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README.md

Phase 2 Project

Project Overview

This project analyzes house sales data in a northwestern county using regression model.

Business Problem

After buiding the regression model, the features that are closely related to house price will be identified.

Therefore, some suggestions could be given to both the buyers and sellers.

- For the buyer, they will know the price of the house based on the characteristics of the house, and also, what's the investment value for the house.
- For the seller, they may know whether they can do something to sell the house with a better price.

Data

This project uses the King County House Sales dataset, which can be found in `kc_house_data.csv` in the data folder in this repo. The description of the column names can be found in `column_names.md` in the same folder.

Methods

Importing necessary libraries

```
# Warning off
import warnings
warnings.filterwarnings('ignore')

# import pandas and numpy
import pandas as pd
import numpy as np

# import data visualization
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('darkgrid')
%matplotlib inline

# import linear regression related modules
from statsmodels.formula.api import ols
from statsmodels.stats.outliers_influence import variance_inflation_factor
import statsmodels.api as sm
import scipy.stats as stats
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
```

Loading data to check the potential features

```
#loading kc_house_data.csv data
df = pd.read_csv('./data/kc_house_data.csv')
df.head() # checking the head for information
```

```
# Describe the dataset using 5-point statistics
df.describe()
```

```
# What data is available to us?
df.info()
```

#We have potentially 19 predictors excluding the id and the target,i.e.,the price #We have a total of 21597 rows, while some rows have null values in some predictors #Several predictors' data type need to be changed

Data Preparation

Deal with data types: sqft_basement & date

```
#sqft_basement: Numerical Data Stored as Strings need to be reformat to float
print(df.sqft_basement.unique())
df.sqft_basement.value_counts()
#there is '?' in the sqft_basement, need to be replaced as nan before reformat to flo
df.sqft_basement = df.sqft_basement.map(lambda x: float(x.replace('?', 'nan')))
df.sqft_basement.unique()
```

```
# For the sold date, since day is not important for the regression model,
# I only extract year and month for the sold date, and add two columns as year_sold a
df['year_sold'] = pd.DatetimeIndex(df['date']).year
df['month_sold'] = pd.DatetimeIndex(df['date']).month

# Based on the yr_built and month_sold, I create another column as age_sold of the ho
df['age_sold'] = df['year_sold'] - df['yr_built'] + 1
df.head()
```

Deal with null values

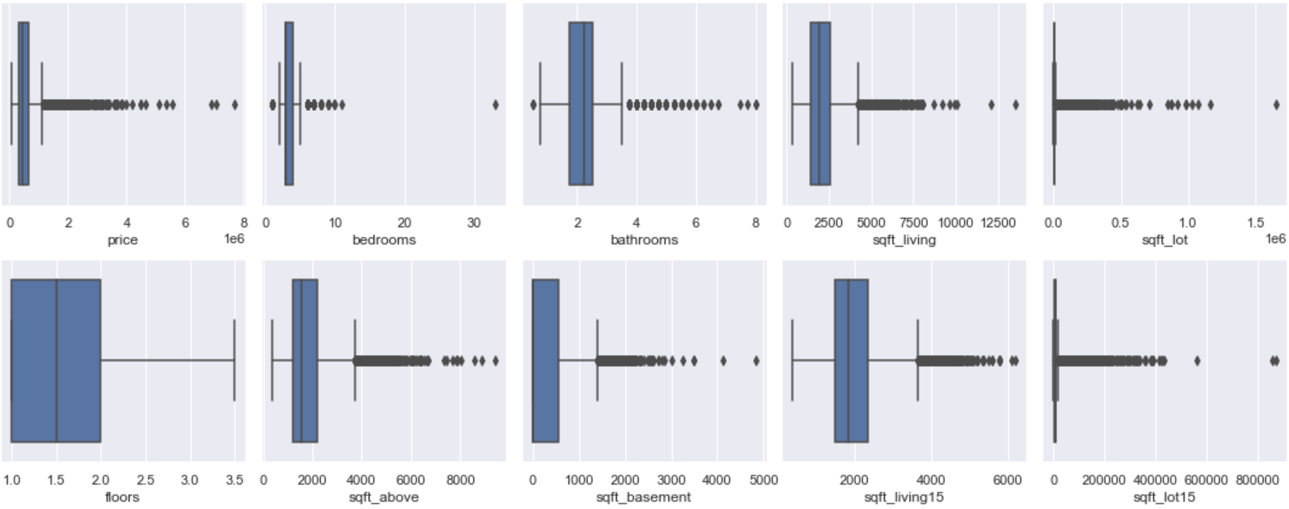
```
# Get the percentage value of null data for each column
df.isnull().sum()*100/df.shape[0]
```

```
# There are some null data in waterfront, view, yr_renovated, sqft_basement
# 1) since the percentage of null data in view is low, I just drop these rows
# 2) For waterfront and yr_renovated, the percentage of null data is high,I will assi

# waterfront is a categorical variable
df.waterfront.value_counts()
# replace nan as a value:
# Originally I used 2.0 as a third category,
# but late I found the price for this missing data is similar as for waterfront == 0
# Therefore, I fill the null as 0
df.waterfront = df.waterfront.fillna(0)
df.waterfront.value_counts()
```

```
# yr_renovated has 17011/17755~96% without renovation,
#  and only 4% with renovation based on the non-null data
df.yr_renovated.value_counts()
# take a look of histogram
fig, axs = plt.subplots(2,figsize=(12,8))
df['yr_renovated'].hist(ax = axs[0]);
axs[0].set_title('All non-null data')
axs[0].set_xlabel('Year')
# with renovation
df[df.yr_renovated > 0].yr_renovated.hist(ax = axs[1])
# dfwrenov['yr_renovated'].hist(ax = axs[1]);
axs[1].set_title('Renovation data')
axs[0].set_xlabel('Year')
# Based on renovated data, I create a caterogrial variable as is_renovated

ds_renovated = df['yr_renovated']
ds_renovated[ds_renovated >0] = 1
# replace nan as a value:
# Originally I used 2.0 as a third category,
# but late I found the price for this missing data is similar as for is_renovated ==
# Therefore, I fill the null as 0
ds_renovated = ds_renovated.fillna(0)
ds_renovated
df['is_renovated'] = ds_renovated
del ds_renovated
df.is_renovated.value_counts()
# assign as -1 to make sure these rows are not dropped in the following operation
df.yr_renovated = df.yr_renovated.fillna(-1)
# for view and sqft_basement, I just drop those rows with null value, since they are
df.dropna(inplace=True)
print(df.info())
print(df.shape)
df.is_renovated.value_counts()
```

Deal with outliers if existed in some columns

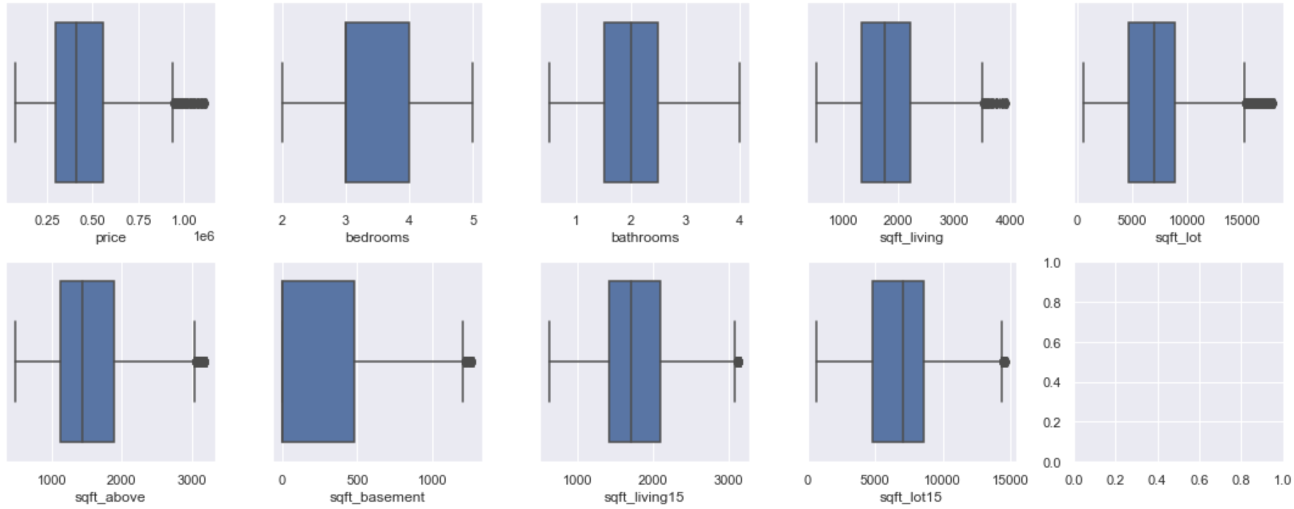
```
# For some selected columns, have a boxplot to examine the outliers
x_cols = ['price','bedrooms','bathrooms','sqft_living','sqft_lot',
          'floors','sqft_above','sqft_basement','sqft_living15','sqft_lot15']
fig, axs = plt.subplots(2,5, figsize = (15,6))
for colii in range(len(x_cols)):
    sns.boxplot(df[x_cols[colii]],ax = axs[colii//5, colii%5])
plt.tight_layout()
```




```
# process of outliers:
# It seems all these items except floors have outliers
# I will drop the outliers as there are sufficient data

x_cols = ['price','bedrooms','bathrooms','sqft_living','sqft_lot',
          'sqft_above','sqft_basement','sqft_living15','sqft_lot15']

for colname in x_cols:
    Q1 = df[colname].quantile(0.25)
    Q3 = df[colname].quantile(0.75)
    IQR = Q3 - Q1
    lenori = len(df[colname])
    df = df[(df[colname] >= Q1 - 1.5*IQR) & (df[colname] <= Q3 + 1.5*IQR)]
    lennew = len(df[colname])
    print(f'Number of rows based on {colname} : {lenori} -> {lennew}')
```

Number of rows based on price : 21082 -> 19951 Number of rows based on bedrooms : 19951 -> 19502 Number of rows based on bathrooms : 19502 -> 19437 Number of rows based on sqft_living : 19437 -> 19181 Number of rows based on sqft_lot : 19181 -> 17163 Number of rows based on sqft_above : 17163 -> 16697 Number of rows based on sqft_basement : 16697 -> 16401 Number of rows based on sqft_living15 : 16401 -> 16195 Number of rows based on sqft_lot15 : 16195 -> 15831

```
# boxplot for the remaining data
fig, axs = plt.subplots(2,5, figsize = (15,6))
for colii in range(len(x_cols)):
    sns.boxplot(df[x_cols[colii]],ax = axs[colii//5, colii%5])
plt.tight_layout()
# now looks all good
```



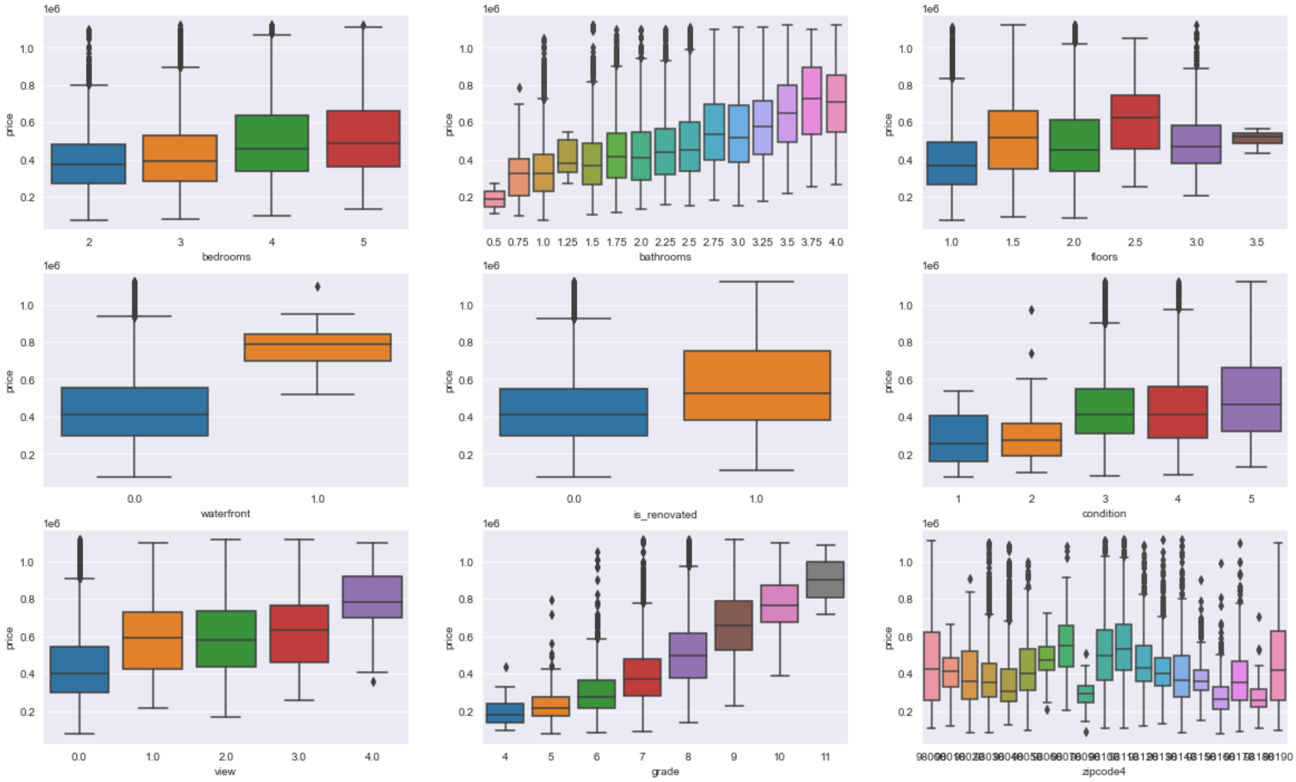

```
# visualization of the final data
# with its histogram:
df.hist(figsize = (20,18));
print(df.waterfront.value_counts())
print(df.condition.value_counts())
print(df.is_renovated.value_counts())
# looks good
df.bathrooms.value_counts()
```

Deal with zipcode

```
# df.zipcode.value_counts()
# I only keep the first four digits since if I only keep the first three digits,it wi
df['zipcode4'] = df.zipcode//10 * 10
df.zipcode4.value_counts()
```

98110 2051 98050 1831 98030 1767 98100 1594 98000 1488 98020 1243 98120 931 98130 689 98040 629 98140 588 98070 524 98190 465 98170 407 98160 369 98150 366 98010 337 98090 229 98060 209 98180 114 Name: zipcode4, dtype: int64

```
# visualization of categorical variables
cat_vars = ['bedrooms','bathrooms','floors','waterfront','is_renovated','condition','
plt.figure(figsize=(20, 12))
for idx in range(len(cat_vars)):
    plt.subplot(3,3,idx+1)
    sns.boxplot(x = cat_vars[idx], y = 'price', data = df)
```



```
# For the zip codes, I implemented the one hot encoding .get_dummies() method
zipcode4_dums = pd.get_dummies(df['zipcode4'])
df = pd.concat([df,zipcode4_dums],axis = 1)
df.head()
```

```
# drop one zipcode to redact redundant information, I will drop 98110, since it has t
df.drop([98110], axis = 1, inplace = True)
df.head()
```

Modeling

After finishing the data preparation, now I start to build the regression model

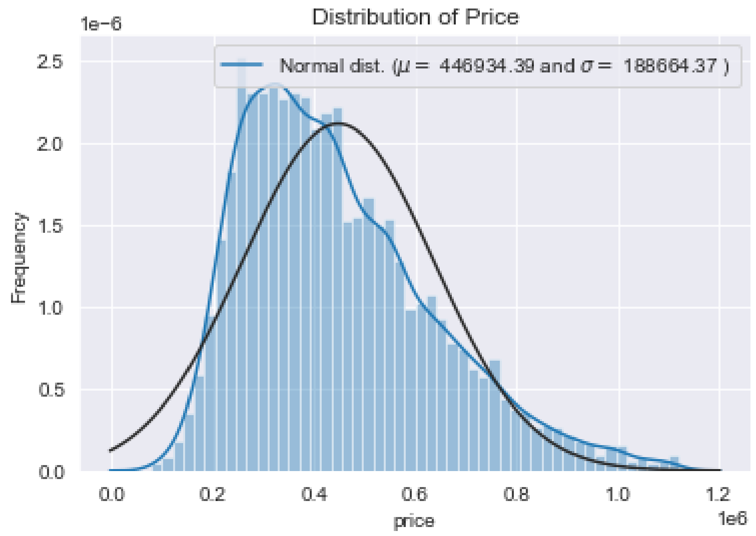
```
# drop id, date, yr_renovated,lat, long, zipcode from df
# the id has not related to the house price
# the date has been transformed into sold_year and sold_month
# the yr_renovated has been transformed into is_renovated
# the lat and long indicate similar information as zipcode
# zipcode has been transformed into zipcode4 and dummy variables
# I keep zipcode4 try to take a look which one is better based on either zipcode4 or
drop_vars = ['id','date','yr_renovated','lat','long','zipcode']
df.drop(drop_vars, axis = 1, inplace = True)
df.head()
```

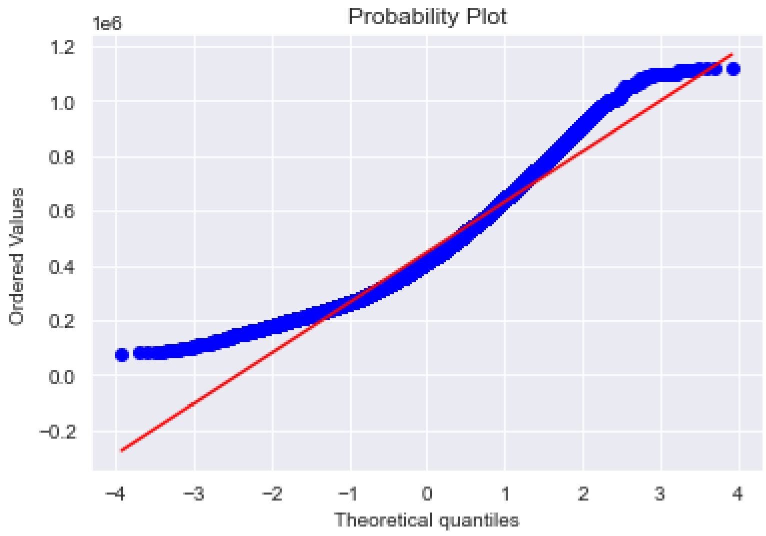
```
# transform column names as string
df.columns = df.columns.astype(str)
df.head()
```

```
# Rescaling the features except the 'dummy' variable
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
num_vars = list(['bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'grade',
       'sqft_above', 'sqft_basement', 'yr_built', 'is_renovated',
       'sqft_living15', 'sqft_lot15', 'year_sold','age_sold',
       'month_sold'])
df_scl = df
df_scl[num_vars] = scaler.fit_transform(df[num_vars])
df_scl.head()
```

```
#Check the distribution of the target: price, to see whether it follows a normal dist
sns.distplot(df_scl['price'] , fit=stats.norm);

# Get the fitted parameters used by the function
(mu, sigma) = stats.norm.fit(df_scl['price'])
print( '\n mean = {:.2f} and std dev = {:.2f}\n'.format(mu, sigma))

#NPlotting the distribution
plt.legend(['Normal dist. ($\mu=$ {:.2f} and $\sigma=$ {:.2f} )'.format(mu, sigma)],
            loc='best')
plt.ylabel('Frequency')
plt.title('Distribution of Price')

#Also the QQ plot
fig = plt.figure()
res = stats.probplot(df_scl['price'], plot=plt)
plt.show()
```

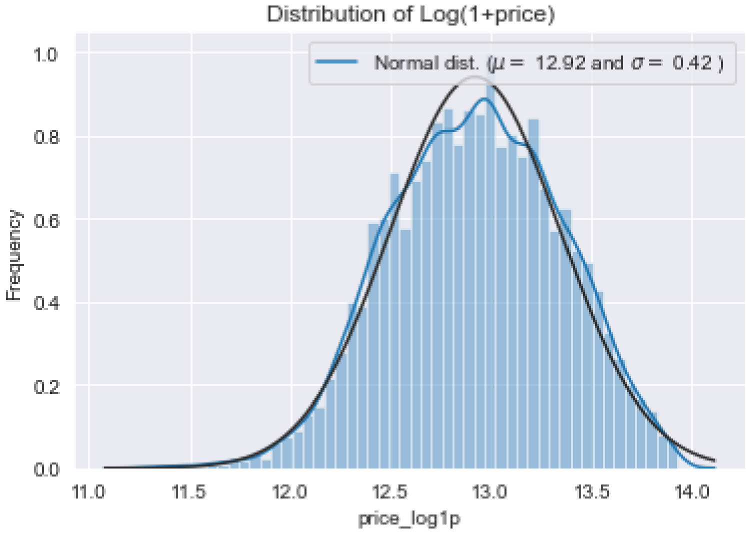
mean = 446934.39 and std dev = 188664.37

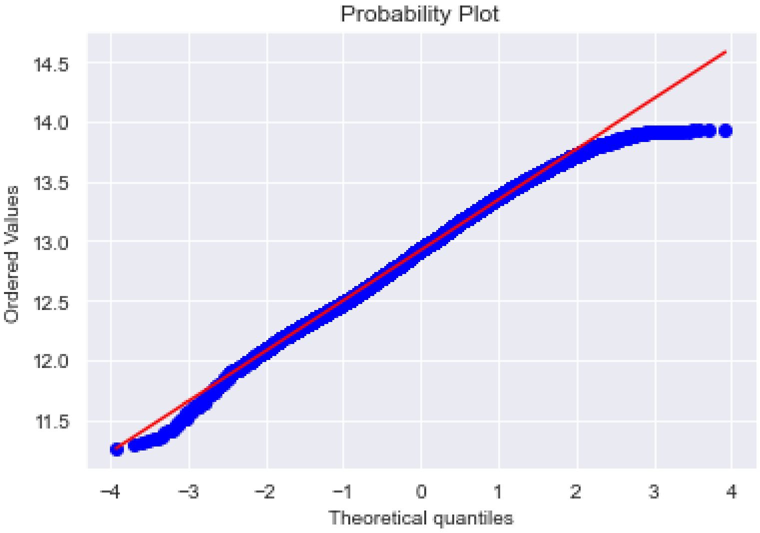





```
# it looks the target is skewed right, therefore, I used a log transformation to make
#Using the log1p function applies log(1+x) to all elements of the column
df_scl['price_log1p'] = np.log1p(df_scl['price'])

#Check the new distribution after log transformation
sns.distplot(df_scl['price_log1p'] , fit=stats.norm);

# Get the fitted parameters used by the function
(mu, sigma) = stats.norm.fit(df_scl['price_log1p'])
print( '\n mean = {:.2f} and std dev = {:.2f}\n'.format(mu, sigma))

#NPlotting the distribution
plt.legend(['Normal dist. ($\mu=$ {:.2f} and $\sigma=$ {:.2f} )'.format(mu, sigma)],
            loc='best')
plt.ylabel('Frequency')
plt.title('Distribution of Log(1+price)')

#Also the QQ plot
fig = plt.figure()
res = stats.probplot(df_scl['price_log1p'], plot=plt)
plt.show()
```

mean = 446934.39 and std dev = 188664.37

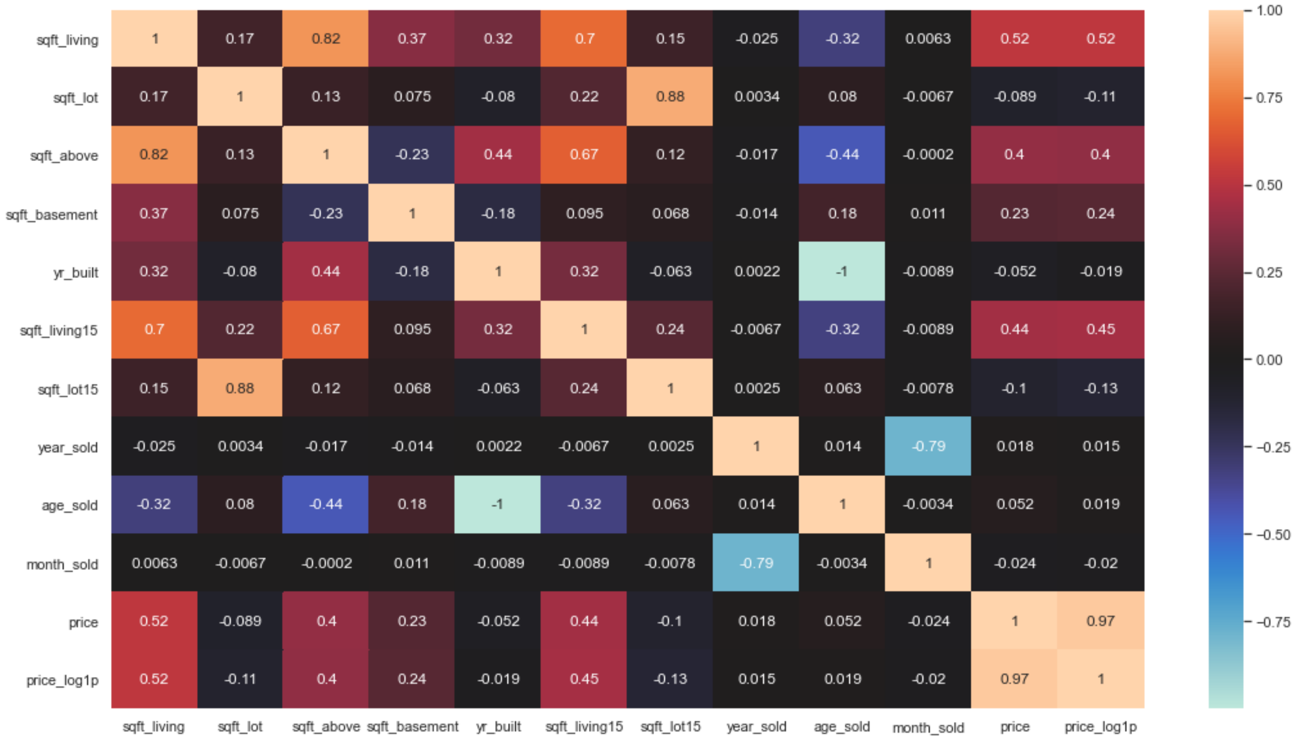





```
# Splitting the Data into Training and Testing
df_train, df_test = train_test_split(df, train_size = 0.8, test_size = 0.2, random_st
print(len(df_train), len(df_test))
df_train.head()
df.columns
```

Checking for Multicollinearity

```
# Check the correlation coefficients to see which variables are highly correlated
num_vars.append('price')
num_vars.append('price_log1p')
corr = df_train[num_vars].corr()
corr
# Using heatmap to visualzation of the correlation coefficients
sns.set(rc = {'figure.figsize':(18,10)})
sns.heatmap(corr, center=0, annot=True);
```



Price seems to be correlated to sqrt_living and grade the most. And some sqft-related and rooms-related variables have high correlation, e.g., sqft_living vs.bedrooms and bathrooms

```
# Fitting the actual model with all available features, zipcode with dummy values
import statsmodels.api as sm

# price vs price_log1p
outcome1 = 'price'
outcome2 = 'price_log1p'
x_cols = list(df_train.columns)
x_cols.remove(outcome1)
x_cols.remove(outcome2)
x_cols.remove('zipcode4')
model1 = sm.OLS(df_train[outcome1],sm.add_constant(df_train[x_cols])).fit()
print(model1.summary())
model2 = sm.OLS(df_train[outcome2],sm.add_constant(df_train[x_cols])).fit()
print(model2.summary())

# zipcode_dummy vs zipcode4
outcome1 = 'price'
outcome2 = 'price_log1p'
# x_cols = list(df.columns)
# x_cols.remove(outcome1)
# x_cols.remove(outcome2)
# # remove zipcdoe_dummies
# for colname in x_cols:
#     if colname.startswith('98') == 1:
#         x_cols.remove(colname)
# print(x_cols)
x_cols = ['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
          'waterfront', 'view', 'condition', 'grade', 'sqft_above',
          'sqft_basement', 'yr_built', 'sqft_living15', 'sqft_lot15',
          'year_sold', 'month_sold', 'age_sold', 'is_renovated', 'zipcode4']
```

```
model3 = sm.OLS(df_train[outcome1],sm.add_constant(df_train[x_cols])).fit()
print(model3.summary())
model4 = sm.OLS(df_train[outcome2],sm.add_constant(df_train[x_cols])).fit()
print(model4.summary())
```

```
# Based on the R-squared values from four models,
# I choose to use outcome = 'price_log1p' and zipcode_dummies for regression model
# price_log1p
outcome = 'price_log1p'
x_cols = list(df_train.columns)
x_cols.remove(outcome)
x_cols.remove('price')
model0 = sm.OLS(df_train[outcome],sm.add_constant(df_train[x_cols])).fit()
print(model0.summary())
```

```
# Remove the insignificant Features and rerun the model
summary = model0.summary()
p_table = summary.tables[1]
p_table = pd.DataFrame(p_table.data)
p_table.columns = p_table.iloc[0]
p_table = p_table.drop(0)
p_table = p_table.set_index(p_table.columns[0])
p_table['P>|t|'] = p_table['P>|t|'].astype(float)
x_cols = list(p_table[p_table['P>|t|'] < 0.05].index)
x_cols.remove('const')
print(len(p_table), len(x_cols))

p_table.head()
x_cols
```

```
model1 = sm.OLS(df_train[outcome],sm.add_constant(df_train[x_cols])).fit()
model1.summary()
```

```
#Investigate the multicollinearity
X = df_train[x_cols]
vif = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
list(zip(x_cols, vif))
```

```
# remove the features with vif >=5
vif_scores = list(zip(x_cols, vif))
x_cols = [x for x,vif in vif_scores if vif < 5]
print(len(vif_scores), len(x_cols))
x_cols
```

```
# Refit model with subset features
model2 = sm.OLS(df_train[outcome],sm.add_constant(df_train[x_cols])).fit()
model2.summary()
```

OLS Regression Results

Dep. Variable:	price_log1p	**R-squared:**	0.449
Model:	OLS	**Adj. R-squared:**	0.447
Method:	Least Squares	**F-statistic:**	342.6
Date:	Thu, 18 Nov 2021	**Prob (F-statistic):**	0.00
Time:	21:44:44	**Log-Likelihood:**	-3325.9
No. Observations:	12664	**AIC:**	6714.
Df Residuals:	12633	**BIC:**	6945.
Df Model:	30		
Covariance Type:	nonrobust		

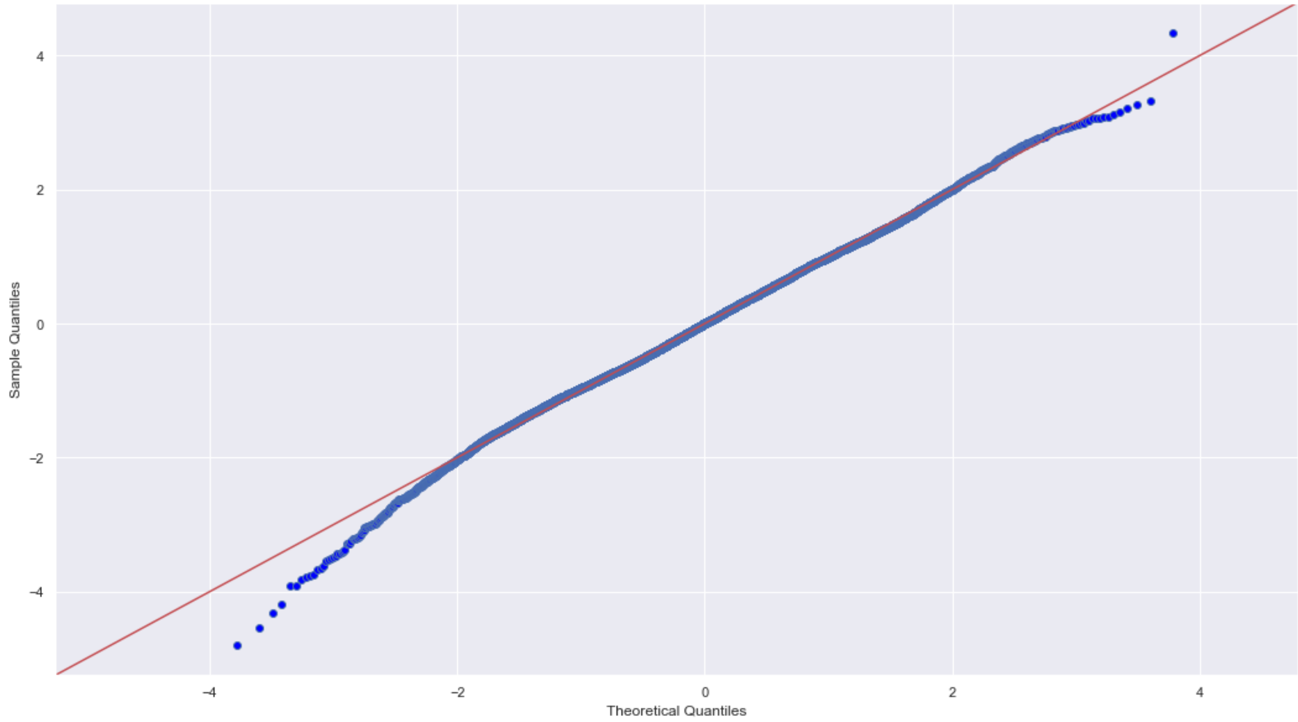
	coef	std err	t	P>|t|	[0.025	0.975]
const	12.3034	0.013	939.565	0.000	12.278	12.329
sqft_lot	0.0019	0.032	0.061	0.951	-0.060	0.064
sqft_living15	1.0967	0.017	62.711	0.000	1.062	1.131
sqft_lot15	-0.1448	0.030	-4.819	0.000	-0.204	-0.086
bedrooms_3	0.0838	0.008	9.855	0.000	0.067	0.100
bedrooms_4	0.1500	0.010	15.497	0.000	0.131	0.169
bedrooms_5	0.1632	0.015	10.968	0.000	0.134	0.192
floors_2.5	0.2261	0.040	5.682	0.000	0.148	0.304
floors_3.0	0.0568	0.017	3.423	0.001	0.024	0.089
waterfront_1.0	0.3989	0.113	3.545	0.000	0.178	0.620
is_renovated_1.0	0.1923	0.017	11.532	0.000	0.160	0.225
view_1.0	0.1377	0.026	5.345	0.000	0.087	0.188
view_2.0	0.1483	0.016	9.056	0.000	0.116	0.180
view_3.0	0.1173	0.027	4.324	0.000	0.064	0.170
view_4.0	0.2436	0.051	4.730	0.000	0.143	0.344
grade_10	0.2589	0.026	9.868	0.000	0.207	0.310

grade_11	0.4181	0.141	2.961	0.003	0.141	0.695
zipcode4_98020	-0.1122	0.011	-9.881	0.000	-0.134	-0.090
zipcode4_98030	-0.0860	0.010	-8.718	0.000	-0.105	-0.067
zipcode4_98040	-0.1567	0.015	-10.469	0.000	-0.186	-0.127
zipcode4_98060	-0.0552	0.027	-2.061	0.039	-0.108	-0.003
zipcode4_98070	0.1285	0.016	7.933	0.000	0.097	0.160
zipcode4_98090	-0.4208	0.024	-17.744	0.000	-0.467	-0.374
zipcode4_98100	0.3045	0.011	26.970	0.000	0.282	0.327
zipcode4_98110	0.3558	0.010	35.292	0.000	0.336	0.376
zipcode4_98120	0.2334	0.013	17.816	0.000	0.208	0.259
zipcode4_98130	0.1495	0.015	10.127	0.000	0.121	0.178
zipcode4_98150	0.0563	0.019	2.944	0.003	0.019	0.094
zipcode4_98160	-0.2256	0.019	-11.681	0.000	-0.263	-0.188
zipcode4_98170	-0.0977	0.018	-5.360	0.000	-0.133	-0.062
zipcode4_98180	-0.2792	0.034	-8.272	0.000	-0.345	-0.213

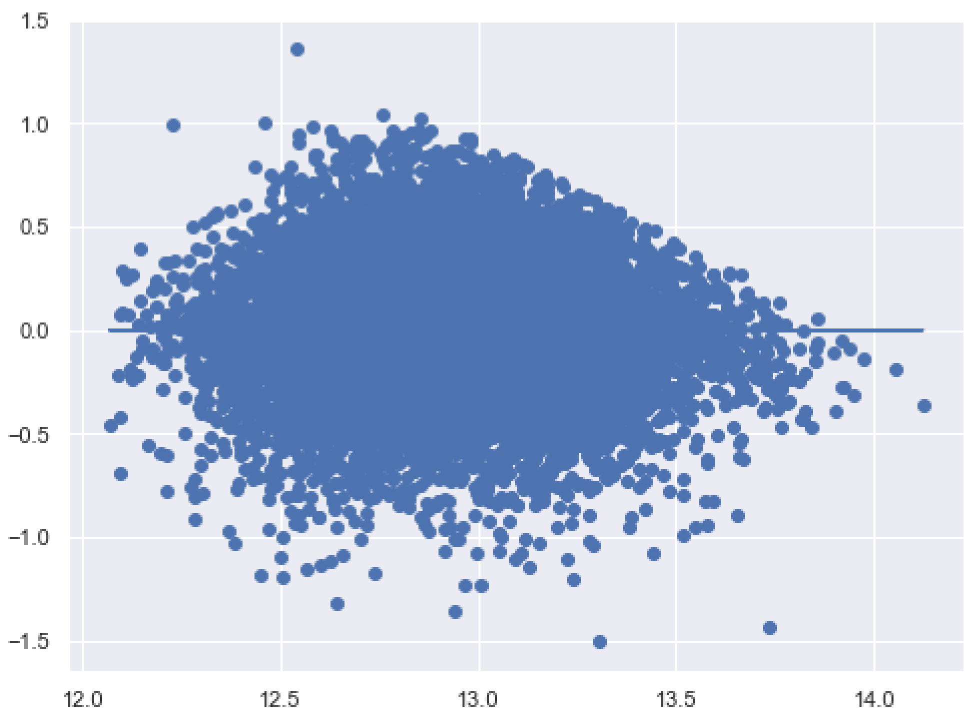
Omnibus:	48.135	**Durbin-Watson:**	2.022
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	59.797
Skew:	-0.069	**Prob(JB):**	1.04e-13
Kurtosis:	3.307	**Cond. No.**	70.9

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
# checking normality
fig = sm.graphics.qqplot(model2.resid, dist=stats.norm, line='45', fit=True)
```




```
#Check Homoscedasticity Assumption
plt.figure(figsize = (8,6))
plt.scatter(model2.predict(sm.add_constant(df_train[x_cols])), model2.resid)
plt.plot(model2.predict(sm.add_constant(df_train[x_cols])), [0 for i in range(len(df_
```



model2 seems pretty good in terms of normality, Homoscedasticity, and R-squared values

Evaluation

```
from sklearn.linear_model import LinearRegression

final_model = LinearRegression()
# Fit the model on X_train_final and y_train
final_model.fit(df_train[x_cols], df_train[outcome])

# Score the model on X_test_final and y_test
# (use the built-in .score method)
print( "Test score:  ", final_model.score(df_test[x_cols], df_test[outcome]))
print( "Train score: ", final_model.score(df_train[x_cols], df_train[outcome]))
```

Test score: 0.44378007421545485 Train score: 0.44859642929281374

```
# use cross validation to evaluate the model
from sklearn.model_selection import cross_validate, ShuffleSplit
splitter = ShuffleSplit(n_splits=3, test_size=0.25, random_state=0)
baseline_scores = cross_validate(
    estimator = final_model,
    X= df[x_cols],
    y= df[outcome],
    return_train_score=True,
    cv=splitter
)
print("Train score:     ", baseline_scores["train_score"].mean())
print("Validation score:", baseline_scores["test_score"].mean())
```

```
Train score:      0.44648159473484395
Validation score: 0.4500640604866031
```

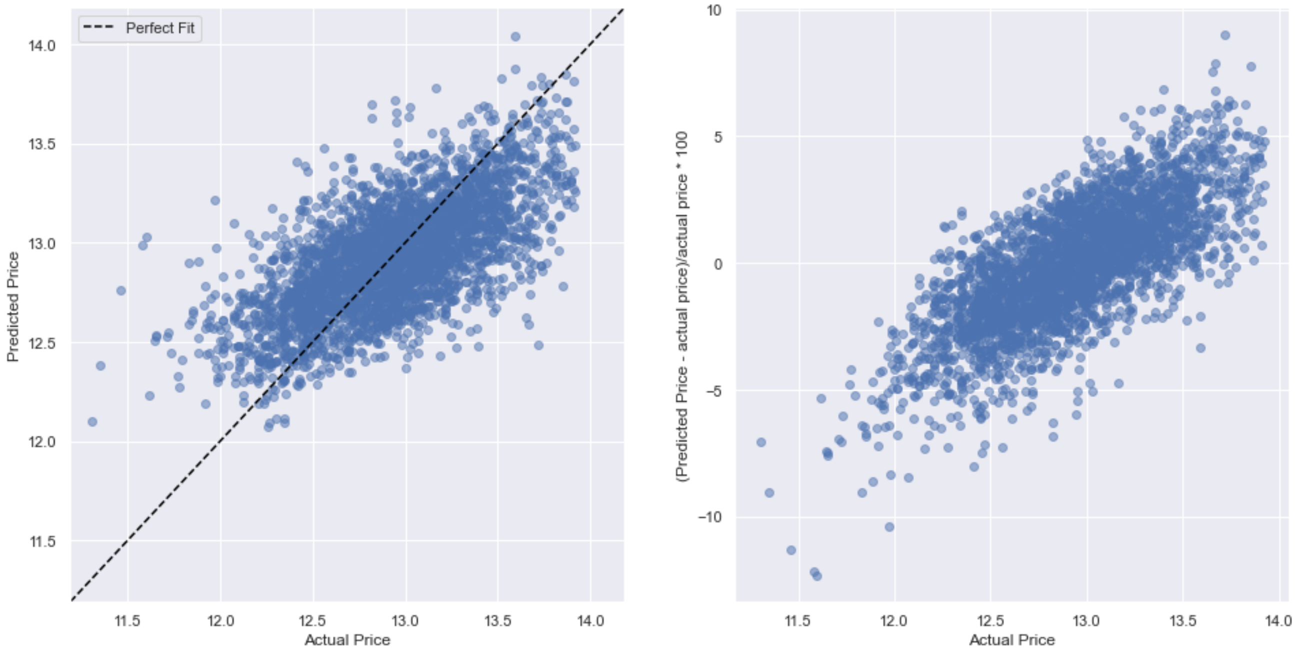
Train and validation scores are similar

```
# check mean squared error, root mean squared error, and Mean absolute error
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import r2_score
import math
print("MSE:       ", mean_squared_error(df_test[outcome], final_model.predict(df_test
print("RMSE:      ", math.sqrt(mean_squared_error(df_test[outcome], final_model.predi
print("MAE:       ", mean_absolute_error(df_test[outcome], final_model.predict(df_tes
print("R-Squared: ", r2_score(df_test[outcome], final_model.predict(df_test[x_cols]))
```

MSE: 0.10077497430795615 RMSE: 0.3174507431208126 MAE: 0.251980604965677 R-Squared: 0.44378007421545485

```
# visualization of real and predicted values for each value
preds = final_model.predict(df_test[x_cols])
```

```
fig, axs = plt.subplots(1,2, figsize =(16,8))
perfect_line = np.arange(min(preds.min(),df_test[outcome].min())*0.99, max(preds.max(
axs[0].plot(perfect_line,perfect_line, linestyle="--", color="black", label="Perfect
axs[0].scatter(df_test[outcome], preds, alpha=0.5)
axs[0].set_xlabel("Actual Price")
axs[0].set_ylabel("Predicted Price")
axs[0].legend();
axs[0].set_xlim([min(preds.min(),df_test[outcome].min())*0.99, max(preds.max(),df_tes
axs[0].set_ylim([min(preds.min(),df_test[outcome].min())*0.99, max(preds.max(),df_tes
axs[1].scatter(df_test[outcome], np.divide((df_test[outcome] - preds),df_test[outcome
axs[1].set_xlabel("Actual Price")
axs[1].set_ylabel("(Predicted Price - actual price)/actual price * 100")
```



From above values and plots, the fitted regression model can predict house price very well

Summary

```
# the beta coefficients for different predictors
print(pd.Series(final_model.coef_, index=x_cols, name="Coefficients"))
print()
print("Intercept:", final_model.intercept_)
```

```
sqft_lot             0.001943
sqft_living15        1.096717
sqft_lot15          -0.144789
bedrooms_3           0.083760
bedrooms_4           0.149979
bedrooms_5           0.163189
floors_2.5           0.226109
floors_3.0           0.056801
waterfront_1.0       0.398927
is_renovated_1.0     0.192348
view_1.0             0.137734
view_2.0             0.148326
view_3.0             0.117277
view_4.0             0.243554
grade_10             0.258860
grade_11             0.418129
zipcode4_98020      -0.112151
zipcode4_98030      -0.086005
zipcode4_98040      -0.156698
zipcode4_98060      -0.055208
zipcode4_98070       0.128485
zipcode4_98090      -0.420847
zipcode4_98100       0.304544
zipcode4_98110       0.355810
zipcode4_98120       0.233377
zipcode4_98130       0.149527
zipcode4_98150       0.056281
zipcode4_98160      -0.225556
zipcode4_98170      -0.097728
zipcode4_98180      -0.279241
Name: Coefficients, dtype: float64

Intercept: 12.30344679761995
```

From coefficients described above, I observed:

1. The grade and sqft_living15 have the strongest relationship with the house price¶
2. It is interesting to see the sqft_lot15 has the negative relationship with the house price
3. Waterfront_1.0 and grade_11 also have postive relationship with the price
4. For some zipcode, e.g., 98100 and 98110, they have high positive relationship with the price

To address the business question:

1. For buyer, they will know the house price is higer for a house with high grade and sqrt_living15
2. For seller, if they want to sell their house with a higher price, they could add waterfront, improve the grade/condition.

Releases

No releases published

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Languages

- **Jupyter Notebook** 100.0%