024.40938652]
538807.9664198823
```

In [38]:
```
score_train = model.score(X=scaled_x_train,y=y_train) # R squared (training)
score_val =model.score(X=scaled_x_val,y=y_val) # R squared (validation)
score_test = model.score(X =scaled_x_test, y = y_test) # R squared (test)
adj_r_squared = 1-(((1-score_val)*(len(x_val)-1))/(len(x_val)-x_val.shape[1]-1)) #adjusted R squared
(validation)
print([score_train, score_val, score_test])
print(adj_r_squared)
```

```
[0.6660936352637814, 0.6848553460218129, 0.6528109887395909]
0.6832637063552565
```

Decision Tree Regressor using all features

In [39]:
```
model = DecisionTreeRegressor(random_state=0).fit(scaled_x_train,y_train)
score_train = model.score(X=scaled_x_train,y=y_train) # R squared (training)
score_val =model.score(X=scaled_x_val,y=y_val) # R squared (validation)
score_test = model.score(X =scaled_x_test, y = y_test) # R squared (test)
adj_r_squared = 1-(((1-score_val)*(len(x_val)-1))/(len(x_val)-x_val.shape[1]-1)) #adjusted R squared
(validation)
print([score_train, score_val, score_test])
print(adj_r_squared)
```

```
[0.9999094048370556, 0.7679809944814076, 0.7706398331287826]
0.7668091813222228
```

KNN Regressor using all features

In [40]:
```
model = KNeighborsRegressor(n_neighbors=5).fit(X=scaled_x_train,y =y_train)
score_train = model.score(X=scaled_x_train,y=y_train) # R squared (training)
score_val =model.score(X=scaled_x_val,y=y_val) # R squared (validation)
score_test = model.score(X =scaled_x_test, y = y_test) # R squared (test)
adj_r_squared = 1-(((1-score_val)*(len(x_val)-1))/(len(x_val)-x_val.shape[1]-1)) #adjusted R squared
(validation)
print([score_train, score_val, score_test])
print(adj_r_squared)
```

```
[0.8417315949604249, 0.7898535226855233, 0.7725373951667546]
0.7887921768405007
```

Multiple Linear Regressor using all features

In [41]:
```
model = LinearRegression().fit(scaled_x_train,y_train)
score_train = model.score(X=scaled_x_train,y=y_train) # R squared (training)
score_val =model.score(X=scaled_x_val,y=y_val) # R squared (validation)
score_test = model.score(X =scaled_x_test, y = y_test) # R squared (test)
adj_r_squared = 1-(((1-score_val)*(len(x_val)-1))/(len(x_val)-x_val.shape[1]-1)) #adjusted R squared
(validation)
print([score_train, score_val, score_test])
print(adj_r_squared)
```

```
[0.6996290941426098, 0.7187306337255207, 0.6929359697389114]
0.717310081370599
```

Random Forrest Regressor using all features

In [42]:
```
model = RandomForestRegressor(random_state=0).fit(scaled_x_train,y_train)
score_train = model.score(X=scaled_x_train,y=y_train) # R squared (training)
score_val = model.score(X=scaled_x_val,y=y_val) # R squared (validation)
score_test = model.score(X =scaled_x_test, y = y_test) # R squared (test)
adj_r_squared = 1-(((1-score_val)*(len(x_val)-1))/(len(x_val)-x_val.shape[1]-1)) #adjusted R squared
(validation)
print([score_train, score_val, score_test])
print(adj_r_squared)
```

```
[0.9701567579133075, 0.8747295712047556, 0.8620238038642775]
0.8740968922714463
```

In [43]:
```
# List of Important Features
imp_features = ['bedrooms',
 'bathrooms',
 'sqft_living',
 'floors',
 'waterfront',
 'view',
 'grade',
 'sqft_above',
 'sqft_basement',
 'yr_renovated',
 'lat',
 'sqft_living15']
```

In [44]:
```
# Dataset with important features
x_train = x_train[imp_features]
x_val = x_val[imp_features]
x_test = x_test[imp_features]
```

In [45]:
```
# Scaling Important Feature Dataset
scaled_x_train = scaler.fit_transform(x_train)
scaled_x_val = scaler.transform(x_val)
scaled_x_test = scaler.transform(x_test)
```

Ridge Regression using Important features

In [46]:
```
model = Ridge(alpha = 1).fit(X=scaled_x_train,y =y_train)
print(model.coef_)
print(model.intercept_)
```

```
[-21908.15876793  -4341.26717426  84088.11933631 -15344.75451501
  40585.18239111  53978.43193891 104145.59110049  73612.81022478
  37199.07657463  21406.32531403  93501.26530863   4604.33644554]
538807.966419882
```

In [47]:
```
score_train = model.score(X=scaled_x_train,y=y_train) # R squared (training)
score_val =model.score(X=scaled_x_val,y=y_val) # R squared (validation)
score_test = model.score(X =scaled_x_test, y = y_test) # R squared (test)
adj_r_squared = 1-(((1-score_val)*(len(x_val)-1))/(len(x_val)-x_val.shape[1]-1)) #adjusted R squared
(validation)
print([score_train, score_val, score_test])
print(adj_r_squared)
```

```
[0.6580630909744568, 0.6836444387263839, 0.653666585768011]
0.6826372042516471
```

Lasso Regression using Important features

In [48]:
```
model = Lasso(alpha=10,random_state=0).fit(X=scaled_x_train,y =y_train)
model.coef_
```

Out[48]:
```
array([-21913.965385  ,  -4369.31651333, 232582.54498758, -15326.84554603,
        40579.42485187,  53978.9532339 , 104170.34291362, -60027.06075497,
       -33849.13815948,  21395.79212208,  93495.40846978,   4537.1784843 ])
```

In [49]:
```
score_train = model.score(X=scaled_x_train,y=y_train) # R squared (training)
score_val = model.score(X=scaled_x_val,y=y_val) # R squared (validation)
score_test = model.score(X =scaled_x_test, y = y_test) # R squared (test)
adj_r_squared = 1-(((1-score_val)*(len(x_val)-1))/(len(x_val)-x_val.shape[1]-1)) #adjusted R squared
(validation)
print([score_train, score_val, score_test])
print(adj_r_squared)
```

```
[0.6580630800394413, 0.683640999182128, 0.6536720919606233]
0.6826337537563347
```

ElasticNet using Important features

In [50]:
```
model = ElasticNet(alpha = 1, l1_ratio = 0.5).fit(X=scaled_x_train,y =y_train)
print(model.coef_)
print(model.intercept_)
```

```
[-2663.47360789 18818.58192195 57407.11170404  1370.7691168
 31297.03215622 44737.32360308 66943.78974041 47586.19148067
 30415.23400517 16880.873587   64642.69036949 33756.77922013]
538807.9664198825
```

In [51]:
```
score_train = model.score(X=scaled_x_train,y=y_train) # R squared (training)
score_val = model.score(X=scaled_x_val,y=y_val) # R squared (validation)
score_test = model.score(X =scaled_x_test, y = y_test) # R squared (test)
adj_r_squared = 1-(((1-score_val)*(len(x_val)-1))/(len(x_val)-x_val.shape[1]-1)) #adjusted R squared
(validation)
print([score_train, score_val, score_test])
print(adj_r_squared)
```

```
[0.6320709061022907, 0.6541556803876882, 0.6206226725909685]
0.6530545575871184
```

Decision Tree Regressor using Important features

In [52]:
```
model = DecisionTreeRegressor(random_state=0).fit(scaled_x_train,y_train)
score_train = model.score(X=scaled_x_train,y=y_train) # R squared (training)
score_val = model.score(X=scaled_x_val,y=y_val) # R squared (validation)
score_test = model.score(X =scaled_x_test, y = y_test) # R squared (test)
adj_r_squared = 1-(((1-score_val)*(len(x_val)-1))/(len(x_val)-x_val.shape[1]-1)) #adjusted R squared
(validation)
print([score_train, score_val, score_test])
print(adj_r_squared)
```

```
[0.9993841300058871, 0.6023396600684414, 0.6195867930647317]
0.6010735618781579
```

KNN Regressor using Important features

In [53]:
```
model = KNeighborsRegressor(n_neighbors=5).fit(X=scaled_x_train,y =y_train)
score_train = model.score(X=scaled_x_train,y=y_train) # R squared (training)
score_val = model.score(X=scaled_x_val,y=y_val) # R squared (validation)
score_test = model.score(X =scaled_x_test, y = y_test) # R squared (test)
adj_r_squared = 1-(((1-score_val)*(len(x_val)-1))/(len(x_val)-x_val.shape[1]-1)) #adjusted R squared
(validation)
print([score_train, score_val, score_test])
print(adj_r_squared)
```

```
[0.811655569838343, 0.7648410447043974, 0.734203076978137]
0.7640923295376298
```

Multiple Linear Regressor using Important features

In [54]:
```
model = LinearRegression().fit(scaled_x_train,y_train)
score_train = model.score(X=scaled_x_train,y=y_train) # R squared (training)
score_val = model.score(X=scaled_x_val,y=y_val) # R squared (validation)
score_test = model.score(X =scaled_x_test, y = y_test) # R squared (test)
adj_r_squared = 1-(((1-score_val)*(len(x_val)-1))/(len(x_val)-x_val.shape[1]-1)) #adjusted R squared
(validation)
print([score_train, score_val, score_test])
print(adj_r_squared)
```

```
[0.6580630942955326, 0.6836439383426597, 0.6536695752128877]
0.6826367022747668
```

Random Forrest Regressor using Important Features

In [55]:
```
model = RandomForestRegressor(random_state=0).fit(scaled_x_train,y_train)
score_train = model.score(X=scaled_x_train,y=y_train) # R squared (training)
score_val = model.score(X=scaled_x_val,y=y_val) # R squared (validation)
score_test = model.score(X =scaled_x_test, y = y_test) # R squared (test)
adj_r_squared = 1-(((1-score_val)*(len(x_val)-1))/(len(x_val)-x_val.shape[1]-1)) #adjusted R squared
(validation)
print([score_train, score_val, score_test])
print(adj_r_squared)
```

```
[0.9571038167086312, 0.804736200215252, 0.7864689753166656]
0.8041145059734327
```

Clustering

(Clustering House Prices based on price)

K-Means CLustering

In [56]:
```
scaled_x_train = scaler.fit_transform(kc_data[imp_features])
```

In [57]:
```
clustering = KMeans(n_clusters=6 ,init='random',random_state=0).fit(scaled_x_train)
clusters = clustering.labels_
```

In [58]:
```
kc_data['k-means_cluster_labels'] = clusters
kc_data.head()
```

Out[58]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	...	sqft_basement
0	7129300520	221900.0	3	1.00	1180	5650	1.0	0	0	3	...	0
1	6414100192	538000.0	3	2.25	2570	7242	2.0	0	0	3	...	400
2	5631500400	180000.0	2	1.00	770	10000	1.0	0	0	3	...	0
3	2487200875	604000.0	4	3.00	1960	5000	1.0	0	0	5	...	910
4	1954400510	510000.0	3	2.00	1680	8080	1.0	0	0	3	...	0

5 rows × 22 columns

Ward's Linkage

In [59]:
```
clustering = AgglomerativeClustering(n_clusters=6,linkage='ward').fit(scaled_x_train)
```

In [60]:
```
clusters = clustering.labels_
```

In [61]:
```
kc_data['ward_cluster_labels'] = clusters
```

Price Map

In [62]:
```
map_data = kc_data[['lat','long','price','k-means_cluster_labels','ward_cluster_labels']]
```

In [63]:
```
map_data.head()
```

Out[63]:

	lat	long	price	k-means_cluster_labels	ward_cluster_labels
0	47.5112	-122.257	221900.0	1	4
1	47.7210	-122.319	538000.0	2	3
2	47.7379	-122.233	180000.0	1	4
3	47.5208	-122.393	604000.0	5	0
4	47.6168	-122.045	510000.0	1	4

Custom Price Range Clustering Map

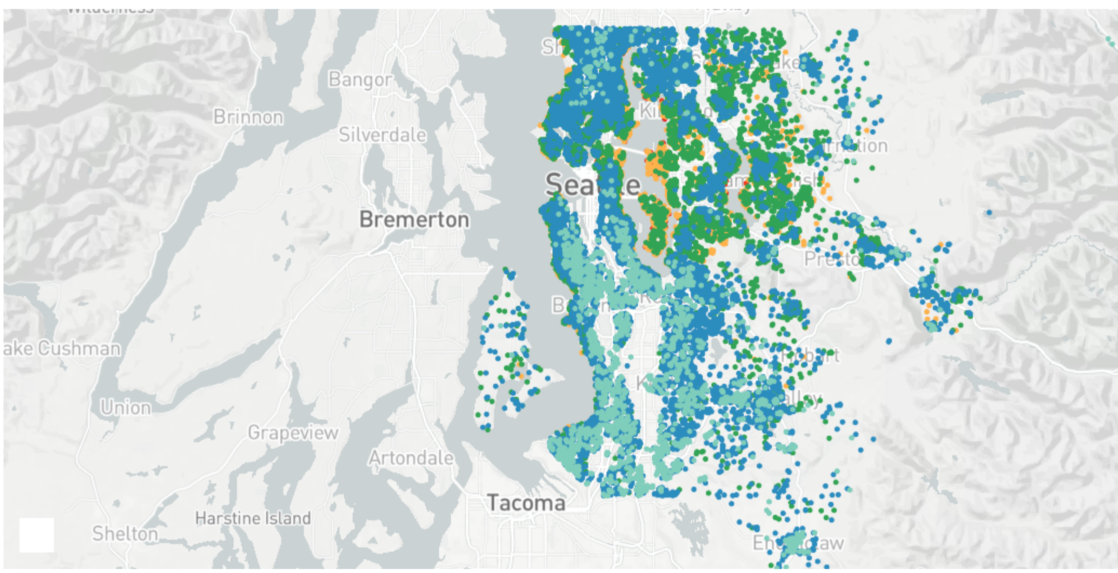
In [64]:
```
# Give colors to different price ranges
map_data['color_price'] = '#de2d26' # Default Color Initialization
map_data['color_price'][map_data['price']>5000000] = '#de2d26' # dark red
map_data['color_price'][(map_data['price']>=3000000) & (map_data['price']<5000000)] = '#f03b20' #Lig
ht red
map_data['color_price'][(map_data['price']>=1000000) & (map_data['price']<3000000)] = '#feb24c' #Yel
low
map_data['color_price'][(map_data['price']>=500000) & (map_data['price']<1000000)] = '#31a354' # Gre
en
map_data['color_price'][(map_data['price']>=250000) & (map_data['price']<500000)] = '#2b8cbe' # Blue
map_data['color_price'][(map_data['price']<250000)] = '#7fcdbb'    # light blue
```

In [65]:
```
map_data.sort_values(by= 'price',ascending=False,inplace=True)
```

In [71]:
```python
import plotly.plotly as py
import plotly
from plotly.graph_objs import *
py.sign_in(username='ck58', api_key='miXnbzUdf0xt0wuh81Xc')
trace_1 = {
    "hoverinfo" : "skip",
    "lat" : list(map_data['lat']),
    "lon" : list(map_data['long']),
    "marker": {
        "color": list(map_data['color_price']),
        "opacity": 1,
        "size": 4
    },
    "mode": "markers",
    "showlegend": False,
    "type": "scattermapbox"
}
data = Data([trace_1])
layout = {
  "autosize": True,
  "hovermode": "closest",
  "mapbox": {
    "bearing": 0,
    "center": {
      "lat": 47.6,
      "lon": -122.2
    },
    "pitch": 0,
    "style":'light',
    "zoom": 9
  },
  "title": "House prices in King County (Custom Price Clustering)"
}
fig = Figure(data=data, layout=layout)
py.iplot(fig)
```

Out[71]:

House prices in King County (Custom Price Clustering)



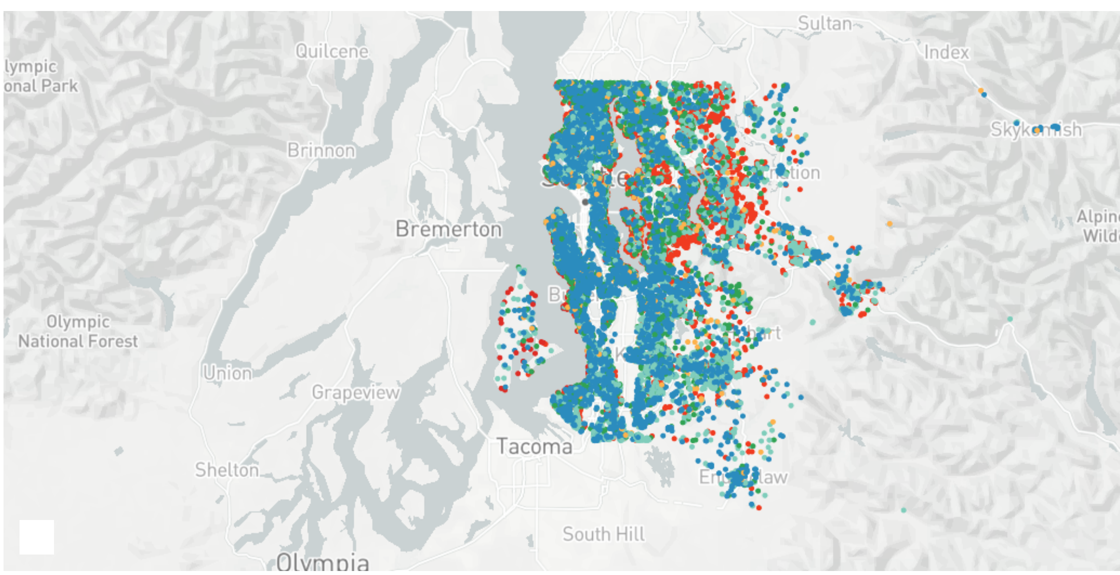
K-Means Cluster Map for Different Prices

In [67]:
```
map_data['color_cluster'] = '#de2d26' # Default Color Initialization
map_data['color_cluster'][map_data['k-means_cluster_labels']==0] = '#de2d26' # dark red
map_data['color_cluster'][map_data['k-means_cluster_labels']==1] = '#2b8cbe' # Blue
map_data['color_cluster'][map_data['k-means_cluster_labels']==2] = '#feb24c' # Yellow
map_data['color_cluster'][map_data['k-means_cluster_labels']==3] = '#7fcdbb' # light blue
map_data['color_cluster'][map_data['k-means_cluster_labels']==4] = '#f03b20' # light red
map_data['color_cluster'][map_data['k-means_cluster_labels']==5] = '#31a354' # Green
```

In [68]:
```
import plotly.plotly as py
import plotly
from plotly.graph_objs import *
py.sign_in(username='ck58', api_key='miXnbzUdf0xt0wuh81Xc')
trace_1 = {
    "hoverinfo" : "skip",
    "lat" : list(map_data['lat']),
    "lon" : list(map_data['long']),
    "marker": {
        "color": list(map_data['color_cluster']),
        "opacity": 1,
        "size": 4
    },
    "mode": "markers",
    "showlegend": False,
    "type": "scattermapbox"
}
data = Data([trace_1])
layout = {
  "autosize": True,
  "hovermode": "closest",
  "mapbox": {
    "bearing": 0,
    "center": {
      "lat": 47.6,
      "lon": -122.2
    },
    "pitch": 0,
    "style":'light',
    "zoom": 9
  },
  "title": "House prices in King County (K-Means) Clsutering"
}
fig = Figure(data=data, layout=layout)
py.iplot(fig)
```

Out[68]:

House prices in King County (K-Means) Clsutering



In [69]:
```
map_data['ward_color_cluster'] = '#de2d26' # Default Color Initialization
map_data['ward_color_cluster'][map_data['ward_cluster_labels']==0] = '#31a354' # Green
map_data['ward_color_cluster'][map_data['ward_cluster_labels']==1] = '#feb24c' #Yellow
map_data['ward_color_cluster'][map_data['ward_cluster_labels']==2] = '#de2d26' # dark red
map_data['ward_color_cluster'][map_data['ward_cluster_labels']==3] = '#7fcdbb' # light blue
map_data['ward_color_cluster'][map_data['ward_cluster_labels']==4] = '#2b8cbe' #  dark Blue
map_data['ward_color_cluster'][map_data['ward_cluster_labels']==5] =  '#f03b20' #light red
```

In [70]:
```
import plotly.plotly as py
import plotly
from plotly.graph_objs import *
py.sign_in(username='ck58', api_key='miXnbzUdf0xt0wuh81Xc')
trace_1 = {
    "hoverinfo" : "skip",
    "lat" : list(map_data['lat']),
    "lon" : list(map_data['long']),
    "marker": {
        "color": list(map_data['ward_color_cluster']),
        "opacity": 1,
        "size": 4
    },
    "mode": "markers",
    "showlegend": False,
    "type": "scattermapbox"
}
data = Data([trace_1])
layout = {
  "autosize": True,
  "hovermode": "closest",
  "mapbox": {
    "bearing": 0,
    "center": {
      "lat": 47.6,
      "lon": -122.2
    },
    "pitch": 0,
    "style":'light',
    "zoom": 9
  },
  "title": "House prices in King County (Ward's Linkage) Clsutering"
}
fig = Figure(data=data, layout=layout)
py.iplot(fig)
```

Out[70]:

House prices in King County (Ward's Linkage) Clsutering

EDIT CHART