1_Baseline_Models

February 13, 2026

1 King Country House Sales

Dataset

1.1 Data Description

Column Name	Description	Data Type
id	Unique numeric number assigned to each house being sold	`int64`
date	Date on which the house was sold out	`str`
price	Price of house (Target variable)	`float64`
bedrooms	Number of bedrooms in a house	`int64`
bathrooms	Number of bathrooms in a bedroom of a house	`float64`
sqft_living	Measurement of house in square foot	`int64`
sqft_lot	Square foot of the lot	`int64`
floors	Total floors (levels) of house	`float64`
waterfront	Waterfront view (0=No, 1=Yes)	`int64`
view	House viewed or not (0=No, 1=Yes)	`int64`
condition	Overall condition of a house (Scale 1-5)	`int64`
grade	Overall grade given to the housing unit (Scale 1-11)	`int64`
sqft_above	Square footage of house apart from basement	`int64`
sqft_basement	Square footage of the basement of the house	`int64`
yr_built	Date of building of the house	`int64`
yr_renovated	Year of renovation of house	`int64`

Column Name	Description	Data Type
zipcode	Zipcode of the location of the house	`int64`
lat	Latitude of the location of the house	`float64`
long	Longitude of the location of the house	`float64`
sqft_living15	Living room area in 2015 (implies some renovations)	`int64`
sqft_lot15	LotSize area in 2015 (implies some renovations)	`int64`

1.2 Imports and config

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px

# Models & Normalization
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LinearRegression, ridge_regression, Lasso

# Evaluation
import statsmodels.api as sm

# Extra
from utils import *
```

1.3 Data Loading

[2]:
```
file_path = "Data/king_ country_ houses_aa.csv"

df = pd.read_csv(file_path)
df.head()
```

[2]:
```
           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]
```

[3]:
```
df.dtypes
```

[3]:
```
id                 int64
date                 str
price            float64
bedrooms           int64
bathrooms        float64
sqft_living        int64
sqft_lot           int64
floors           float64
waterfront         int64
view               int64
condition          int64
grade              int64
sqft_above         int64
sqft_basement      int64
yr_built           int64
yr_renovated       int64
zipcode            int64
lat              float64
long             float64
sqft_living15      int64
sqft_lot15         int64
dtype: object
```

[4]:
```python
# Unique values for each column
df.nunique()
```

[4]:
```
id               21436
date               372
price             4028
bedrooms            13
bathrooms           30
sqft_living       1038
sqft_lot          9782
floors               6
waterfront           2
view                 5
condition            5
grade               12
sqft_above         946
sqft_basement      306
yr_built           116
yr_renovated        70
zipcode             70
lat               5034
long               752
sqft_living15      777
sqft_lot15        8689
dtype: int64
```

1.4 Minimal Data Cleaning and Transformation

To perform the fitting to the baseline model, we would like to perform the minimum data cleaning and transformation possible.

We are transforming the date column into 3 different columns containing the day, the month and the year. This transformation is important to keep the information about the date which was previously in a format that cannot be fed to the regression models, while verifying which part of the date has relevance to the prediction.

[5]:
```python
df.date = pd.to_datetime(df.date)
df["year_sold"] = df.date.dt.year
df["month_sold"] = df.date.dt.month
df["day_sold"] = df.date.dt.day
```

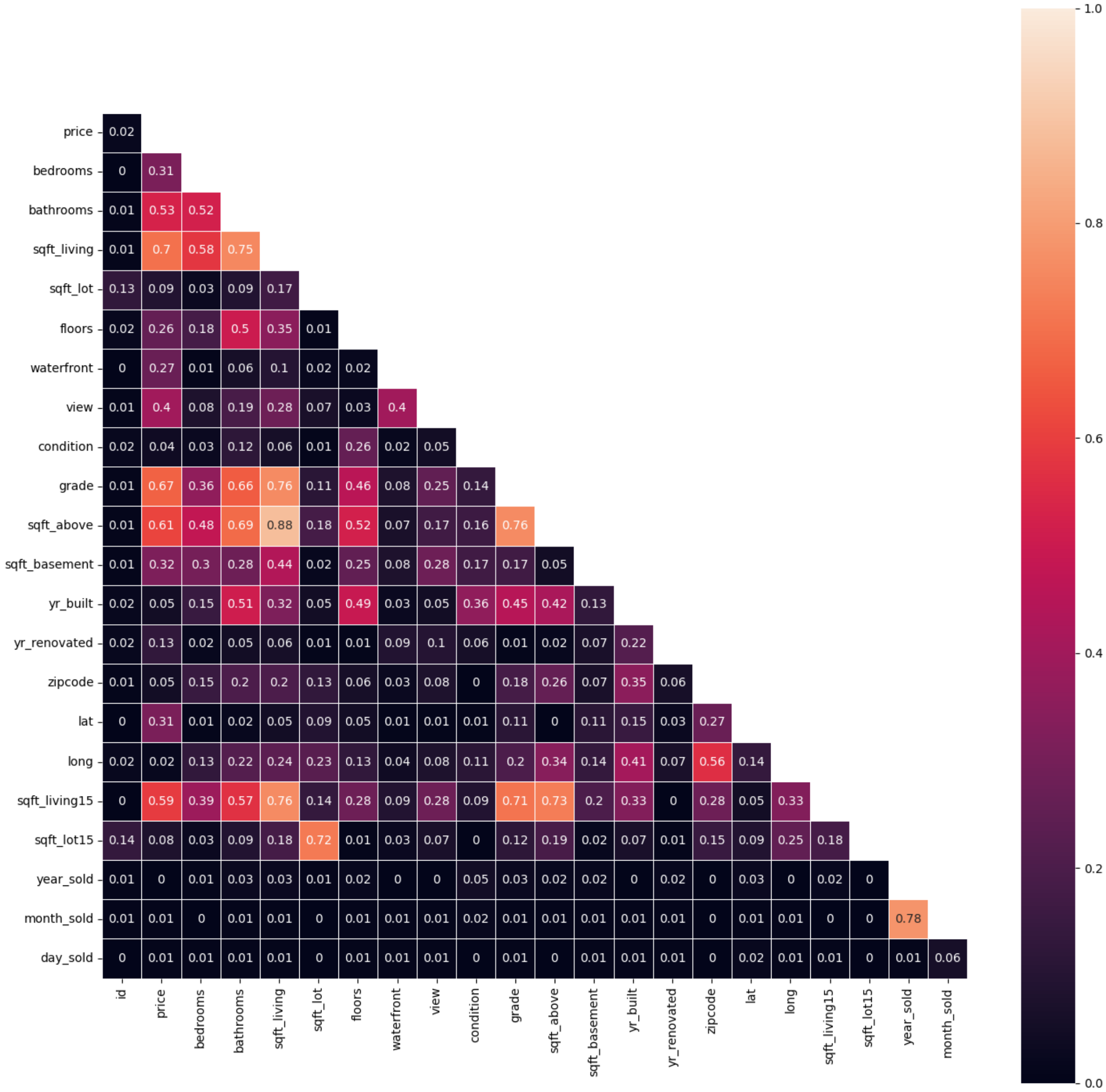
[6]:
```python
df.describe()
```

[6]:
```
                 id                           date         price      bedrooms  \
count  2.161300e+04                          21613  2.161300e+04  21613.000000
mean   4.580302e+09  2014-10-29 04:38:01.959931  5.400881e+05      3.370842
min    1.000102e+06         2014-05-02 00:00:00  7.500000e+04      0.000000
25%    2.123049e+09         2014-07-22 00:00:00  3.219500e+05      3.000000
```

```
50%    3.904930e+09       2014-10-16 00:00:00  4.500000e+05      3.000000
75%    7.308900e+09       2015-02-17 00:00:00  6.450000e+05      4.000000
max    9.900000e+09       2015-05-27 00:00:00  7.700000e+06     33.000000
std    2.876566e+09                       NaN  3.671272e+05      0.930062

          bathrooms   sqft_living      sqft_lot        floors    waterfront  \
count  21613.000000  21613.000000  2.161300e+04  21613.000000  21613.000000
mean       2.114757   2079.899736  1.510697e+04      1.494309      0.007542
min        0.000000    290.000000  5.200000e+02      1.000000      0.000000
25%        1.750000   1427.000000  5.040000e+03      1.000000      0.000000
50%        2.250000   1910.000000  7.618000e+03      1.500000      0.000000
75%        2.500000   2550.000000  1.068800e+04      2.000000      0.000000
max        8.000000  13540.000000  1.651359e+06      3.500000      1.000000
std        0.770163    918.440897  4.142051e+04      0.539989      0.086517

               view  …      yr_built  yr_renovated       zipcode  \
count  21613.000000  …  21613.000000  21613.000000  21613.000000
mean       0.234303  …   1971.005136     84.402258  98077.939805
min        0.000000  …   1900.000000      0.000000  98001.000000
25%        0.000000  …   1951.000000      0.000000  98033.000000
50%        0.000000  …   1975.000000      0.000000  98065.000000
75%        0.000000  …   1997.000000      0.000000  98118.000000
max        4.000000  …   2015.000000   2015.000000  98199.000000
std        0.766318  …     29.373411    401.679240     53.505026

                lat          long  sqft_living15     sqft_lot15     year_sold  \
count  21613.000000  21613.000000   21613.000000   21613.000000  21613.000000
mean      47.560053   -122.213896    1986.552492   12768.455652   2014.322954
min       47.155900   -122.519000     399.000000     651.000000   2014.000000
25%       47.471000   -122.328000    1490.000000    5100.000000   2014.000000
50%       47.571800   -122.230000    1840.000000    7620.000000   2014.000000
75%       47.678000   -122.125000    2360.000000   10083.000000   2015.000000
max       47.777600   -121.315000    6210.000000  871200.000000   2015.000000
std        0.138564      0.140828     685.391304   27304.179631      0.467616

         month_sold      day_sold
count  21613.000000  21613.000000
mean       6.574423     15.688197
min        1.000000      1.000000
25%        4.000000      8.000000
50%        6.000000     16.000000
75%        9.000000     23.000000
max       12.000000     31.000000
std        3.115308      8.635063

[8 rows x 24 columns]
```

1.4.1 Correlation between the features

[7]:
```
generate_heatmap(df.select_dtypes(include="number"))
```



[8]:
```
# remove the id since its an identifier and has no relevance in the house␣
↪pricing.
# remove the date after its transformation
df_clean = df.drop(["id", "date"], axis=1)
```

[9]:
```
# Export cleaned and transformed data
# filename = "Data/cleaned_house_sales.csv"
# df_clean.to_csv(filename, index=False)
```

[10]:
```python
# The price is the target variable
y = df_clean["price"]

# All other variables are the features for the baseline model
X = df_clean.drop("price", axis=1)
```

1.5 Baseline Model

[11]:
```python
# Split into train and test
seed = 13
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=seed)
```

[12]:
```python
X_train
```

[12]:
```
       bedrooms  bathrooms  sqft_living  sqft_lot  floors  waterfront  view  \
1571          4       1.50         2000      6778     1.0           0     0
16330         4       2.50         2630     48706     2.0           0     0
12786         4       2.50         2620      9525     2.5           0     0
12524         3       2.50         1610      6000     2.0           0     0
16179         3       1.00          880     18205     1.0           0     0
…           …          …            …         …       …         …   …
153           4       3.25         5180     19850     2.0           0     3
866           3       2.50         3460      6590     2.0           0     0
74            3       1.75         1790     50529     1.0           0     0
14512         2       1.00          820      5040     1.0           0     0
338           3       1.75         1420      8250     1.0           0     0

       condition  grade  sqft_above  …  yr_built  yr_renovated  zipcode  \
1571           4      7        1170  …      1962             0    98198
16330          3      8        2630  …      1986             0    98072
12786          4      9        2620  …      1974             0    98040
12524          4      7        1610  …      1993             0    98038
16179          4      6         880  …      1945             0    98178
…            …    …         …  …       …           …      …
153            3     12        3540  …      2006             0    98006
866            3      7        3460  …      2001             0    98056
74             5      7        1090  …      1965             0    98042
14512          3      7         820  …      1953             0    98199
338            3      7        1420  …      1954             0    98133

           lat     long  sqft_living15  sqft_lot15  year_sold  month_sold  \
1571   47.3708 -122.311           1940        7531       2015           3
16330  47.7750 -122.125           2680       48706       2014           5
12786  47.5631 -122.219           2580        9525       2014           8
12524  47.3490 -122.036           1570        6000       2014           8
16179  47.5013 -122.244           1110       16115       2014           6
```

```
…         …       …              …        …        …          …
153    47.5620 -122.162       3160      9750      2015            4
866    47.4802 -122.188       2490      6312      2015            4
74     47.3511 -122.073       1940     50529      2015            3
14512  47.6498 -122.388       1730      5760      2014            8
338    47.7535 -122.354       1740      8000      2014            8

       day_sold
1571         23
16330        21
12786         5
12524        26
16179        24
…          …
153           1
866          27
74           16
14512        20
338          26

[17290 rows x 21 columns]
```

[13]:
```
y_train
```

[13]:
```
1571      284950.0
16330     625000.0
12786     838400.0
12524     282000.0
16179     218000.0
            …
153      2250000.0
866       467000.0
74        349000.0
14512     508000.0
338       265000.0
Name: price, Length: 17290, dtype: float64
```

1.5.1 Metrics Dataframe

Column	Description
Model	Name of the algorithm used (e.g., Linear Regression, Random Forest).
Split	Indicates the dataset partition (Train or Test) to check for overfitting/underfitting.
R2	R-Squared: The proportion of variance in the target variable explained by the model (0 to 1).
Adjusted_R2	**R2** corrected for the number of predictors. Use this to compare models with different numbers of features.

Column	Description
MAE	Mean Absolute Error: The average absolute difference between predicted and actual values. Robust to outliers.
RMSE	Root Mean Squared Error: The square root of average squared errors. Penalizes large errors more heavily than MAE.
MAPE	Mean Absolute Percentage Error: The average error expressed as a percentage. Easy to interpret for business stakeholders.
Comments	Custom notes on model configuration, hyperparameters, or specific observations.

[14]:
```
# Create dataframe to save all metrics
metrics_df = create_metrics_df()
metrics_df
```

[14]:
```
Empty DataFrame
Columns: [Model, Split, R2, Adjusted_R2, MAE, RMSE, MAPE, Comments]
Index: []
```

1.5.2 Linear Model: Not normalized

[15]:
```
# Not normalized:
lr_not_norm = LinearRegression()
lr_not_norm.fit(X_train, y_train)

y_train_pred_nn = lr_not_norm.predict(X_train)
y_test_pred_nn = lr_not_norm.predict(X_test)


get_r_squared(y_train=y_train, y_pred_train=y_train_pred_nn, y_test = y_test,␣
↪y_pred_test=y_test_pred_nn)
```

```
R2 score:
train | 0.6977440607209231
test  | 0.7161824379295636
```

[15]:
```
(0.6977440607209231, 0.7161824379295636)
```

[16]:
```
metrics_df = add_new_metrics(metrics_df,
                             lr_not_norm,
                             X_train,
                             y_train,
                             split="train",
                             comments="Baseline model")
```

[17]:
```
metrics_df = add_new_metrics(metrics_df,
                             lr_not_norm,
```

```
                                X_test,
                                y_test,
                                split="test",
                                comments="Baseline model")
```

[18]:
```
metrics_df
```

[18]:
```
              Model  Split      R2  Adjusted_R2          MAE    MAPE  \
0  LinearRegression  train  0.6977       0.6974  125948.1118  0.2561
1  LinearRegression   test  0.7162       0.7148  125985.6747  0.2596

          RMSE       Comments
0  202864.5703  Baseline model
1  191531.3335  Baseline model
```

[19]:
```
# OLS: not normalized

import statsmodels.api as sm
estimator_nn = sm.OLS(y_train, X_train) # Creates an object OLS estimator
estimator_nn = estimator_nn.fit()
estimator_nn.summary()
```

[19]:

Dep. Variable:	price	**R-squared (uncentered):**	0.904
Model:	OLS	**Adj. R-squared (uncentered):**	0.903
Method:	Least Squares	**F-statistic:**	8088.
Date:	Fri, 13 Feb 2026	**Prob (F-statistic):**	0.00
Time:	18:23:22	**Log-Likelihood:**	-2.3584e+05
No. Observations:	17290	**AIC:**	4.717e+05
Df Residuals:	17270	**BIC:**	4.719e+05
Df Model:	20		
Covariance Type:	nonrobust		

	coef	std err	t	P> |t|	[0.025	0.975]
bedrooms	-3.637e+04	2114.370	-17.202	0.000	-4.05e+04	-3.22e+04
bathrooms	4.161e+04	3683.098	11.297	0.000	3.44e+04	4.88e+04
sqft_living	111.0403	2.552	43.509	0.000	106.038	116.043
sqft_lot	0.1139	0.054	2.123	0.034	0.009	0.219
floors	5371.0191	4071.934	1.319	0.187	-2610.383	1.34e+04
waterfront	5.778e+05	1.99e+04	29.076	0.000	5.39e+05	6.17e+05
view	5.206e+04	2426.290	21.458	0.000	4.73e+04	5.68e+04
condition	2.551e+04	2646.231	9.641	0.000	2.03e+04	3.07e+04
grade	9.669e+04	2423.262	39.902	0.000	9.19e+04	1.01e+05
sqft_above	73.1607	2.532	28.894	0.000	68.198	78.124
sqft_basement	37.8796	2.990	12.671	0.000	32.020	43.739
yr_built	-2653.8504	81.477	-32.572	0.000	-2813.554	-2494.146
yr_renovated	20.1984	4.139	4.881	0.000	12.086	28.310
zipcode	-644.8994	36.078	-17.875	0.000	-715.616	-574.183
lat	6.072e+05	1.21e+04	50.121	0.000	5.83e+05	6.31e+05
long	-2.257e+05	1.48e+04	-15.286	0.000	-2.55e+05	-1.97e+05
sqft_living15	19.6702	3.876	5.074	0.000	12.072	27.268
sqft_lot15	-0.3846	0.083	-4.644	0.000	-0.547	-0.222
year_sold	5635.3040	1568.428	3.593	0.000	2561.027	8709.581
month_sold	-2811.1927	529.712	-5.307	0.000	-3849.481	-1772.904
day_sold	-424.6159	179.656	-2.363	0.018	-776.760	-72.472

Omnibus:	15223.220	**Durbin-Watson:**	2.018
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1731607.437
Skew:	3.738	**Prob(JB):**	0.00
Kurtosis:	51.453	**Cond. No.**	5.85e+17

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[3] The smallest eigenvalue is 5.12e-22. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

1.5.3 Linear Model: Normalized

[20]:
```
# normalization

normalizer = MinMaxScaler()

X_train_norm = normalizer.fit_transform(X_train)
X_test_norm = normalizer.fit_transform(X_test)
```

[21]:
```
# Linear Regression: normalized

lr = LinearRegression()
lr.fit(X_train_norm, y_train)
```

```
y_train_pred = lr.predict(X_train_norm)
y_test_pred = lr.predict(X_test_norm)


get_r_squared(y_train=y_train, y_pred_train=y_train_pred, y_test = y_test,␣
 ↪y_pred_test=y_test_pred)
```

```
R2 score:
train | 0.6977440607209233
test  | 0.6834108053685031
```

[21]: (0.6977440607209233, 0.6834108053685031)

[22]:
```
# train
metrics_df = add_new_metrics(metrics_df,
                             lr,
                             X_train_norm,
                             y_train,
                             split = "train",
                             comments="Normalized version of the baseline"
)

# test
metrics_df = add_new_metrics(metrics_df,
                             lr,
                             X_test_norm,
                             y_test,
                             split = "test",
                             comments="Normalized version of the baseline"
)
```

[23]:
```
metrics_df
```

[23]:
```
              Model  Split      R2  Adjusted_R2          MAE    MAPE  \
0  LinearRegression  train  0.6977       0.6974  125948.1118  0.2561
1  LinearRegression   test  0.7162       0.7148  125985.6747  0.2596
2  LinearRegression  train  0.6977       0.6974  125948.1118  0.2561
3  LinearRegression   test  0.6834       0.6819  137988.4158  0.2836

          RMSE                            Comments
0  202864.5703                      Baseline model
1  191531.3335                      Baseline model
2  202864.5703  Normalized version of the baseline
3  202287.1258  Normalized version of the baseline
```

[24]:
```
estimator = sm.OLS(y_train, X_train_norm) # Creates an object OLS estimator
estimator = estimator.fit()
estimator.summary()
```

[24]:

Dep. Variable:	price	**R-squared (uncentered):**	0.902
Model:	OLS	**Adj. R-squared (uncentered):**	0.902
Method:	Least Squares	**F-statistic:**	7984.
Date:	Fri, 13 Feb 2026	**Prob (F-statistic):**	0.00
Time:	18:23:22	**Log-Likelihood:**	-2.3594e+05
No. Observations:	17290	**AIC:**	4.719e+05
Df Residuals:	17270	**BIC:**	4.721e+05
Df Model:	20		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
x1	-1.564e+06	6.58e+04	-23.766	0.000	-1.69e+06	-1.44e+06
x2	3.188e+05	2.96e+04	10.764	0.000	2.61e+05	3.77e+05
x3	9.373e+05	1.75e+04	53.441	0.000	9.03e+05	9.72e+05
x4	1.685e+05	8.9e+04	1.893	0.058	-5999.748	3.43e+05
x5	2.793e+04	1.02e+04	2.742	0.006	7964.623	4.79e+04
x6	5.677e+05	2e+04	28.414	0.000	5.29e+05	6.07e+05
x7	2.115e+05	9762.143	21.669	0.000	1.92e+05	2.31e+05
x8	2.435e+04	9176.473	2.654	0.008	6365.955	4.23e+04
x9	8.356e+05	2.28e+04	36.611	0.000	7.91e+05	8.8e+05
x10	1.188e+06	2.41e+04	49.291	0.000	1.14e+06	1.23e+06
x11	3.9e+05	1.75e+04	22.316	0.000	3.56e+05	4.24e+05
x12	-3.377e+05	9139.698	-36.953	0.000	-3.56e+05	-3.2e+05
x13	2.434e+04	8307.838	2.930	0.003	8060.319	4.06e+04
x14	-1.606e+05	6859.606	-23.406	0.000	-1.74e+05	-1.47e+05
x15	3.519e+05	7379.332	47.682	0.000	3.37e+05	3.66e+05
x16	-3.519e+05	1.71e+04	-20.547	0.000	-3.85e+05	-3.18e+05
x17	1.099e+05	2.27e+04	4.844	0.000	6.54e+04	1.54e+05
x18	-3.397e+05	7.25e+04	-4.684	0.000	-4.82e+05	-1.98e+05
x19	2726.7556	4961.512	0.550	0.583	-6998.311	1.25e+04
x20	-4.898e+04	8118.907	-6.033	0.000	-6.49e+04	-3.31e+04
x21	-2.83e+04	5308.269	-5.331	0.000	-3.87e+04	-1.79e+04

Omnibus:	14877.120	**Durbin-Watson:**	2.019
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1551903.144
Skew:	3.624	**Prob(JB):**	0.00
Kurtosis:	48.844	**Cond. No.**	2.78e+16

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[3] The smallest eigenvalue is 5.56e-29. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

[25]:
```python
i = 1

for item in X_train.columns:
    print(i, item)
    i+=1
```

```
1 bedrooms
2 bathrooms
3 sqft_living
4 sqft_lot
5 floors
6 waterfront
7 view
8 condition
9 grade
10 sqft_above
11 sqft_basement
12 yr_built
13 yr_renovated
14 zipcode
15 lat
16 long
17 sqft_living15
18 sqft_lot15
19 year_sold
20 month_sold
21 day_sold
```

1.6 Random Forest

[26]:
```python
# most common hyperparameters or the default ones
from sklearn.ensemble import RandomForestRegressor

rf_regressor = RandomForestRegressor(random_state=seed)#default values +␣
 ↪random_state = 13
rf_regressor.fit(X_train, y_train)
```

[26]:
```
RandomForestRegressor(random_state=13)
```

[27]:
```python
metrics_df = add_new_metrics(metrics_df,
                             rf_regressor,
                             X_train,
                             y_train,
                             split = "train",
                             comments="Baseline, no normalization, random_state␣
 ↪13, default values.")
```

[28]:
```
metrics_df = add_new_metrics(metrics_df,
                             rf_regressor,
                             X_test,
                             y_test,
                             split = "test",
                             comments="Baseline, no normalization, random_state␣
 ↪13, default values.")
```

[29]:
```
metrics_df
```

[29]:
```
                   Model  Split      R2  Adjusted_R2          MAE    MAPE  \
0       LinearRegression  train  0.6977       0.6974  125948.1118  0.2561
1       LinearRegression   test  0.7162       0.7148  125985.6747  0.2596
2       LinearRegression  train  0.6977       0.6974  125948.1118  0.2561
3       LinearRegression   test  0.6834       0.6819  137988.4158  0.2836
4  RandomForestRegressor  train  0.9820       0.9819   25948.4444  0.0486
5  RandomForestRegressor   test  0.8959       0.8954   67269.8770  0.1271

          RMSE                                      Comments
0  202864.5703                                Baseline model
1  191531.3335                                Baseline model
2  202864.5703            Normalized version of the baseline
3  202287.1258            Normalized version of the baseline
4   49547.1197  Baseline, no normalization, random_state 13, d…
5  115994.2051  Baseline, no normalization, random_state 13, d…
```

1.7 XGBoost

[30]:
```
import xgboost as xgb

xgb_clf = xgb.XGBRegressor(seed = seed)
xgb_clf.fit(X_train, y_train)
```

[30]:
```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             feature_weights=None, gamma=None, grow_policy=None,
             importance_type=None, interaction_constraints=None,
             learning_rate=None, max_bin=None, max_cat_threshold=None,
             max_cat_to_onehot=None, max_delta_step=None, max_depth=None,
             max_leaves=None, min_child_weight=None, missing=nan,
             monotone_constraints=None, multi_strategy=None, n_estimators=None,
             n_jobs=None, num_parallel_tree=None, …)
```

[31]:
```
metrics_df = add_new_metrics(metrics_df,
                             xgb_clf,
```

```
                                X_train,
                                y_train,
                                split = "train",
                                comments="Baseline, no normalization, default␣
↪values.")
```

[32]:
```
metrics_df = add_new_metrics(metrics_df,
                                xgb_clf,
                                X_test,
                                y_test,
                                split = "test",
                                comments="Baseline, no normalization, default␣
↪values.")
```

[33]:
```
metrics_df
```

[33]:
```
                    Model  Split      R2  Adjusted_R2          MAE    MAPE  \
0        LinearRegression  train  0.6977       0.6974  125948.1118  0.2561
1        LinearRegression   test  0.7162       0.7148  125985.6747  0.2596
2        LinearRegression  train  0.6977       0.6974  125948.1118  0.2561
3        LinearRegression   test  0.6834       0.6819  137988.4158  0.2836
4   RandomForestRegressor  train  0.9820       0.9819   25948.4444  0.0486
5   RandomForestRegressor   test  0.8959       0.8954   67269.8770  0.1271
6            XGBRegressor  train  0.9780       0.9780   39126.7558  0.0872
7            XGBRegressor   test  0.9015       0.9010   65712.7448  0.1246

         RMSE                                        Comments
0  202864.5703                                  Baseline model
1  191531.3335                                  Baseline model
2  202864.5703             Normalized version of the baseline
3  202287.1258             Normalized version of the baseline
4   49547.1197  Baseline, no normalization, random_state 13, d…
5  115994.2051  Baseline, no normalization, random_state 13, d…
6   54676.7727        Baseline, no normalization, default values.
7  112860.4995        Baseline, no normalization, default values.
```

1.7.1 Insights

1.8 Conclusions & Export

[34]:
```
# metrics_df.to_csv("Metrics/baseline_metrics.csv", index=False)
```

[ ]:
```
```