PREDICTION HOUSE SALES IN KING COUNTRY, USA

```python
# Import library for exploring dataset
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# To ignores the warnings
import warnings
warnings.filterwarnings('ignore')
```

Read the Dataset

```python
# Read the dataset
df = pd.read_csv('kc_house_data.csv')
df.head()
```

```
           id             date     price  bedrooms  bathrooms
sqft_living  \
0  7129300520  20141013T000000  221900.0         3       1.00
1180
1  6414100192  20141209T000000  538000.0         3       2.25
2570
2  5631500400  20150225T000000  180000.0         2       1.00
770
3  2487200875  20141209T000000  604000.0         4       3.00
1960
4  1954400510  20150218T000000  510000.0         3       2.00
1680

   sqft_lot  floors  waterfront  view  ...  grade  sqft_above
sqft_basement  \
0      5650     1.0           0     0  ...      7        1180
0
1      7242     2.0           0     0  ...      7        2170
400
2     10000     1.0           0     0  ...      6         770
0
3      5000     1.0           0     0  ...      7        1050
910
4      8080     1.0           0     0  ...      8        1680
0

   yr_built  yr_renovated  zipcode      lat     long  sqft_living15  \
0      1955             0    98178  47.5112 -122.257           1340
1      1951          1991    98125  47.7210 -122.319           1690
2      1933             0    98028  47.7379 -122.233           2720
```

```
3      1965            0    98136  47.5208 -122.393            1360
4      1987            0    98074  47.6168 -122.045            1800

   sqft_lot15
0        5650
1        7639
2        8062
3        5000
4        7503

[5 rows x 21 columns]
```

```python
# See the general info of dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21613 entries, 0 to 21612
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   id             21613 non-null  int64  
 1   date           21613 non-null  object 
 2   price          21613 non-null  float64
 3   bedrooms       21613 non-null  int64  
 4   bathrooms      21613 non-null  float64
 5   sqft_living    21613 non-null  int64  
 6   sqft_lot       21613 non-null  int64  
 7   floors         21613 non-null  float64
 8   waterfront     21613 non-null  int64  
 9   view           21613 non-null  int64  
 10  condition      21613 non-null  int64  
 11  grade          21613 non-null  int64  
 12  sqft_above     21613 non-null  int64  
 13  sqft_basement  21613 non-null  int64  
 14  yr_built       21613 non-null  int64  
 15  yr_renovated   21613 non-null  int64  
 16  zipcode        21613 non-null  int64  
 17  lat            21613 non-null  float64
 18  long           21613 non-null  float64
 19  sqft_living15  21613 non-null  int64  
 20  sqft_lot15     21613 non-null  int64  
dtypes: float64(5), int64(15), object(1)
memory usage: 3.5+ MB
```

```python
# Check for duplicated rows
print("Number of duplicate rows: ", sum(df.duplicated()))
```

```
Number of duplicate rows:  0
```

As we can see that our dataset has 21 columns, 21613 rows with various datatype, had no missing value and no duplicated rows. So then we will drop the `id` and `date` variable source :

- https://rstudio-pubs-static.s3.amazonaws.com/155304_cc51f448116744069664b35e7762999f.html
- https://www.kaggle.com/datasets/harlfoxem/housesalesprediction

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Data Cleaning

In this step, we will process of drop the unimportant variable and incorrectly formatted data within a dataset. Having clean data will ultimately increase overall productivity and allow for the highest quality information in your decision-making

```
# Drop variables id & date
df = df.drop(['id','date'], axis = 1)
df.head(5)
```

```
      price  bedrooms  bathrooms  sqft_living  sqft_lot  floors  
waterfront  \
0  221900.0         3       1.00         1180      5650     1.0  
0   
1  538000.0         3       2.25         2570      7242     2.0  
0   
2  180000.0         2       1.00          770     10000     1.0  
0   
3  604000.0         4       3.00         1960      5000     1.0  
0   
4  510000.0         3       2.00         1680      8080     1.0  
0   

   view  condition  grade  sqft_above  sqft_basement  yr_built  
yr_renovated  \
0     0          3      7        1180              0      1955  
0   
1     0          3      7        2170            400      1951  
1991   
2     0          3      6         770              0      1933  
0   
3     0          5      7        1050            910      1965  
0   
4     0          3      8        1680              0      1987  
0   

   zipcode      lat     long  sqft_living15  sqft_lot15  
0    98178  47.5112 -122.257           1340        5650  
1    98125  47.7210 -122.319           1690        7639  
2    98028  47.7379 -122.233           2720        8062  
3    98136  47.5208 -122.393           1360        5000  
4    98074  47.6168 -122.045           1800        7503  
```

After that, we will round all the decimal variable (corrected) to the integer (*exclude `lat` & `long` variables*)

```
# Define df_1
df_1 = (df.loc[:, ~df.columns.isin(['lat',
'long'])]).round(0).astype(int)
df_1.head(5)
```

```
    price  bedrooms  bathrooms  sqft_living  sqft_lot  floors
waterfront  \
0  221900         3          1         1180      5650       1
0
1  538000         3          2         2570      7242       2
0
2  180000         2          1          770     10000       1
0
3  604000         4          3         1960      5000       1
0
4  510000         3          2         1680      8080       1
0

   view  condition  grade  sqft_above  sqft_basement  yr_built
yr_renovated  \
0     0          3      7        1180              0      1955
0
1     0          3      7        2170            400      1951
1991
2     0          3      6         770              0      1933
0
3     0          5      7        1050            910      1965
0
4     0          3      8        1680              0      1987
0

   zipcode  sqft_living15  sqft_lot15
0    98178           1340        5650
1    98125           1690        7639
2    98028           2720        8062
3    98136           1360        5000
4    98074           1800        7503
```

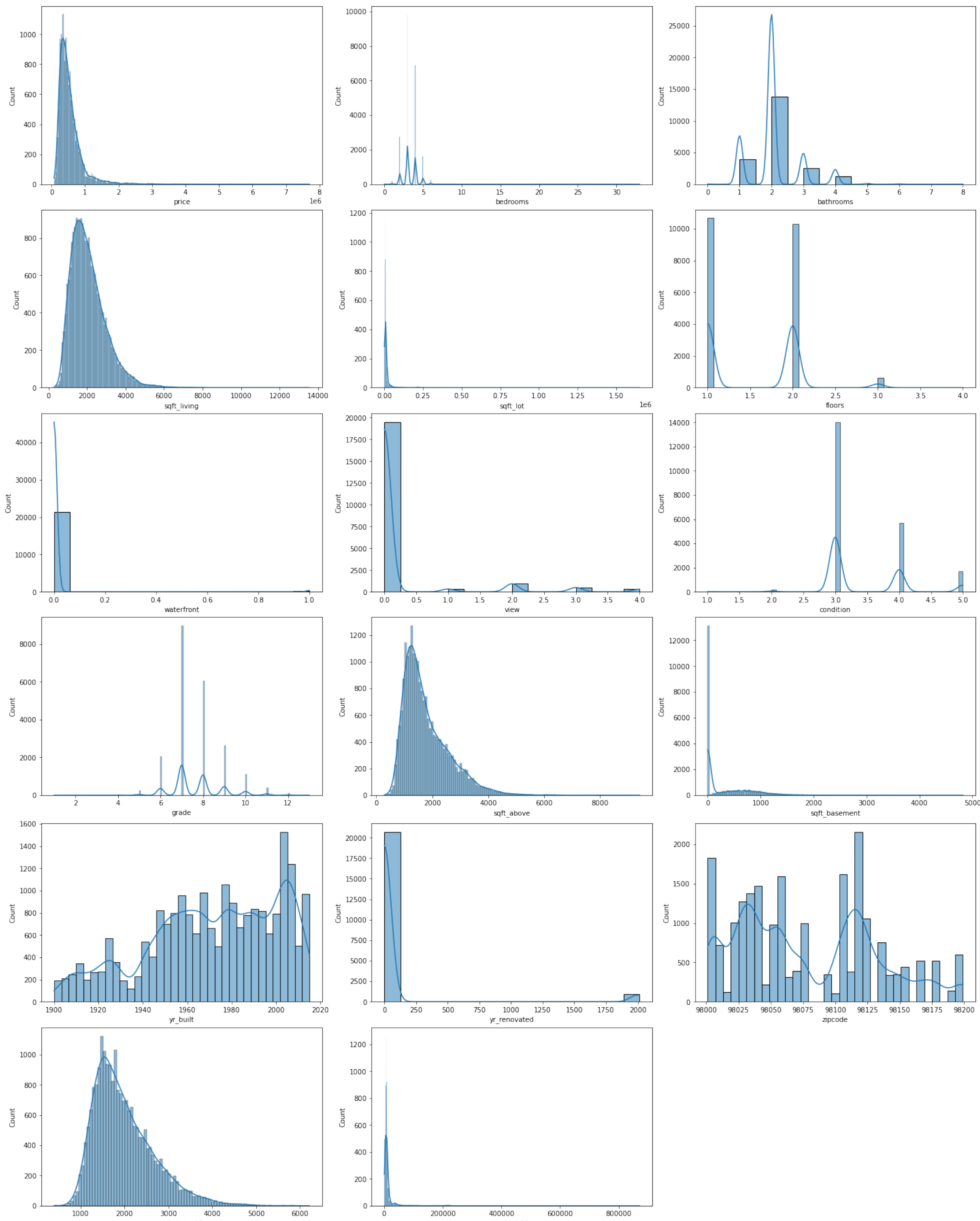
Exploratory Data Analysis

Exploratory data analysis is applied to investigate the data and summarize the key insights. It will give us the basic understanding of our data, it's distribution, null values and much more. So we do the Exploratory Data Analysis (EDA) to our data for better understanding

First, we will see the distribution each variable of our dataset

Graph each variable's distribution

```python
# Graph each variable's distribution
fig = plt.figure(figsize=(20, 25), constrained_layout=True)
for i in range(len(df_1.columns)):
    plt.subplot(6, 3, i+1)
    sns.histplot(data=df_1, x=df_1[df_1.columns[i]], kde=True)
```



Key Points :

- The `price` of house in King Country mostly in range < USD 2000000

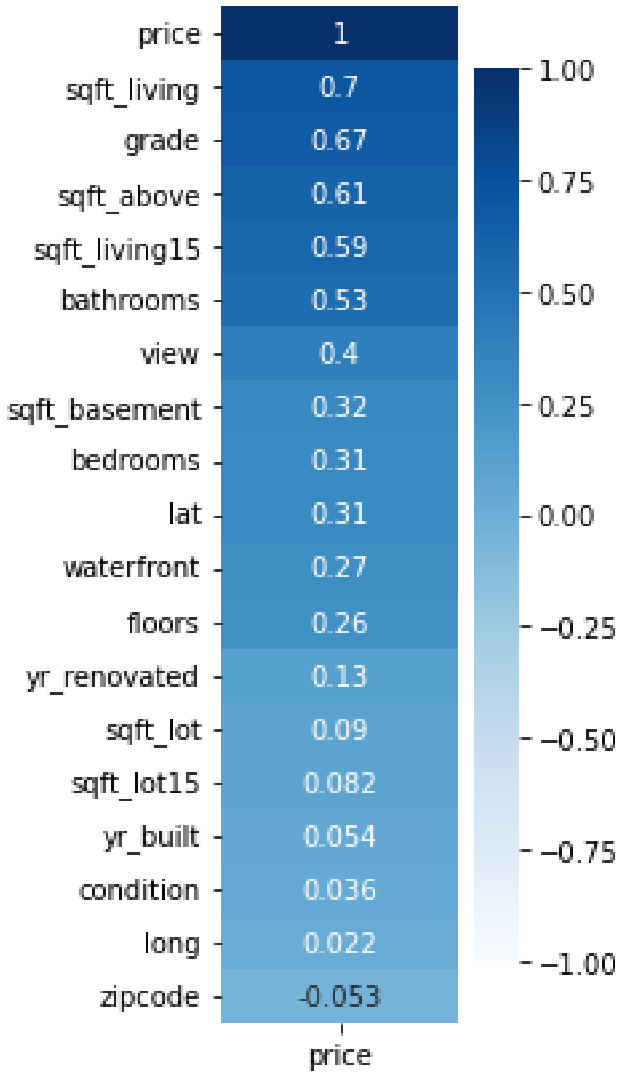
- Most of house in King Country have 1 - 5 `bedrooms`
- Most of house in King Country have 2 `bathrooms`

- The `sqft_living` of house in King Country mostly in range 0 - 6000
- The `sqft_lot` of house in King Country mostly in range < 250000
- Most of house in King Country have 1 - 2 `floors`
- Most of house in King Country not have a `waterfront`
- Most of house in King Country have zero score of `view`
- Most of house in King Country in a good `condition`
- Most of house in King Country have a `grade` on 5 - 12
- Like sqft_living, most of house King Country have `sqft_above` in range 0 - 6000
- Most of house in King Country not have a `sqft_basement`
- Based on `yr_built`, the peak of house construction in King Country is on 1940 - 2020
- Based on `yr_renovated`, Most of house in King Country doesn't get renovated
- The `zipcode` of house in King Country is on number 98000 - 98200
- The `sqft_living15` of house in King Country mostly in range 1000 - 5000
- The `sqft_lot15` of house in King Country mostly in range < 200000

Correlationg features with target

The target of this dataset is `price`, so we will correlated this target to all features

```
# Correlating features with target
plt.figure(figsize=(2, 7))
heatmap = sns.heatmap(df.corr()[['price']].sort_values(by='price',
ascending=False), vmin=-1, vmax=1, annot=True, cmap='Blues')
```

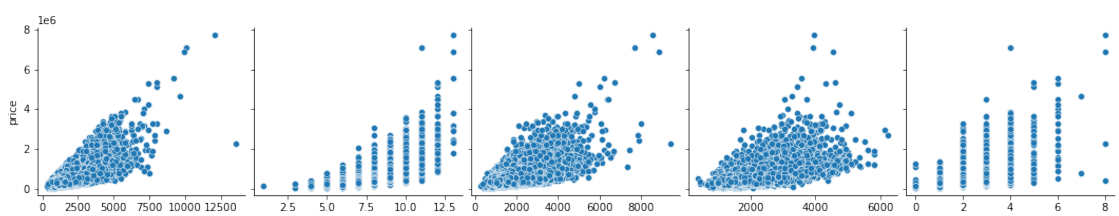


As we can see, `price` variable has a strong correlation with `sqft_living`, `grade`, `sqft_above`, `sqft_living15`, and `bathrooms`

Pairplot variable target with strong-correlation-variables-target-with

```
# Pairplot variable target with strong correlation variables target -with
sns.pairplot(df_1, x_vars=['sqft_living', 'grade', 'sqft_above',
'sqft_living15', 'bathrooms'], y_vars=['price'], height=3, aspect=1)
```

```
<seaborn.axisgrid.PairGrid at 0x20af82f4c70>
```

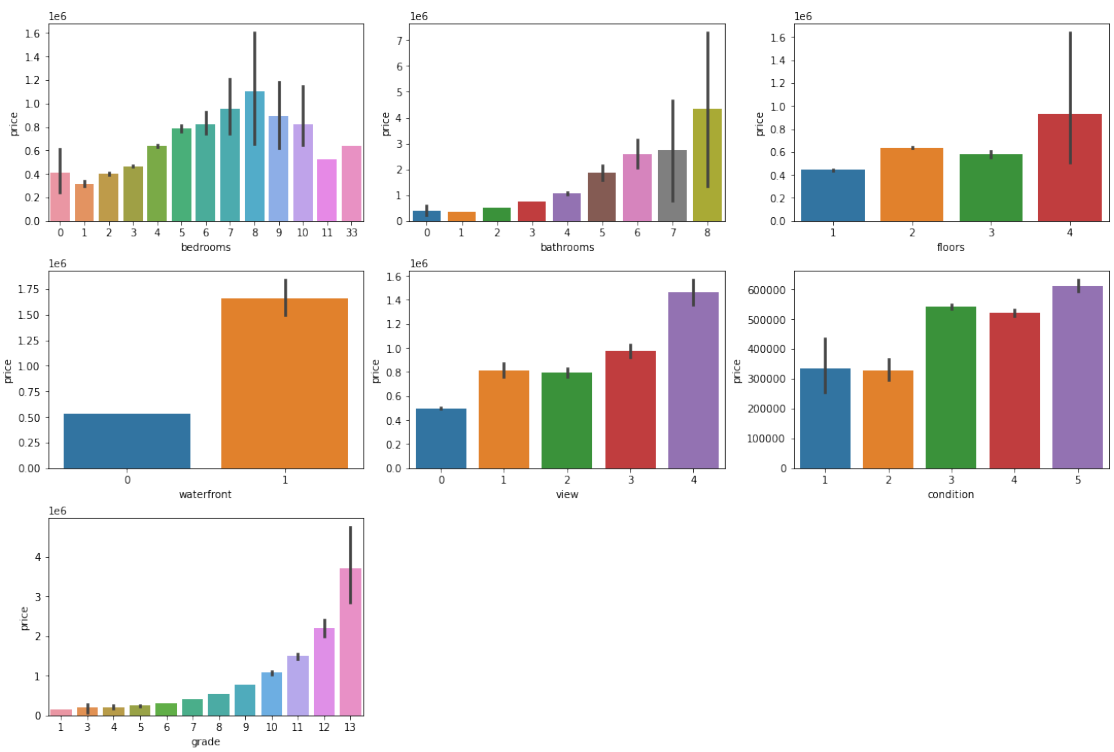


Based on the pairplot above, we can see that :

- (likely) more large sqft_living, the house is more pricey
- (likely) more high grade, the house is more pricey
- (likely) more large sqft_above, the house is more pricey
- (likely) more large sqft_living15, the house is more pricey

Graph each small amount variable with response

```
# Describe the small amount variable
sav = df_1[(['bedrooms', 'bathrooms', 'floors', 'waterfront', 'view',
'condition', 'grade'])]

# Graph each small amount variable with response
fig = plt.figure(figsize=(15,10), constrained_layout=True)
for i in range(len(sav.columns)):
    plt.subplot(3, 3, i+1)
    sns.barplot(data=sav, x=sav[sav.columns[i]], y=df_1['price'])
```



Key Points :

- The more `bathrooms` house had, the more pricey that house
- The more `floors` house had, the more pricey that house
- `waterfront` makes the house more pricey
- The more `view` house had, the more pricey that house
- The more good `condition` house had, the more pricey that house
- The more `grade` house had, the more pricey that house

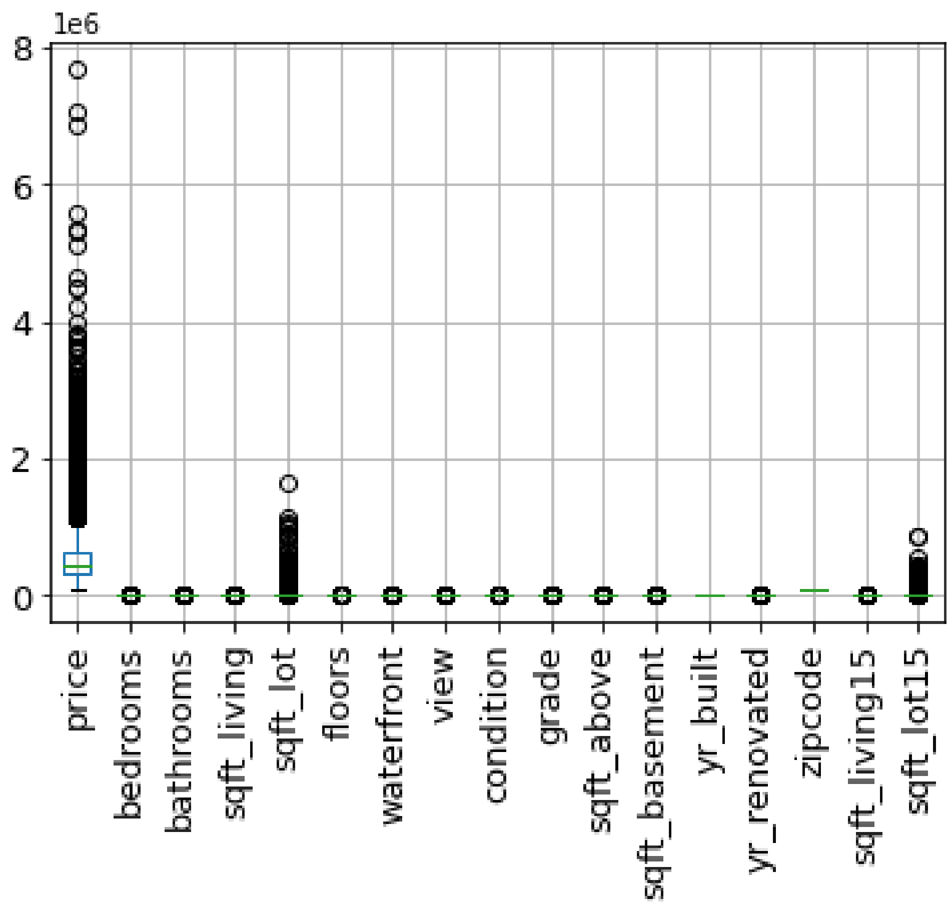
Preprocessing

In this step we will process the dataset to see the outlier and getting the data transformation so we can go any further in the next step

Outlier detection

```
# Outlier detection
df_1.boxplot(grid=True, rot=90, fontsize=13)
```

```
<AxesSubplot:>
```



As we can see, that there is an outlier on three variables (`price`, `sqft_lot` & `sqft_lot15`). But most of the outliers are near each other so we assume that this value of outliers is true (contains a good information) and we will keep all the data

Data transformation

at first, we will split the variable price from other variables

```
# Drop the target variable
df_1.drop(['price'], axis=1, inplace=True)
```

```
df_1.head(5)
```

```
   bedrooms  bathrooms  sqft_living  sqft_lot  floors  waterfront
view  \
0         3          1         1180      5650       1           0
0
1         3          2         2570      7242       2           0
0
2         2          1          770     10000       1           0
0
3         4          3         1960      5000       1           0
0
4         3          2         1680      8080       1           0
0

   condition  grade  sqft_above  sqft_basement  yr_built  yr_renovated
\
0          3      7        1180              0      1955             0

1          3      7        2170            400      1951          1991

2          3      6         770              0      1933             0

3          5      7        1050            910      1965             0

4          3      8        1680              0      1987             0


   zipcode  sqft_living15  sqft_lot15
0    98178           1340        5650
1    98125           1690        7639
2    98028           2720        8062
3    98136           1360        5000
4    98074           1800        7503
```

```
# insert `lat` & `long` variables to df_1
lat = df['lat']
long = df['long']
df_1['lat'] = lat
df_1['long'] = long
```

```
# Previewed clean data
df_1.head(5)
```

```
   bedrooms  bathrooms  sqft_living  sqft_lot  floors  waterfront
view  \
0         3          1         1180      5650       1           0
0
1         3          2         2570      7242       2           0
0
```

```
2          2          1          770      10000        1           0
0
3          4          3         1960       5000        1           0
0
4          3          2         1680       8080        1           0
0

   condition  grade  sqft_above  sqft_basement  yr_built  yr_renovated
\
0          3      7        1180              0      1955             0

1          3      7        2170            400      1951          1991

2          3      6         770              0      1933             0

3          5      7        1050            910      1965             0

4          3      8        1680              0      1987             0


   zipcode  sqft_living15  sqft_lot15      lat     long
0    98178           1340        5650  47.5112 -122.257
1    98125           1690        7639  47.7210 -122.319
2    98028           2720        8062  47.7379 -122.233
3    98136           1360        5000  47.5208 -122.393
4    98074           1800        7503  47.6168 -122.045
```

Modeling

```
# Import module
from sklearn import metrics
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import explained_variance_score
from scipy.stats import pearsonr

# LinearRegression
from sklearn.linear_model import LinearRegression
from sklearn import tree, linear_model

# XGBoost
import xgboost

# Data Splitting
X = df_1.values
y = df.price.values
X_train, X_test, y_train, y_test = train_test_split(X,
y ,test_size=0.3, random_state=2022)
```

Linear Regression

```
# Train a simple linear regression model
lm = linear_model.LinearRegression()

lm.fit(X_train,y_train)

LinearRegression()

# Describe y_predicted
y_predicted=lm.predict(X_test)
y_predicted

array([ 441789.64192401,  176483.15587769,  552072.25514344, ...,
        485992.07560727, 1716342.61920378,  821853.95589027])

lm.score(X_test,y_test)

0.7062443844613606
```

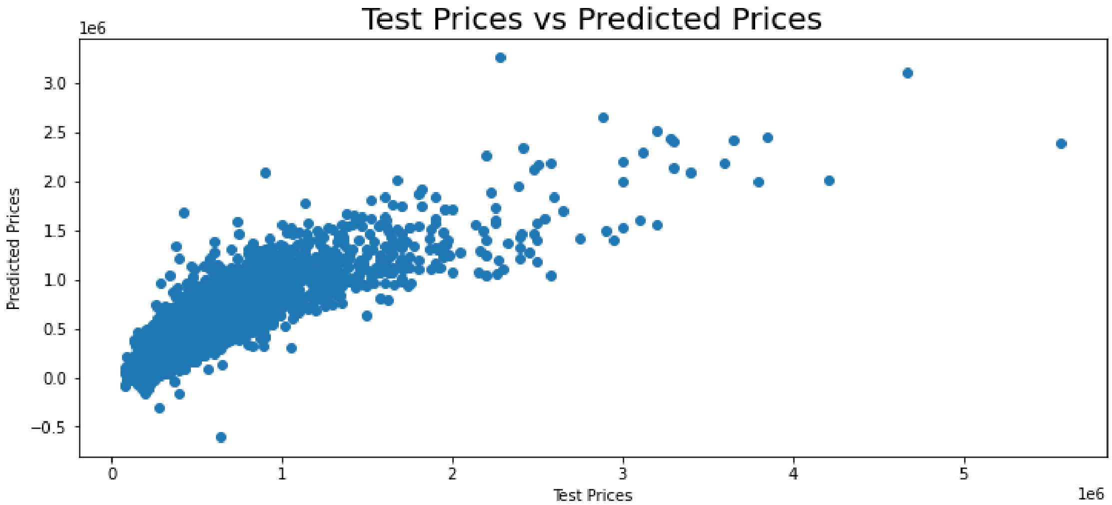
XGBoost

```
# Train sxgboost
xgb = xgboost.XGBRegressor(n_estimators=100, learning_rate=0.08, 
gamma=0, subsample=0.75,
                           colsample_bytree=1, max_depth=7)

traindf, testdf = train_test_split(X_train, test_size = 0.3)
xgb.fit(X_train,y_train)

XGBRegressor(base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, 
colsample_bytree=1,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, gamma=0, gpu_id=-1, 
grow_policy='depthwise',
             importance_type=None, interaction_constraints='',
             learning_rate=0.08, max_bin=256, max_cat_to_onehot=4,
             max_delta_step=0, max_depth=7, max_leaves=0, 
min_child_weight=1,
             missing=nan, monotone_constraints='()', n_estimators=100, 
n_jobs=0,
             num_parallel_tree=1, predictor='auto', random_state=0, 
reg_alpha=0,
             reg_lambda=1, ...)

predictions = xgb.predict(X_test)
print(explained_variance_score(predictions,y_test))

0.861996627700701
```

Show Test Prices vs Predicted Prices

```
plt.figure(figsize=(12,5))
plt.scatter(x=y_test, y=y_predicted)
```

```
plt.xlabel("Test Prices")
plt.ylabel("Predicted Prices")
plt.title("Test Prices vs Predicted Prices", size=20)
plt.show()
```



Feature Importances

```
xgb.feature_importances_

array([0.00302371, 0.00417268, 0.1802934 , 0.00688145, 0.00478461,
       0.0988211 , 0.03602384, 0.00691884, 0.45069456, 0.02139369,
       0.00604957, 0.02217523, 0.0068976 , 0.01565308, 0.02236574,
       0.0086388 , 0.06369729, 0.04151485], dtype=float32)

variables = ['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot',
'floors',
       'waterfront', 'view', 'condition', 'grade', 'sqft_above',
       'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode',
'sqft_living15',
       'sqft_lot15', 'lat', 'long']
np.array(variables)

array(['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
       'waterfront', 'view', 'condition', 'grade', 'sqft_above',
       'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode',
       'sqft_living15', 'sqft_lot15', 'lat', 'long'], dtype='<U13')

feature_importances = pd.DataFrame({'variables': ['bedrooms',
'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
       'waterfront', 'view', 'condition', 'grade', 'sqft_above',
       'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode',
'sqft_living15',
       'sqft_lot15', 'lat', 'long'],
                    'score': [0.00302371, 0.00417268, 0.1802934 ,
0.00688145, 0.00478461,
       0.0988211 , 0.03602384, 0.00691884, 0.45069456, 0.02139369,
```

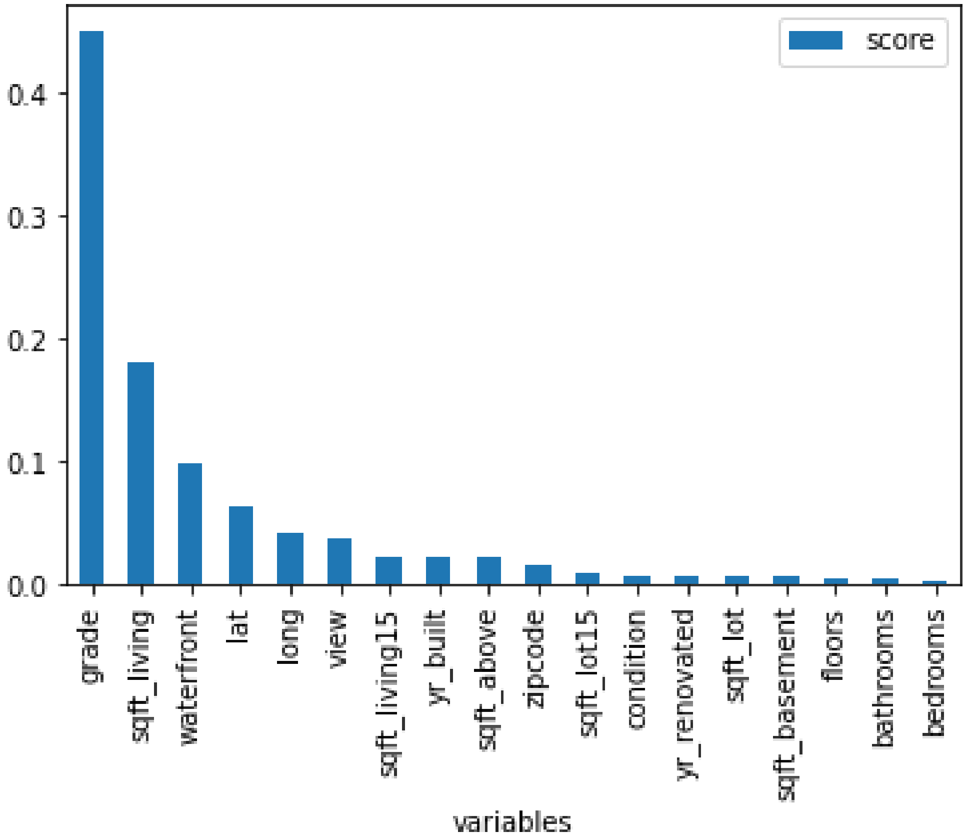
```
       0.00604957, 0.02217523, 0.0068976 , 0.01565308, 0.02236574,
       0.0086388 , 0.06369729, 0.04151485]})
```

```
feature_importances
```

	variables	score
0	bedrooms	0.003024
1	bathrooms	0.004173
2	sqft_living	0.180293
3	sqft_lot	0.006881
4	floors	0.004785
5	waterfront	0.098821
6	view	0.036024
7	condition	0.006919
8	grade	0.450695
9	sqft_above	0.021394
10	sqft_basement	0.006050
11	yr_built	0.022175
12	yr_renovated	0.006898
13	zipcode	0.015653
14	sqft_living15	0.022366
15	sqft_lot15	0.008639
16	lat	0.063697
17	long	0.041515

```
fn = feature_importances.sort_values(by='score', ascending=False)
```

```
ax = fn.plot.bar(x='variables', y='score')
```



As we can see, that `grade`, `sqft_living`, `waterfront`, `lat` and `long` variables are the top importances variable that influence our modeling