# Final project in Module 2

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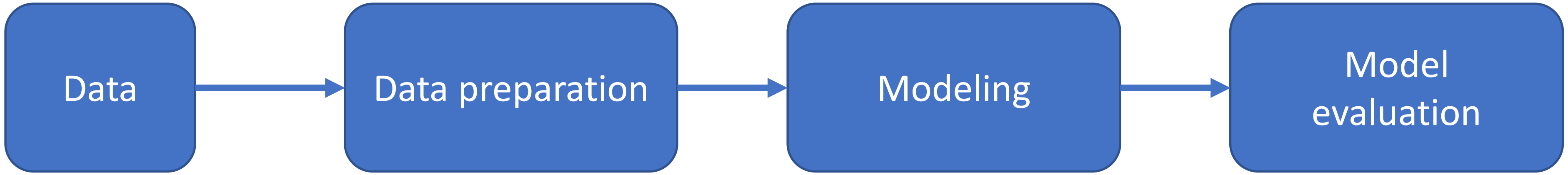
Self-paced

# Outline

- The aim of the project:
  - To provide suggestions regarding the price of house
    - For house buyer, they will know the approximate price of the house and the investment value of the house for future sale, based on the characteristics of the house
    - 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 selected house characteristics to achieve the goal of the project
- Conclusion

# A linear regression model



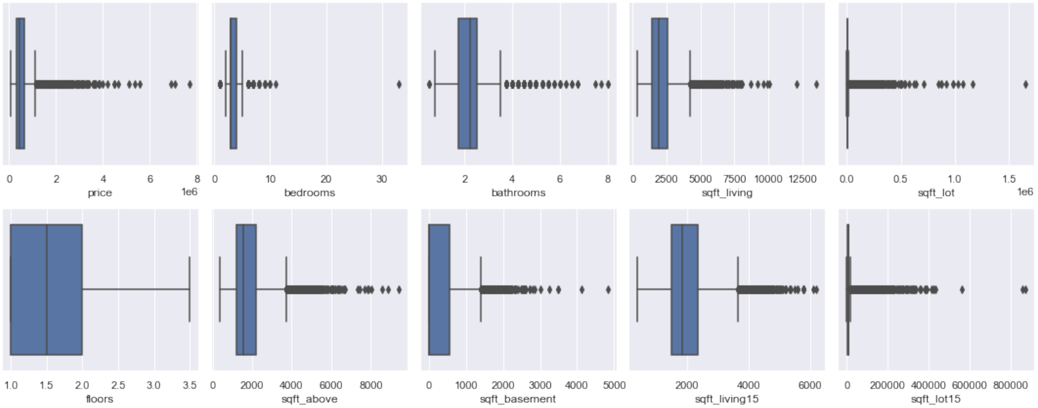
# Data

- 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

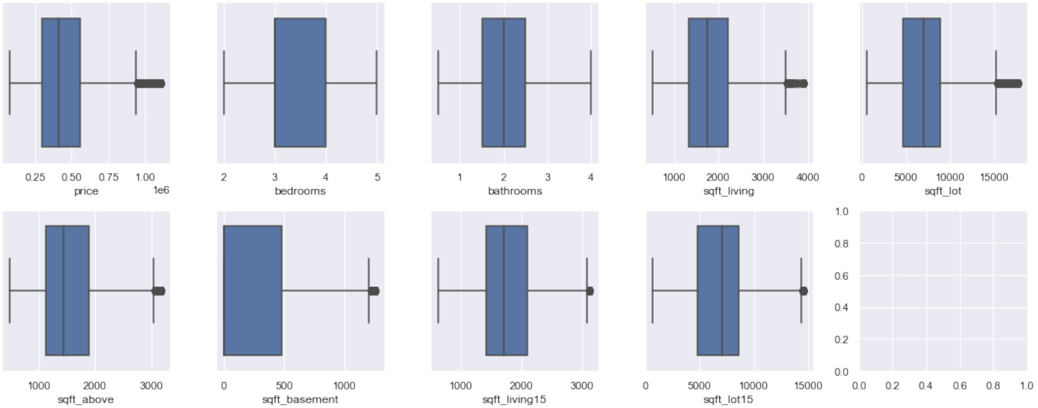
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21597 non-null  int64
 1   date           21597 non-null  object
 2   price          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

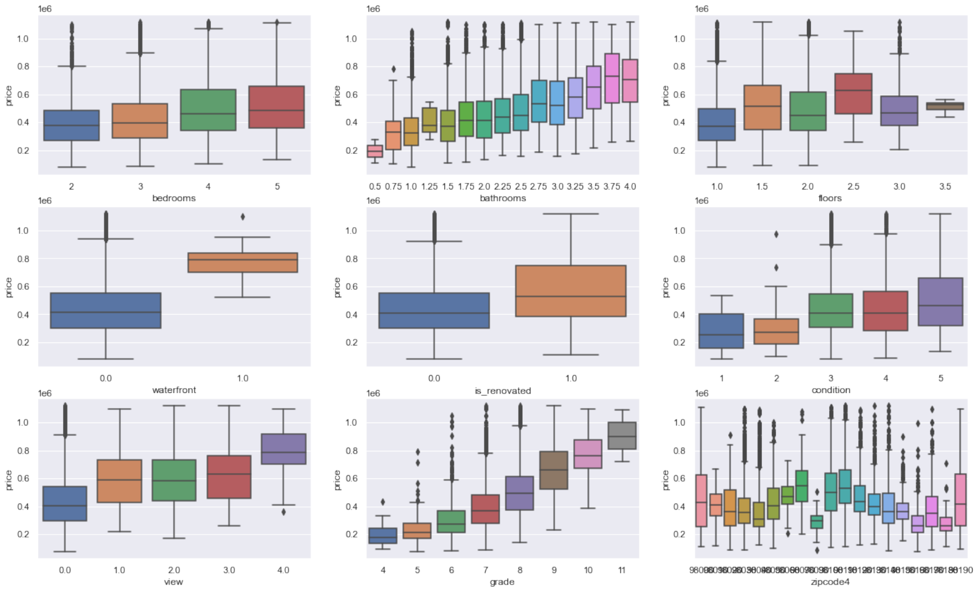



After removing outliers

# Data Preparation

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

Visualization of categorical variables




The predictors

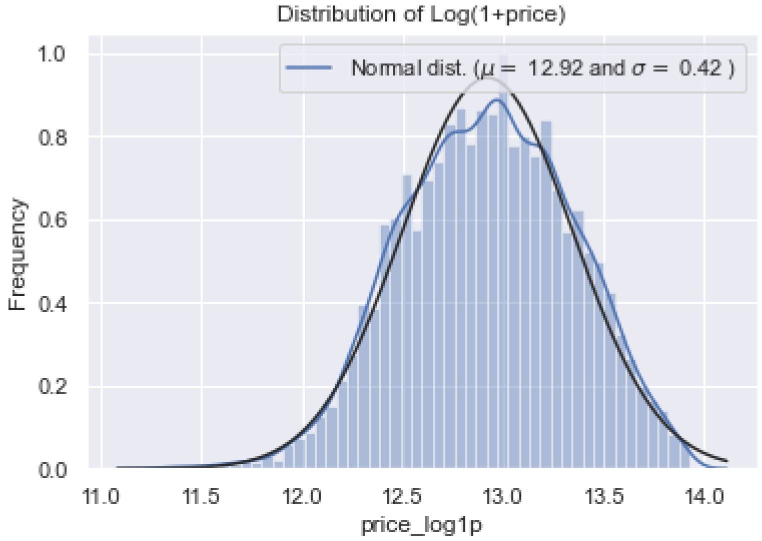
```
df_scl.columns
```

```
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

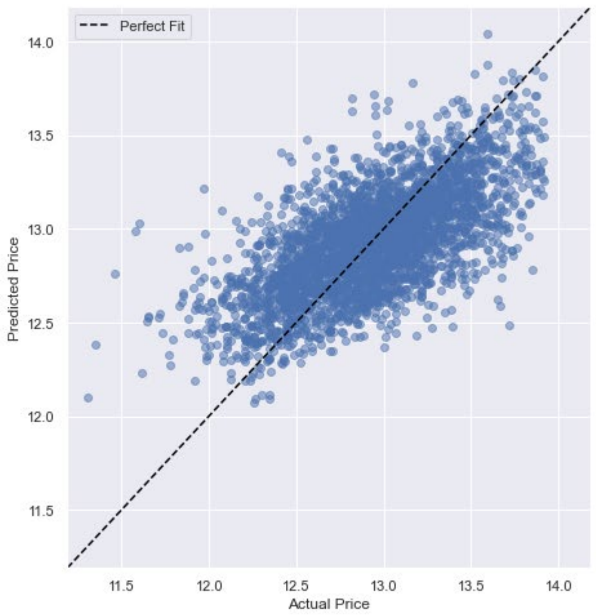
OLS Regression Results

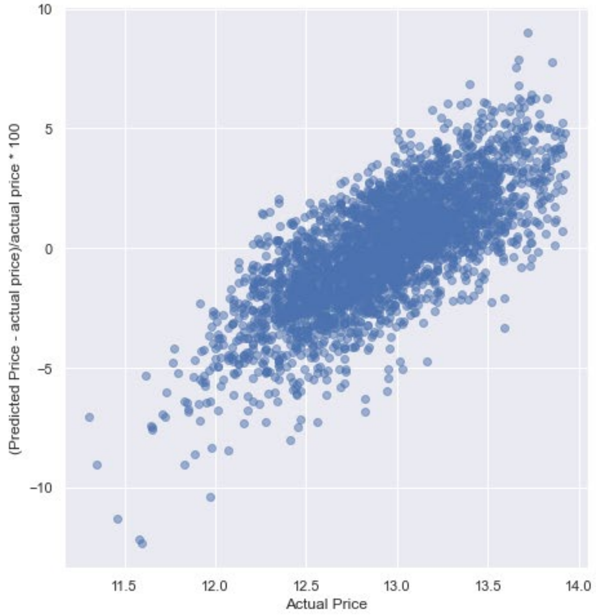
| | | | |
|---|---|---|---|
| Dep. Variable: | price_log1p | R-squared: | 0.449 |
| Model: | OLS | Adj. R-squared: | 0.447 |
| Method: | Least Squares | F-statistic: | 342.6 |
| Date: | Thu, 18 Nov 2021 | Prob (F-statistic): | 0.00 |
| Time: | 23:18:42 | Log-Likelihood: | -3325.9 |
| No. Observations: | 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

- 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

# Conclusion

- 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
```