Final project in Module 2

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Self-paced

Outline

- The aim of the project:
  - To provide suggestions regarding the price of house
    - For house buyer, based on the characteristics of the house, they will know the price of the house and the investment value of the house for future sale
    - For house seller, they will know what they need to do to sell the house with a better price
- A linear regression model will be built based on the different selection of house characteristics to achieve the goal of the project
- Conclusion

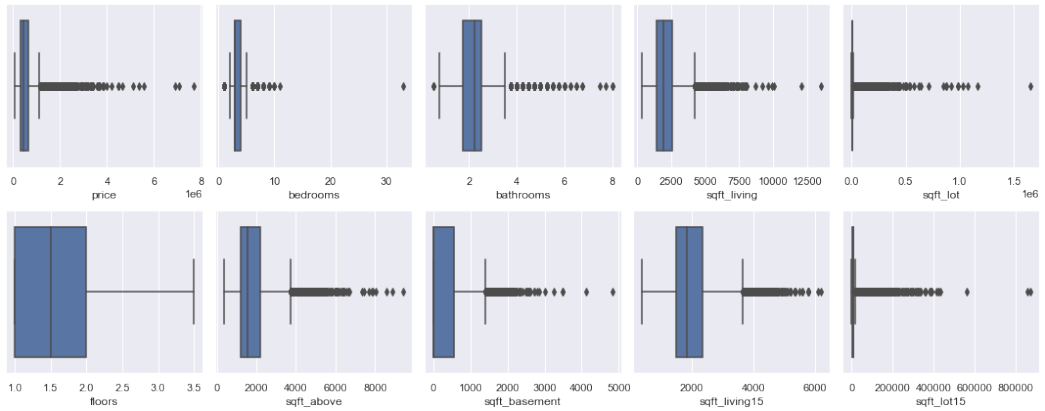
Data

- Data source: kc_house_data.csv
- Data understanding:
  - A total of 19 predictors available after excluding the id and the target (price)
  - A total of 21597 rows, while some rows have null values in some predictors
  - Several predictors' data type need to be changed, e.g., date and sqft_basement

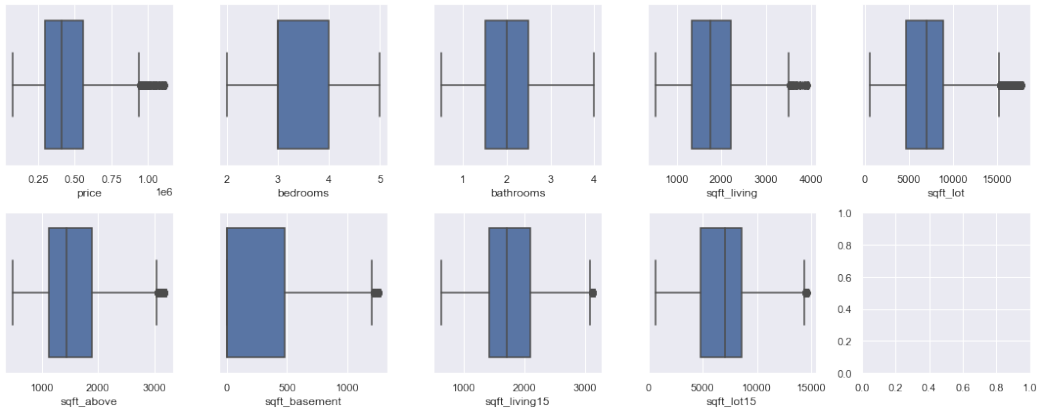
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21597 non-null  int64
 1   date           21597 non-null  object
 2   price          21597 non-null  float64
 3   bedrooms       21597 non-null  int64
 4   bathrooms      21597 non-null  float64
 5   sqft_living    21597 non-null  int64
 6   sqft_lot       21597 non-null  int64
 7   floors         21597 non-null  float64
 8   waterfront     19221 non-null  float64
 9   view           21534 non-null  float64
 10  condition      21597 non-null  int64
 11  grade          21597 non-null  int64
 12  sqft_above     21597 non-null  int64
 13  sqft_basement  21597 non-null  object
 14  yr_built       21597 non-null  int64
 15  yr_renovated   17755 non-null  float64
 16  zipcode        21597 non-null  int64
 17  lat            21597 non-null  float64
 18  long           21597 non-null  float64
 19  sqft_living15  21597 non-null  int64
 20  sqft_lot15     21597 non-null  int64
dtypes: float64(8), int64(11), object(2)
memory usage: 3.5+ MB
```

Data Preparation

- Deal with data types: sqft_basement and date
- Deal with null values:
  - View and sqft_basement: drop those rows with null values
  - Waterfront, and yr_renovated: they are over 10% of null values with special process
- Deal with outliers:



Original

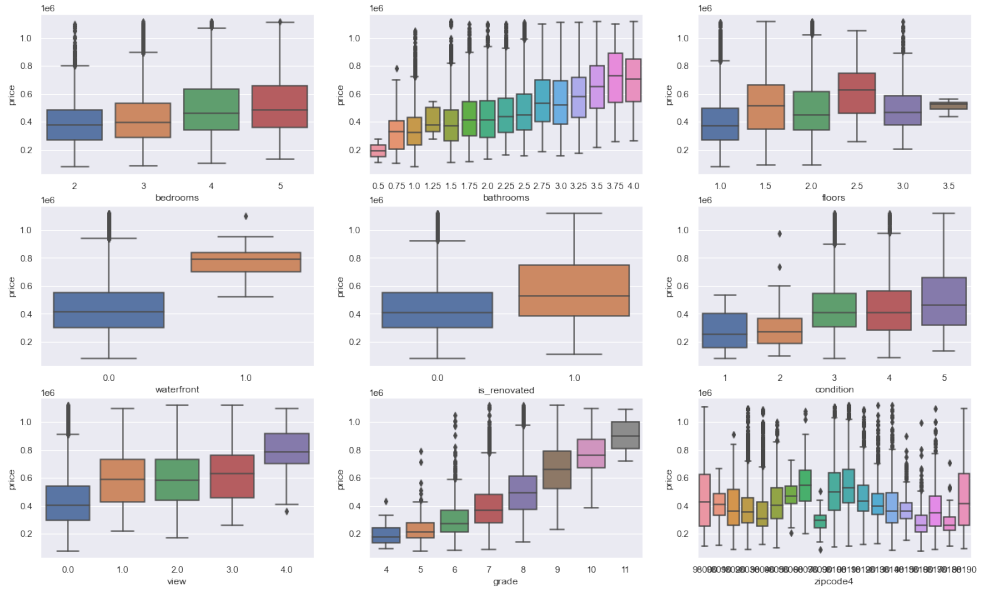


After removing outliers

Data Preparation

- Deal with categorical variables
  - 'bedrooms','bathrooms','floors','waterfront','is_renovated','condition','view','grade','zipcode4'

Visualization of categorical variables



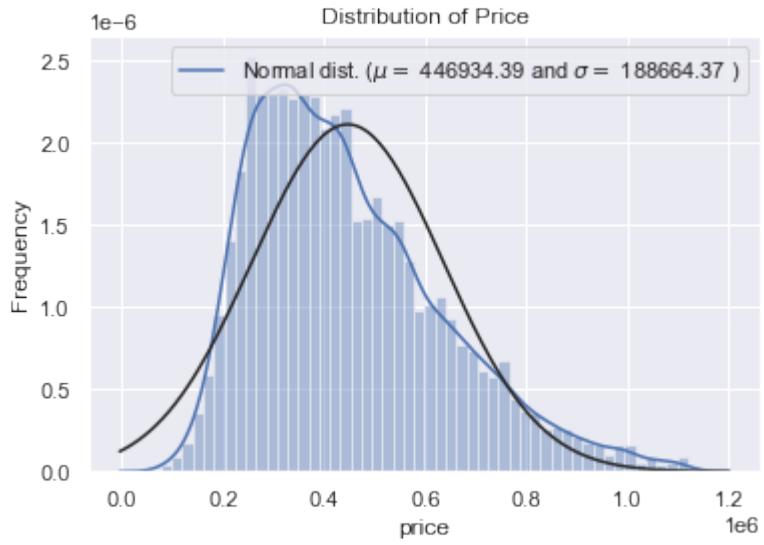
The predictors

```
df_scl.columns
```

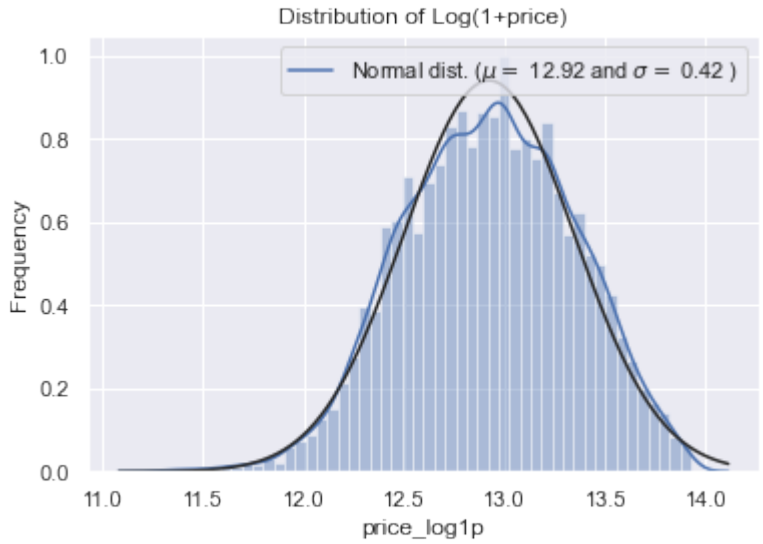
```
Index(['price', 'sqft_living', 'sqft_lot', 'sqft_above', 'sqft_basement',
       'yr_built', 'sqft_living15', 'sqft_lot15', 'year_sold', 'month_sold',
       'age_sold', 'bedrooms_3', 'bedrooms_4', 'bedrooms_5', 'bathrooms_0.75',
       'bathrooms_1.0', 'bathrooms_1.25', 'bathrooms_1.5', 'bathrooms_1.75',
       'bathrooms_2.0', 'bathrooms_2.25', 'bathrooms_2.5', 'bathrooms_2.75',
       'bathrooms_3.0', 'bathrooms_3.25', 'bathrooms_3.5', 'bathrooms_3.75',
       'bathrooms_4.0', 'floors_1.5', 'floors_2.0', 'floors_2.5', 'floors_3.0',
       'floors_3.5', 'waterfront_1.0', 'is_renovated_1.0', 'condition_2',
       'condition_3', 'condition_4', 'condition_5', 'view_1.0', 'view_2.0',
       'view_3.0', 'view_4.0', 'grade_5', 'grade_6', 'grade_7', 'grade_8',
       'grade_9', 'grade_10', 'grade_11', 'zipcode4_98010', 'zipcode4_98020',
       'zipcode4_98030', 'zipcode4_98040', 'zipcode4_98050', 'zipcode4_98060',
       'zipcode4_98070', 'zipcode4_98090', 'zipcode4_98100', 'zipcode4_98110',
       'zipcode4_98120', 'zipcode4_98130', 'zipcode4_98140', 'zipcode4_98150',
       'zipcode4_98160', 'zipcode4_98170', 'zipcode4_98180', 'zipcode4_98190'],
      dtype='object')
```

Data Preparation

- Deal with target variable: price
  - Logarithm transform to make it more normal distribution



Log(1+price)



Modeling

- Regression model with all available predictors
  - Using price or log-transformed price as the target

OLS Regression Results

Dep. Variable:	price	R-squared:	0.597
Model:	OLS	Adj. R-squared:	0.595
Method:	Least Squares	F-statistic:	291.5
Date:	Thu, 18 Nov 2021	Prob (F-statistic):	0.00
Time:	22:28:20	Log-Likelihood:	-1.6601e+05
No. Observations:	12664	AIC:	3.322e+05
Df Residuals:	12599	BIC:	3.326e+05
Df Model:	64		
Covariance Type:	nonrobust		

OLS Regression Results

Dep. Variable:	price_log1p	R-squared:	0.598
Model:	OLS	Adj. R-squared:	0.595
Method:	Least Squares	F-statistic:	292.2
Date:	Thu, 18 Nov 2021	Prob (F-statistic):	0.00
Time:	22:28:20	Log-Likelihood:	-1332.8
No. Observations:	12664	AIC:	2796.
Df Residuals:	12599	BIC:	3280.
Df Model:	64		
Covariance Type:	nonrobust		

From R-squared values, it seems log-transformed price is a little better

Modeling

- Regression model with all predictors that are significantly related to the target: $p > 0.05$

	coef	std err	t	P>|t|	[0.025	0.975]
const	7.4111	0.082	90.876	0.000	7.251	7.571
sqft_living	0.1990	0.012	15.974	0.000	0.175	0.223
sqft_lot	-0.0778	0.028	-2.814	0.005	-0.132	-0.024
sqft_above	0.2990	0.015	19.764	0.000	0.269	0.329
sqft_basement	0.1290	0.011	12.253	0.000	0.108	0.150
yr_built	3.4663	0.041	83.645	0.000	3.385	3.548
sqft_living15	0.4635	0.020	23.218	0.000	0.424	0.503
sqft_lot15	-0.0924	0.027	-3.486	0.000	-0.144	-0.040
year_sold	0.0106	0.008	1.280	0.201	-0.006	0.027
month_sold	0.0086	0.014	0.632	0.527	-0.018	0.035
age_sold	3.9109	0.042	94.086	0.000	3.829	3.992
bedrooms_3	-0.0321	0.008	-4.033	0.000	-0.048	-0.016
bedrooms_4	-0.0521	0.010	-5.354	0.000	-0.071	-0.033
bedrooms_5	-0.0706	0.015	-4.865	0.000	-0.099	-0.042
bathrooms_0.75	0.5217	0.057	9.211	0.000	0.411	0.633
bathrooms_1.0	0.4406	0.016	28.375	0.000	0.410	0.471

Predictors: 68 -> 56

OLS Regression Results

Dep. Variable:	price_log1p	**R-squared:**	0.597
Model:	OLS	**Adj. R-squared:**	0.595
Method:	Least Squares	**F-statistic:**	346.1
Date:	Thu, 18 Nov 2021	**Prob (F-statistic):**	0.00
Time:	22:28:20	**Log-Likelihood:**	-1338.6
No. Observations:	12664	**AIC:**	2787.
Df Residuals:	12609	**BIC:**	3197.
Df Model:	54		
Covariance Type:	nonrobust		

Modeling

- Regression model after further excluding some predictors with high collinearity

Predictors: 56 -> 30

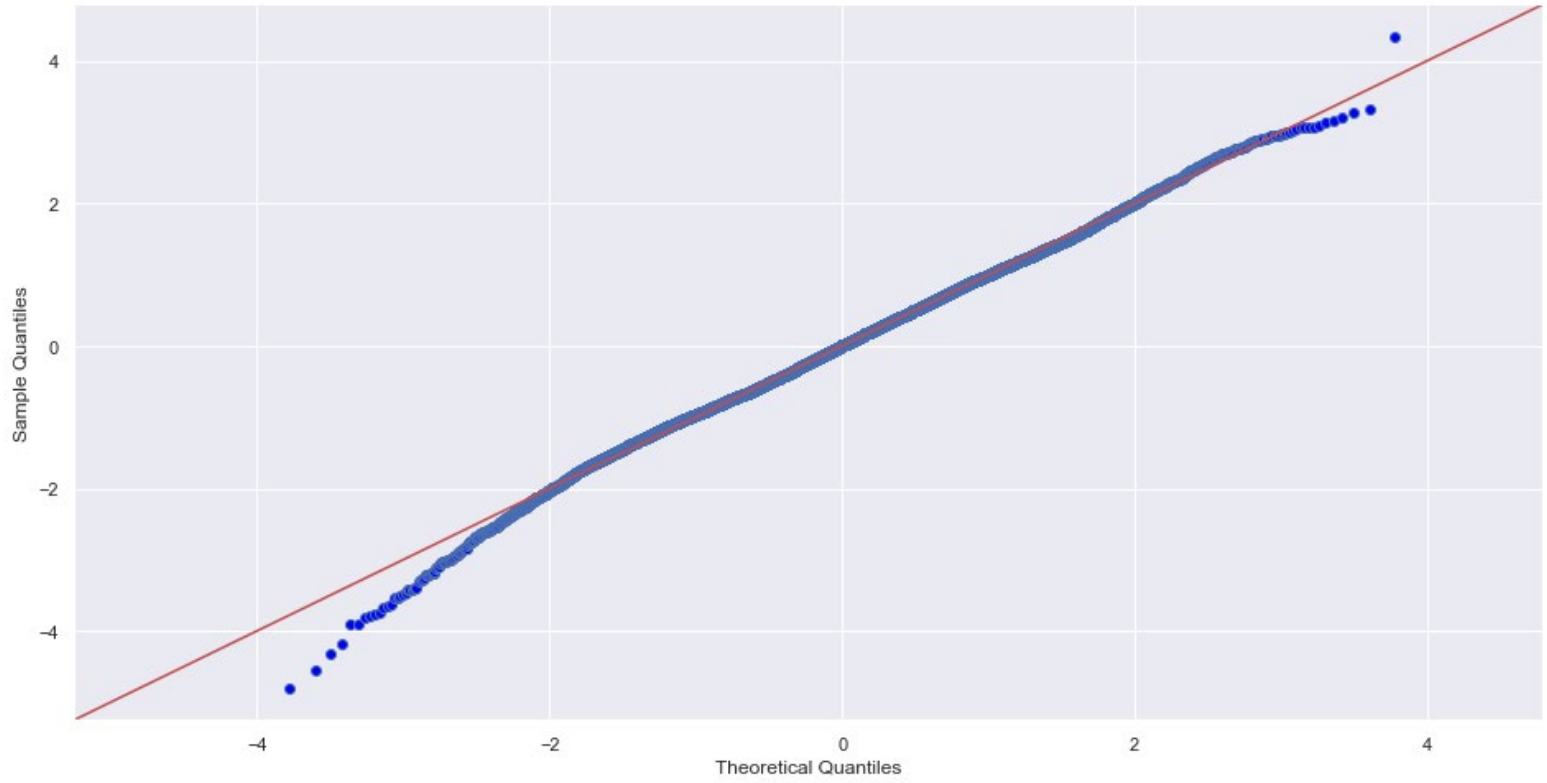
OLS Regression Results

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:	23:18:42	**Log-Likelihood:**	-3325.9
No. Observations:	12664	**AIC:**	6714.
Df Residuals:	12633	**BIC:**	6945.
Df Model:	30		
Covariance Type:	nonrobust		

```
['sqft_lot',
 'sqft_living15',
 'sqft_lot15',
 'bedrooms_3',
 'bedrooms_4',
 'bedrooms_5',
 'floors_2.5',
 'floors_3.0',
 'waterfront_1.0',
 'is_renovated_1.0'
 'view_1.0',
 'view_2.0',
 'view_3.0',
 'view_4.0',
 'grade_10',
 'grade_11',
 'zipcode4_98020',
 'zipcode4_98030',
 'zipcode4_98040',
 'zipcode4_98060',
 'zipcode4_98070',
 'zipcode4_98090',
 'zipcode4_98100',
 'zipcode4_98110',
 'zipcode4_98120',
 'zipcode4_98130',
 'zipcode4_98150',
 'zipcode4_98160',
 'zipcode4_98170',
 'zipcode4_98180']
```

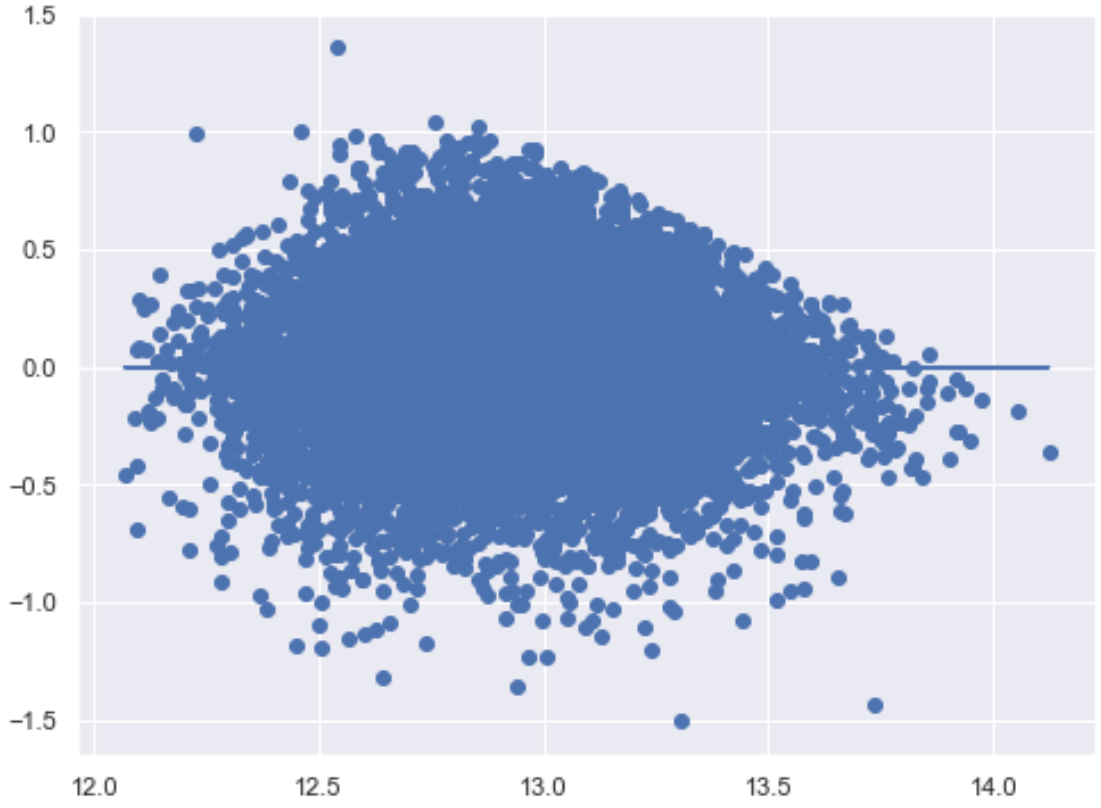
Regression model evaluation

- Normality: qqplot



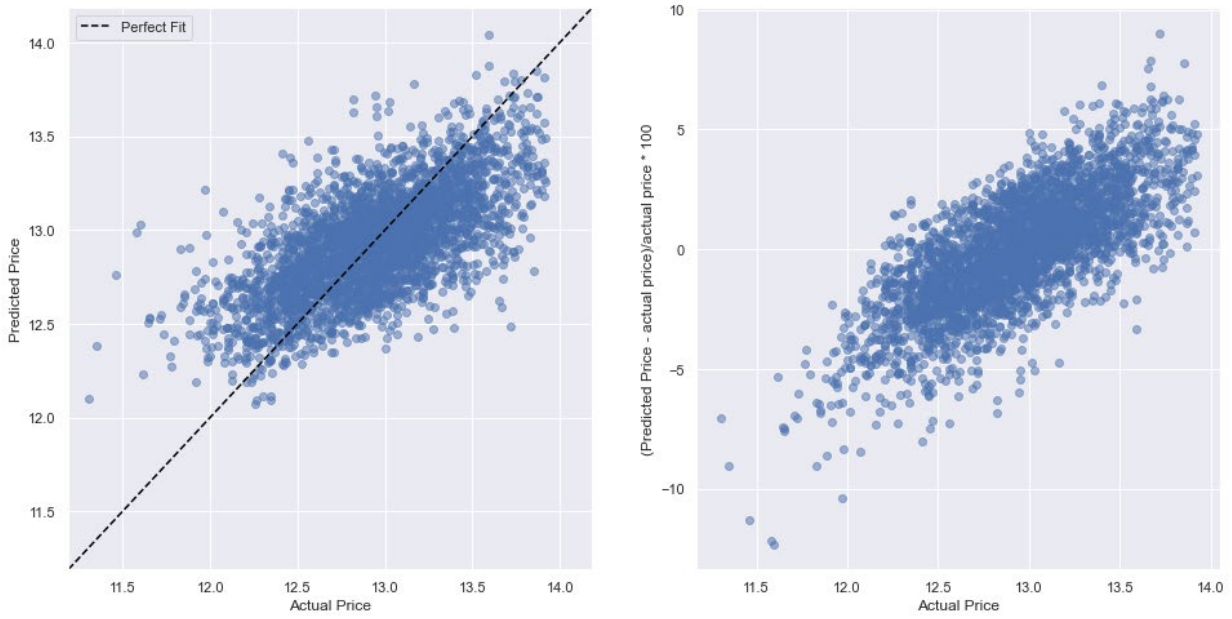
Regression model evaluation

- Homoscedasticity



Regression model evaluation

- Cross-validation
  - Train score: 0.4465
  - Validation score: 0.4501
- Mean squared error, root mean squared error, mean absolute error, and Mean absolute error
  - MSE: 0.1007
  - RMSE: 0.3174
  - MAE: 0.2519
  - R-Squared: 0.4437
- Examine the predicted values with the real values



The fitted regression model can predict house price very well

Summary

- Observations from coefficients
  - The grade and sqft_living15 have the strongest relationship with the house price
  - It is interesting to see sqft_lot15 has a negative relationship with the house price
  - Waterfront_1.0 and grade_11 also have a positive relationship with the price
  - For some zipcode, e.g., 98100 and 98110, they have high positive relationships with the price
- To address the business questions:
  - For buyer, they will know that the house price is higher for a house with the high grade and sqrt_living15 values
  - For seller, if they want to sell their house with a higher price, they could add waterfront and improve the grade.

```
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
```