3_Outliers_Analysis

February 13, 2026

1 Analyse the Influence of Outliers

1.1 Imports

[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
```

1.2 Open the clean data

[2]:
```
file_path = "Data/cleaned_house_sales.csv"

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

[2]:

	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	…	yr_built	yr_renovated	zipcode	lat	\
0	0	3	7	…	1955	0	98178	47.5112	
1	0	3	7	…	1951	1991	98125	47.7210	
2	0	3	6	…	1933	0	98028	47.7379	
3	0	5	7	…	1965	0	98136	47.5208	
4	0	3	8	…	1987	0	98074	47.6168	

	long	sqft_living15	sqft_lot15	year_sold	month_sold	day_sold
0	-122.257	1340	5650	2014	10	13
1	-122.319	1690	7639	2014	12	9

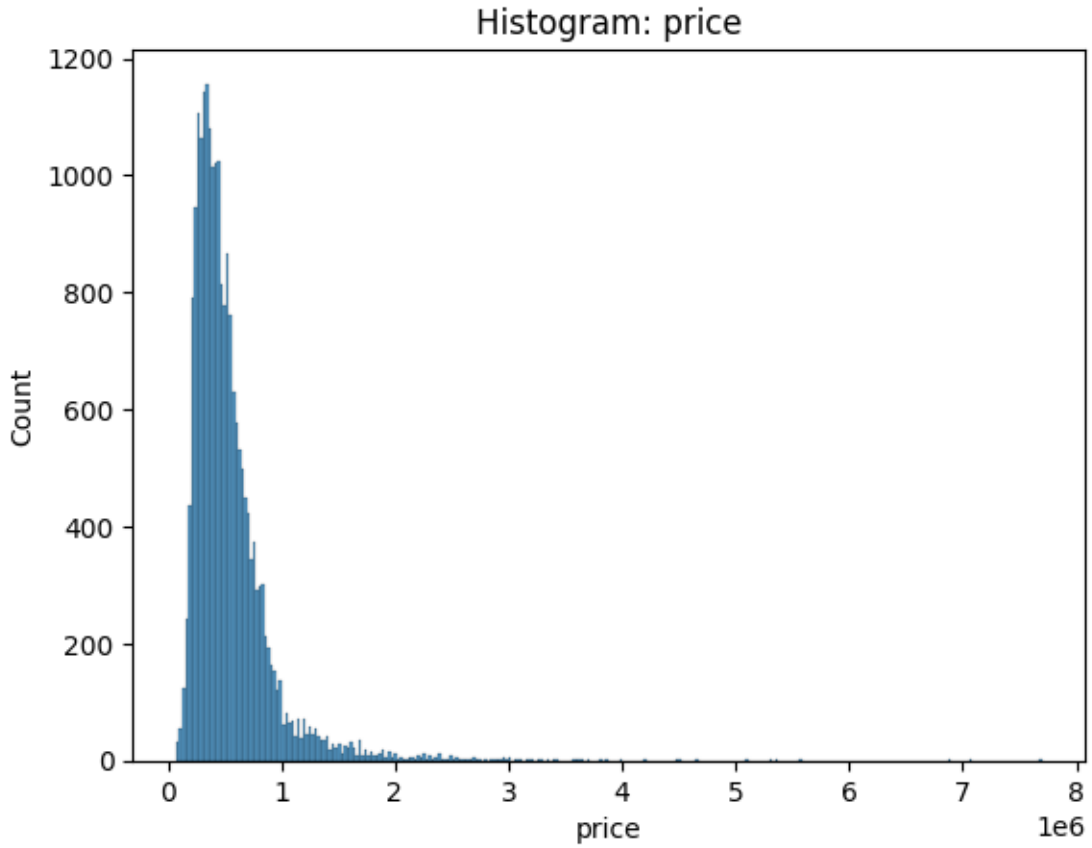
```
2 -122.233          2720        8062        2015          2         25
3 -122.393          1360        5000        2014         12          9
4 -122.045          1800        7503        2015          2         18

[5 rows x 22 columns]
```

1.3 Analysing Prices

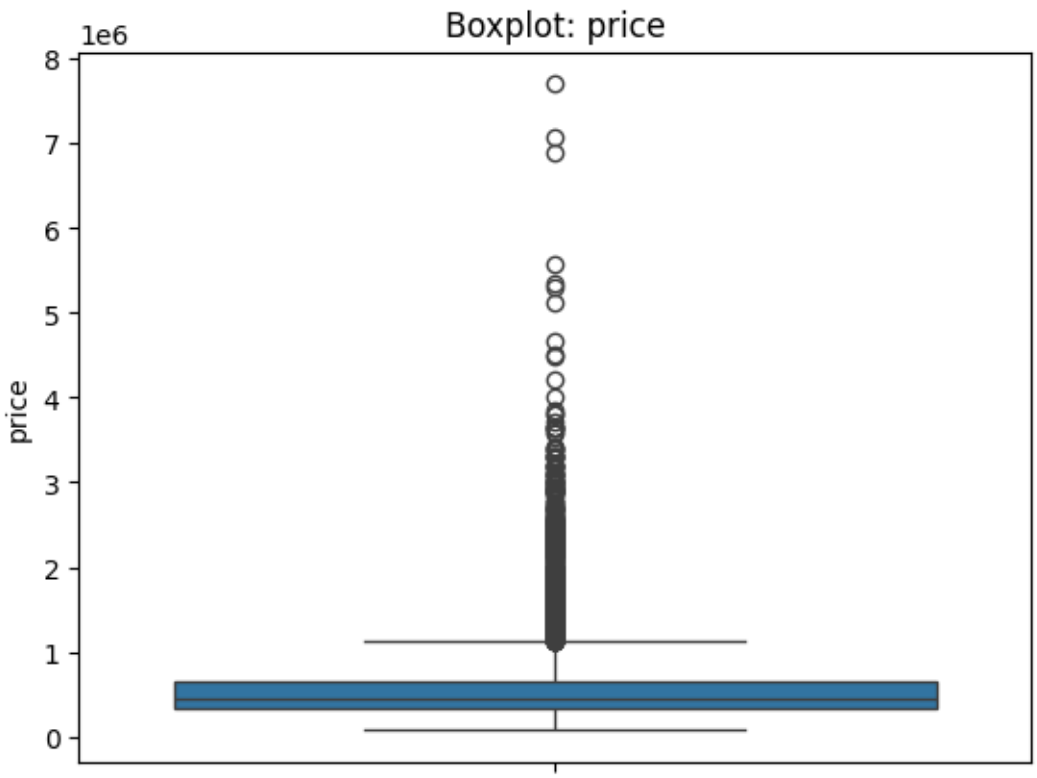
[3]:
```
sns.histplot(df_clean.price)
plt.title("Histogram: price")
```

[3]:
```
Text(0.5, 1.0, 'Histogram: price')
```



[4]:
```
sns.boxplot(df_clean.price)
plt.title("Boxplot: price")
```

[4]:
```
Text(0.5, 1.0, 'Boxplot: price')
```



[5]:
```
df_clean["price"].describe()
```

[5]:
```
count    2.161300e+04
mean     5.400881e+05
std      3.671272e+05
min      7.500000e+04
25%      3.219500e+05
50%      4.500000e+05
75%      6.450000e+05
max      7.700000e+06
Name: price, dtype: float64
```

[6]:
```
# 11 houses over 4 million
df_clean[df_clean.price > 4e6]
```

[6]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	\
1164	5110800.0	5	5.25	8010	45517	2.0	
1315	5300000.0	6	6.00	7390	24829	2.0	
1448	5350000.0	5	5.00	8000	23985	2.0	
2626	4500000.0	5	5.50	6640	40014	2.0	
3914	7062500.0	5	4.50	10040	37325	2.0	
4411	5570000.0	5	5.75	9200	35069	2.0	

```
7252   7700000.0         6       8.00        12050     27600     2.5
8092   4668000.0         5       6.75         9640     13068     1.0
8638   4489000.0         4       3.00         6430     27517     2.0
9254   6885000.0         6       7.75         9890     31374     2.0
12370  4208000.0         5       6.00         7440     21540     2.0

       waterfront  view  condition  grade  …  yr_built  yr_renovated  \
1164            1     4          3     12  …      1999             0
1315            1     4          4     12  …      1991             0
1448            0     4          3     12  …      2009             0
2626            1     4          3     12  …      2004             0
3914            1     2          3     11  …      1940          2001
4411            0     0          3     13  …      2001             0
7252            0     3          4     13  …      1910          1987
8092            1     4          3     12  …      1983          2009
8638            0     0          3     12  …      2001             0
9254            0     4          3     13  …      2001             0
12370           0     0          3     12  …      2003             0

       zipcode      lat     long  sqft_living15  sqft_lot15  year_sold  \
1164     98033  47.6767 -122.211           3430       26788       2014
1315     98040  47.5631 -122.210           4320       24619       2015
1448     98004  47.6232 -122.220           4600       21750       2015
2626     98155  47.7493 -122.280           3030       23408       2014
3914     98004  47.6500 -122.214           3930       25449       2014
4411     98039  47.6289 -122.233           3560       24345       2014
7252     98102  47.6298 -122.323           3940        8800       2014
8092     98040  47.5570 -122.210           3270       10454       2014
8638     98004  47.6208 -122.219           3720       14592       2014
9254     98039  47.6305 -122.240           4540       42730       2014
12370    98006  47.5692 -122.189           4740       19329       2015

       month_sold  day_sold
1164           10        20
1315            4        13
1448            4        13
2626            8        15
3914            6        11
4411            8         4
7252           10        13
8092            6        17
8638            6        18
9254            9        19
12370           5         6

[11 rows x 22 columns]
```

1.4 How much of the data is represented by outliers?

[7]:
```
df_sorted = df_clean["price"].sort_values()

# Cumulative Quatiles
fig = px.ecdf(df_sorted, x="price", title="Cumulative Distribution of House␣
 ↪Prices")

# Add a marker line at the 95th and 99th percentiles
fig.add_hline(y=0.95, line_dash="dot", annotation_text="95% of data",␣
 ↪annotation_position="bottom right")
fig.show()
```

[8]:
```
# quantiles
quantile_99 = df_clean.price.quantile(0.99)
quantile_95 = df_clean.price.quantile(0.95)

print("Quantile 99: ", quantile_99)
print("Quantile 95: ", quantile_95)
```

```
Quantile 99:  1964400.0000000051
Quantile 95:  1156479.9999999974
```

[9]:
```
# Flag the datapoints inside each quantiles 99 and 95
df_clean["q_99"] = (df_clean.price < quantile_99).astype(int)
df_clean["q_95"] = (df_clean.price < quantile_95).astype(int)

df_clean.head()
```

[9]:

	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	…	zipcode	lat	long	sqft_living15	\
0	0	3	7	…	98178	47.5112	-122.257	1340	
1	0	3	7	…	98125	47.7210	-122.319	1690	
2	0	3	6	…	98028	47.7379	-122.233	2720	
3	0	5	7	…	98136	47.5208	-122.393	1360	
4	0	3	8	…	98074	47.6168	-122.045	1800	

	sqft_lot15	year_sold	month_sold	day_sold	q_99	q_95
0	5650	2014	10	13	1	1
1	7639	2014	12	9	1	1
2	8062	2015	2	25	1	1
3	5000	2014	12	9	1	1

```
4         7503        2015            2         18      1      1

[5 rows x 24 columns]
```

[10]:
```
print(f"The 99th quantile exclude {df_clean.shape[0] - df_clean.q_99.sum()}␣
 ↪datapoints")
print(f"The 95th quantile exclude {df_clean.shape[0] - df_clean.q_95.sum()}␣
 ↪datapoints")
```

```
The 99th quantile exclude 217 datapoints
The 95th quantile exclude 1081 datapoints
```

1.5 Sensitivity to outliers (metrics)

[11]:
```
from utils import *

metrics_df = create_metrics_df()
```

1.5.1 Random Forest flagging the outliers

[12]:
```
# Split into train and test
seed = 13
# 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)

# Train Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=seed)
```

[13]:
```
X_train
```

[13]:

	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  …  zipcode      lat     long  \
1571          4      7        1170  …    98198  47.3708 -122.311
16330         3      8        2630  …    98072  47.7750 -122.125
12786         4      9        2620  …    98040  47.5631 -122.219
12524         4      7        1610  …    98038  47.3490 -122.036
16179         4      6         880  …    98178  47.5013 -122.244
…           …    …          …  …       …       …      …
153           3     12        3540  …    98006  47.5620 -122.162
866           3      7        3460  …    98056  47.4802 -122.188
74            5      7        1090  …    98042  47.3511 -122.073
14512         3      7         820  …    98199  47.6498 -122.388
338           3      7        1420  …    98133  47.7535 -122.354

      sqft_living15  sqft_lot15  year_sold  month_sold  day_sold  q_99  q_95
1571           1940        7531       2015           3        23     1     1
16330          2680       48706       2014           5        21     1     1
12786          2580        9525       2014           8         5     1     1
12524          1570        6000       2014           8        26     1     1
16179          1110       16115       2014           6        24     1     1
…              …          …          …          …       …    …    …
153            3160        9750       2015           4         1     0     0
866            2490        6312       2015           4        27     1     1
74             1940       50529       2015           3        16     1     1
14512          1730        5760       2014           8        20     1     1
338            1740        8000       2014           8        26     1     1

[17290 rows x 23 columns]
```

[14]:
```
# 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)


metrics_df = add_new_metrics(metrics_df,
                             rf_regressor,
                             X_train,
                             y_train,
                             split = "train",
                             comments="Outliers flagging, no normalization.")

metrics_df = add_new_metrics(metrics_df,
                             rf_regressor,
                             X_test,
                             y_test,
```

```
                                split = "test",
                                comments="Outliers flagging, no normalization.")
```

[15]:
```
metrics_df
```

[15]:
```
                   Model  Split      R2  Adjusted_R2         MAE    MAPE  \
0  RandomForestRegressor  train  0.9879       0.9879  22769.7215  0.0456
1  RandomForestRegressor   test  0.9322       0.9319  59863.8409  0.1203

          RMSE                                Comments
0  40566.2303  Outliers flagging, no normalization.
1  93599.4998  Outliers flagging, no normalization.
```

1.5.2 Random Forest removing top 1% outliers

[16]:
```
# Split into train and test
# The price is the target variable
y = df_clean[df_clean.q_99 == 1]["price"]

# All other variables are the features for the baseline model
X = df_clean[df_clean.q_99 == 1].drop(["price", "q_99", "q_95"], axis=1)

# Train Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=seed)
```

[17]:
```
X_train
```

[17]:
```
       bedrooms  bathrooms  sqft_living  sqft_lot  floors  waterfront  view  \
16385         3       1.50         1290      8175     1.0           0     0
16816         3       2.00         1830     10873     1.0           0     0
6038          3       1.75         1840      8086     1.0           0     0
16785         3       1.75         1540     10545     2.0           0     0
15744         3       2.00         2090     15790     1.0           0     0
…           …          …            …         …       …           …   …
155           3       1.00         1180      7669     1.0           0     0
878           3       1.00         1020      8100     1.0           0     0
75            4       4.00         3430     35102     2.0           0     0
14650         4       3.00         2530      5625     1.0           0     0
345           4       1.00         1000      7134     1.0           0     0

       condition  grade  sqft_above  …  yr_built  yr_renovated  zipcode  \
16385          4      7         820  …      1952             0    98004
16816          3      8        1830  …      1989             0    98023
6038           4      8        1840  …      1964             0    98052
16785          4      6        1540  …      1978             0    98045
15744          3      9        2090  …      1992             0    98034
```

```
…          …    …         …  …       …            …      …
155          4      7       1180  …      1967             0    98058
878          3      7       1020  …      1954             0    98198
75           4     10       2390  …      1986             0    98075
14650        3      8       1470  …      1976             0    98034
345          3      6       1000  …      1943             0    98178

            lat     long  sqft_living15  sqft_lot15  year_sold  month_sold  \
16385   47.6296 -122.205           2130        8577       2014           8
16816   47.3066 -122.394           2490        8976       2014           7
6038    47.6700 -122.155           1840        8060       2014           6
16785   47.4451 -121.763           1540       10000       2015           3
15744   47.7296 -122.199           1820        8770       2014          11
…          …       …              …          …          …           …
155     47.4479 -122.176           1190        7669       2014           7
878     47.3586 -122.314           1020        8100       2014          12
75      47.5822 -121.987           3240       35020       2014          11
14650   47.7094 -122.233           1840        7070       2014           7
345     47.4897 -122.240           1020        7138       2014           7

        day_sold
16385         20
16816         31
6038          23
16785         11
15744         20
…            …
155           28
878           19
75             5
14650         11
345           23

[17116 rows x 21 columns]
```

[18]:
```
# 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)


metrics_df = add_new_metrics(metrics_df,
                             rf_regressor,
                             X_train,
                             y_train,
```

```
                                split = "train",
                                comments="Removing top 1%, no normalization.")

metrics_df = add_new_metrics(metrics_df,
                                rf_regressor,
                                X_test,
                                y_test,
                                split = "test",
                                comments="Removing top 1%, no normalization.")
```

[19]:
```
metrics_df
```

[19]:

	Model	Split	R2	Adjusted_R2	MAE	MAPE	RMSE	Comments
0	RandomForestRegressor	train	0.9879	0.9879	22769.7215	0.0456	40566.2303	Outliers flagging, no normalization.
1	RandomForestRegressor	test	0.9322	0.9319	59863.8409	0.1203	93599.4998	Outliers flagging, no normalization.
2	RandomForestRegressor	train	0.9826	0.9826	23185.3777	0.0475	37273.0054	Removing top 1%, no normalization.
3	RandomForestRegressor	test	0.8739	0.8733	64327.4972	0.1290	104088.2866	Removing top 1%, no normalization.

1.5.3 Random Forest removing top 5% outliers

[20]:
```
# Split into train and test
# The price is the target variable
y = df_clean[df_clean.q_95 == 1]["price"]

# All other variables are the features for the baseline model
X = df_clean[df_clean.q_95 == 1].drop(["price", "q_99", "q_95"], axis=1)

# Train Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=seed)
```

[21]:
```
X_train
```

[21]:

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	…
7523	3	1.00	1200	7810	1.0	0	0	
20438	4	2.50	3250	4500	2.0	0	0	
8571	4	2.50	2180	3893	2.0	0	0	
15677	3	1.75	1990	5600	1.0	0	1	
8032	3	1.75	2360	4063	1.0	0	0	
…	…	…	…	…	…	…	…	…
159	4	1.75	1760	11180	1.0	0	0	

```
907           3       1.75         1410      9315     1.0           0     0
78            3       1.00         1410      5060     1.0           0     0
15224         4       2.50         2570      8178     1.0           0     2
353           2       1.00          990      3120     1.0           0     2

       condition  grade  sqft_above  …  yr_built  yr_renovated  zipcode  \
7523           4      7        1200  …      1967             0    98038
20438          3      8        3250  …      2008             0    98059
8571           3      8        2180  …      1999             0    98117
15677          3      8        1330  …      1941             0    98199
8032           5      7        1180  …      1940             0    98117
…            …    …          …  …        …           …       …
159            4      8        1760  …      1968             0    98059
907            5      7        1410  …      1960             0    98031
78             4      7         910  …      1956             0    98133
15224          3      8        1710  …      1961             0    98118
353            5      7         790  …      1907             0    98103

           lat     long  sqft_living15  sqft_lot15  year_sold  month_sold  \
7523   47.3631 -122.050           1590        7800       2015           4
20438  47.4944 -122.150           3030        4598       2014          11
8571   47.6886 -122.388           1710        4550       2014          12
15677  47.6500 -122.415           2630        6780       2014           9
8032   47.6902 -122.382           1660        4063       2014           8
…        …       …             …         …          …         …
159    47.4715 -122.118           1730       11180       2014          10
907    47.3969 -122.198           1630        8250       2014          10
78     47.7073 -122.340           1130        5693       2014           6
15224  47.5483 -122.261           2050        7500       2015           3
353    47.6800 -122.353           1930        3120       2014          12

       day_sold
7523         25
20438         4
8571          8
15677         3
8032         18
…          …
159           3
907           7
78            9
15224         9
353           3

[16425 rows x 21 columns]
```

[22]:
```
# 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)


metrics_df = add_new_metrics(metrics_df,
                             rf_regressor,
                             X_train,
                             y_train,
                             split = "train",
                             comments="Removing top 5%, no normalization.")

metrics_df = add_new_metrics(metrics_df,
                             rf_regressor,
                             X_test,
                             y_test,
                             split = "test",
                             comments="Removing top 5%, no normalization.")
```

[23]:
```
metrics_df
```

[23]:

	Model	Split	R2	Adjusted_R2	MAE	MAPE	RMSE	Comments
0	RandomForestRegressor	train	0.9879	0.9879	22769.7215	0.0456	40566.2303	Outliers flagging, no normalization.
1	RandomForestRegressor	test	0.9322	0.9319	59863.8409	0.1203	93599.4998	Outliers flagging, no normalization.
2	RandomForestRegressor	train	0.9826	0.9826	23185.3777	0.0475	37273.0054	Removing top 1%, no normalization.
3	RandomForestRegressor	test	0.8739	0.8733	64327.4972	0.1290	104088.2866	Removing top 1%, no normalization.
4	RandomForestRegressor	train	0.9806	0.9806	19934.8930	0.0458	29386.2798	Removing top 5%, no normalization.
5	RandomForestRegressor	test	0.8717	0.8710	53038.5069	0.1212	76308.9748	Removing top 5%, no normalization.

1.5.4 XGBoost flagging the outliers

[24]:
```
# Split into train and test
seed = 13
# 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)

# Train Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=seed)
```

[25]:
```
import xgboost as xgb

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

[25]:
```
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, …)
```

[26]:
```
metrics_df = add_new_metrics(metrics_df,
                             xgb_clf,
                             X_train,
                             y_train,
                             split = "train",
                             comments="Outliers flagging, no normalization.")


metrics_df = add_new_metrics(metrics_df,
                             xgb_clf,
                             X_test,
                             y_test,
                             split = "test",
                             comments="Outliers flagging, no normalization.")
```

[27]:
```
metrics_df
```

[27]:

	Model	Split	R2	Adjusted_R2	MAE	MAPE	\
0	RandomForestRegressor	train	0.9879	0.9879	22769.7215	0.0456	
1	RandomForestRegressor	test	0.9322	0.9319	59863.8409	0.1203	
2	RandomForestRegressor	train	0.9826	0.9826	23185.3777	0.0475	
3	RandomForestRegressor	test	0.8739	0.8733	64327.4972	0.1290	
4	RandomForestRegressor	train	0.9806	0.9806	19934.8930	0.0458	

```
5  RandomForestRegressor   test  0.8717       0.8710  53038.5069  0.1212
6           XGBRegressor  train  0.9825       0.9825  35584.0027  0.0818
7           XGBRegressor   test  0.9260       0.9256  59532.0485  0.1184

          RMSE                                Comments
0   40566.2303  Outliers flagging, no normalization.
1   93599.4998  Outliers flagging, no normalization.
2   37273.0054    Removing top 1%, no normalization.
3  104088.2866    Removing top 1%, no normalization.
4   29386.2798    Removing top 5%, no normalization.
5   76308.9748    Removing top 5%, no normalization.
6   48751.1351  Outliers flagging, no normalization.
7   97798.9764  Outliers flagging, no normalization.
```

1.5.5 XGBoost removing top 1%

[28]:
```
# Split into train and test
# The price is the target variable
y = df_clean[df_clean.q_99 == 1]["price"]

# All other variables are the features for the baseline model
X = df_clean[df_clean.q_99 == 1].drop(["price", "q_99", "q_95"], axis=1)

# Train Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=seed)
```

[29]:
```
X_train
```

[29]:
```
       bedrooms  bathrooms  sqft_living  sqft_lot  floors  waterfront  view  \
16385         3       1.50         1290      8175     1.0           0     0
16816         3       2.00         1830     10873     1.0           0     0
6038          3       1.75         1840      8086     1.0           0     0
16785         3       1.75         1540     10545     2.0           0     0
15744         3       2.00         2090     15790     1.0           0     0
…           …          …            …         …       …           …   …
155           3       1.00         1180      7669     1.0           0     0
878           3       1.00         1020      8100     1.0           0     0
75            4       4.00         3430     35102     2.0           0     0
14650         4       3.00         2530      5625     1.0           0     0
345           4       1.00         1000      7134     1.0           0     0

       condition  grade  sqft_above  …  yr_built  yr_renovated  zipcode  \
16385          4      7         820  …      1952             0    98004
16816          3      8        1830  …      1989             0    98023
6038           4      8        1840  …      1964             0    98052
16785          4      6        1540  …      1978             0    98045
```

```
15744          3      9        2090  …      1992             0    98034
…            …    …          …  …        …           …       …
155            4      7        1180  …      1967             0    98058
878            3      7        1020  …      1954             0    98198
75             4     10        2390  …      1986             0    98075
14650          3      8        1470  …      1976             0    98034
345            3      6        1000  …      1943             0    98178

           lat     long  sqft_living15  sqft_lot15  year_sold  month_sold  \
16385  47.6296 -122.205           2130        8577       2014           8
16816  47.3066 -122.394           2490        8976       2014           7
6038   47.6700 -122.155           1840        8060       2014           6
16785  47.4451 -121.763           1540       10000       2015           3
15744  47.7296 -122.199           1820        8770       2014          11
…        …       …             …          …         …          …
155    47.4479 -122.176           1190        7669       2014           7
878    47.3586 -122.314           1020        8100       2014          12
75     47.5822 -121.987           3240       35020       2014          11
14650  47.7094 -122.233           1840        7070       2014           7
345    47.4897 -122.240           1020        7138       2014           7

       day_sold
16385        20
16816        31
6038         23
16785        11
15744        20
…          …
155          28
878          19
75            5
14650        11
345          23

[17116 rows x 21 columns]
```

[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="Removing top 1%, no normalization.")


metrics_df = add_new_metrics(metrics_df,
                             xgb_clf,
                             X_test,
                             y_test,
                             split = "test",
                             comments="Removing top 1%, no normalization.")
```

[32]:
```
metrics_df
```

[32]:

	Model	Split	R2	Adjusted_R2	MAE	MAPE	RMSE	Comments
0	RandomForestRegressor	train	0.9879	0.9879	22769.7215	0.0456	40566.2303	Outliers flagging, no normalization.
1	RandomForestRegressor	test	0.9322	0.9319	59863.8409	0.1203	93599.4998	Outliers flagging, no normalization.
2	RandomForestRegressor	train	0.9826	0.9826	23185.3777	0.0475	37273.0054	Removing top 1%, no normalization.
3	RandomForestRegressor	test	0.8739	0.8733	64327.4972	0.1290	104088.2866	Removing top 1%, no normalization.
4	RandomForestRegressor	train	0.9806	0.9806	19934.8930	0.0458	29386.2798	Removing top 5%, no normalization.
5	RandomForestRegressor	test	0.8717	0.8710	53038.5069	0.1212	76308.9748	Removing top 5%, no normalization.
6	XGBRegressor	train	0.9825	0.9825	35584.0027	0.0818	48751.1351	Outliers flagging, no normalization.
7	XGBRegressor	test	0.9260	0.9256	59532.0485	0.1184	97798.9764	Outliers flagging, no normalization.
8	XGBRegressor	train	0.9679	0.9679	36410.9174	0.0830	50584.7096	Removing top 1%, no normalization.
9	XGBRegressor	test	0.8891	0.8885	61265.8381	0.1234	97618.3705	Removing top 1%, no normalization.

1.5.6 XGBoost removing top 5%

[33]:
```
# Split into train and test
# The price is the target variable
y = df_clean[df_clean.q_95 == 1]["price"]

# All other variables are the features for the baseline model
X = df_clean[df_clean.q_95 == 1].drop(["price", "q_99", "q_95"], axis=1)

# Train Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=seed)
```

[34]:
```
import xgboost as xgb

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

[34]:
```
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, …)
```

[35]:
```
metrics_df = add_new_metrics(metrics_df,
                             xgb_clf,
                             X_train,
                             y_train,
                             split = "train",
                             comments="Removing top 5%, no normalization.")


metrics_df = add_new_metrics(metrics_df,
                             xgb_clf,
                             X_test,
                             y_test,
                             split = "test",
                             comments="Removing top 5%, no normalization.")
```

[36]:
```
metrics_df
```

[36]:

	Model	Split	R2	Adjusted_R2	MAE	MAPE	RMSE	Comments
0	RandomForestRegressor	train	0.9879	0.9879	22769.7215	0.0456	40566.2303	Outliers flagging, no normalization.
1	RandomForestRegressor	test	0.9322	0.9319	59863.8409	0.1203	93599.4998	Outliers flagging, no normalization.
2	RandomForestRegressor	train	0.9826	0.9826	23185.3777	0.0475	37273.0054	Removing top 1%, no normalization.
3	RandomForestRegressor	test	0.8739	0.8733	64327.4972	0.1290	104088.2866	Removing top 1%, no normalization.
4	RandomForestRegressor	train	0.9806	0.9806	19934.8930	0.0458	29386.2798	Removing top 5%, no normalization.
5	RandomForestRegressor	test	0.8717	0.8710	53038.5069	0.1212	76308.9748	Removing top 5%, no normalization.
6	XGBRegressor	train	0.9825	0.9825	35584.0027	0.0818	48751.1351	Outliers flagging, no normalization.
7	XGBRegressor	test	0.9260	0.9256	59532.0485	0.1184	97798.9764	Outliers flagging, no normalization.
8	XGBRegressor	train	0.9679	0.9679	36410.9174	0.0830	50584.7096	Removing top 1%, no normalization.
9	XGBRegressor	test	0.8891	0.8885	61265.8381	0.1234	97618.3705	Removing top 1%, no normalization.
10	XGBRegressor	train	0.9569	0.9568	32103.1211	0.0783	43810.9507	Removing top 5%, no normalization.
11	XGBRegressor	test	0.8806	0.8800	51602.5277	0.1189	73599.3380	Removing top 5%, no normalization.

The feature flagging for both 99% and 95% worked better than removing the outliers, which means that the information about the top priced houses is still important to accurately predict the prices. In that sense, we will continue the analysis using the flagging of the columns instead of dropping them.

1.5.7 Export dataset and metrics

[41]:
```
filename_metrics = "Metrics/outlier_analysis_metrics.csv"

metrics_df.to_csv(filename_metrics, index = False)
```

[38]:
```
df_clean
```

[38]:

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

```
21608  360000.0         3       2.50         1530      1131     3.0
21609  400000.0         4       2.50         2310      5813     2.0
21610  402101.0         2       0.75         1020      1350     2.0
21611  400000.0         3       2.50         1600      2388     2.0
21612  325000.0         2       0.75         1020      1076     2.0

       waterfront  view  condition  grade  …  zipcode      lat     long  \
0               0     0          3      7  …    98178  47.5112 -122.257
1               0     0          3      7  …    98125  47.7210 -122.319
2               0     0          3      6  …    98028  47.7379 -122.233
3               0     0          5      7  …    98136  47.5208 -122.393
4               0     0          3      8  …    98074  47.6168 -122.045
…             …   …        …    …      …  …      …       …       …
21608           0     0          3      8  …    98103  47.6993 -122.346
21609           0     0          3      8  …    98146  47.5107 -122.362
21610           0     0          3      7  …    98144  47.5944 -122.299
21611           0     0          3      8  …    98027  47.5345 -122.069
21612           0     0          3      7  …    98144  47.5941 -122.299

       sqft_living15  sqft_lot15  year_sold  month_sold  day_sold  q_99  q_95
0               1340        5650       2014          10        13     1     1
1               1690        7639       2014          12         9     1     1
2               2720        8062       2015           2        25     1     1
3               1360        5000       2014          12         9     1     1
4               1800        7503       2015           2        18     1     1
…               …           …          …              …        …     …     …
21608           1530        1509       2014           5        21     1     1
21609           1830        7200       2015           2        23     1     1
21610           1020        2007       2014           6        23     1     1
21611           1410        1287       2015           1        16     1     1
21612           1020        1357       2014          10        15     1     1

[21613 rows x 24 columns]
```

[42]:
```
filename_data = "Data/v1_house_sales.csv"

df_clean.to_csv(filename_data, index = False)
```

[ ]:
```

```