3_Outliers_Analysis

February 14, 2026

1 Analyse the Influence of Outliers

1.1 Imports

[1]:
```
import pandas as pd
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.ensemble import RandomForestRegressor
import xgboost as xgb

# Hypothesis testing
from sklearn.model_selection import cross_val_score
from scipy import stats
import numpy as np


from utils import *
```

[2]:
```
# Exporting plotly plots to pdf
import plotly.io as pio

# Configuration:

# Set to False for interactive zooming/hovering (Exploration)
# Set to True for static images (PDF Export)
EXPORT_MODE = True

if EXPORT_MODE:
    # Forces all charts to be static images (requires 'pip install -U kaleido')
    pio.renderers.default = "png" # Use "png" if svg gives you trouble
    print("  EXPORT_MODE is ON. Charts will be static images.")
else:
    # Default interactive plotly
    pio.renderers.default = "notebook_connected"
```

```
    print("  Interactive mode. Charts will include zoom/hover.")
```

```
EXPORT_MODE is ON. Charts will be static images.
```

1.2 Open the clean data

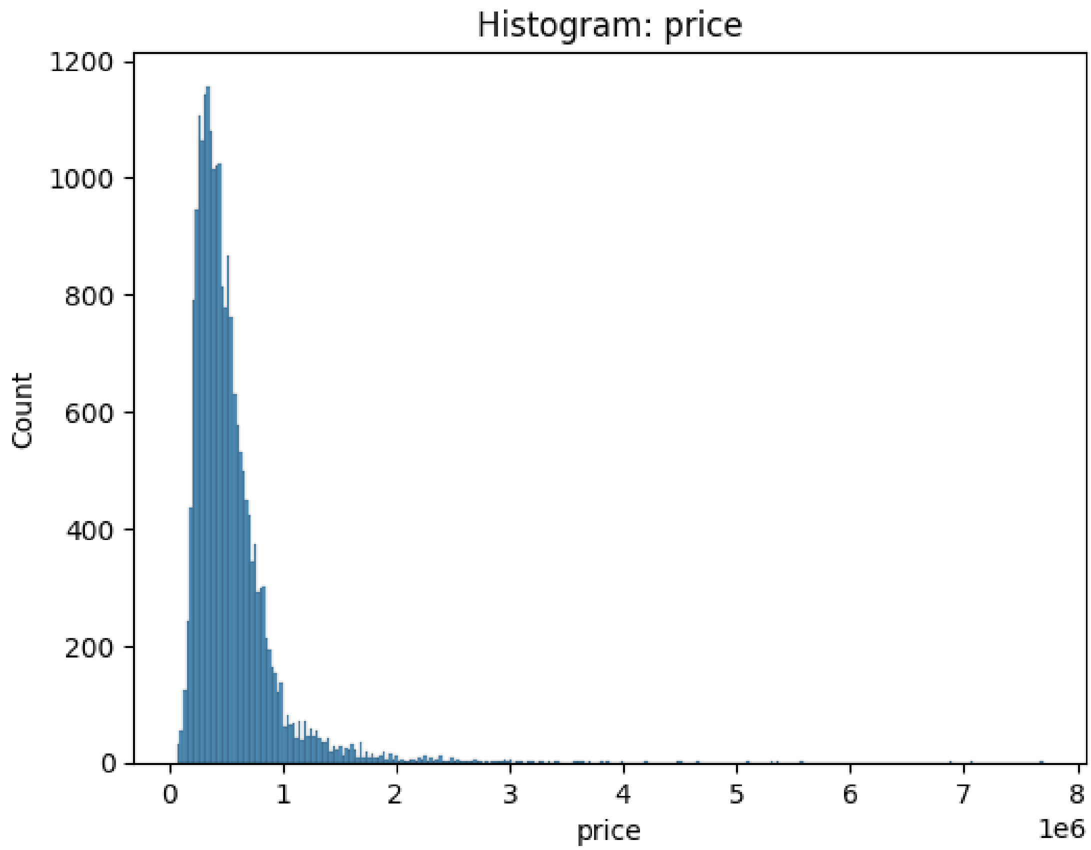
[3]:
```python
file_path = "Data/v0_cleaned_house_sales.csv"

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

[3]:
```
      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

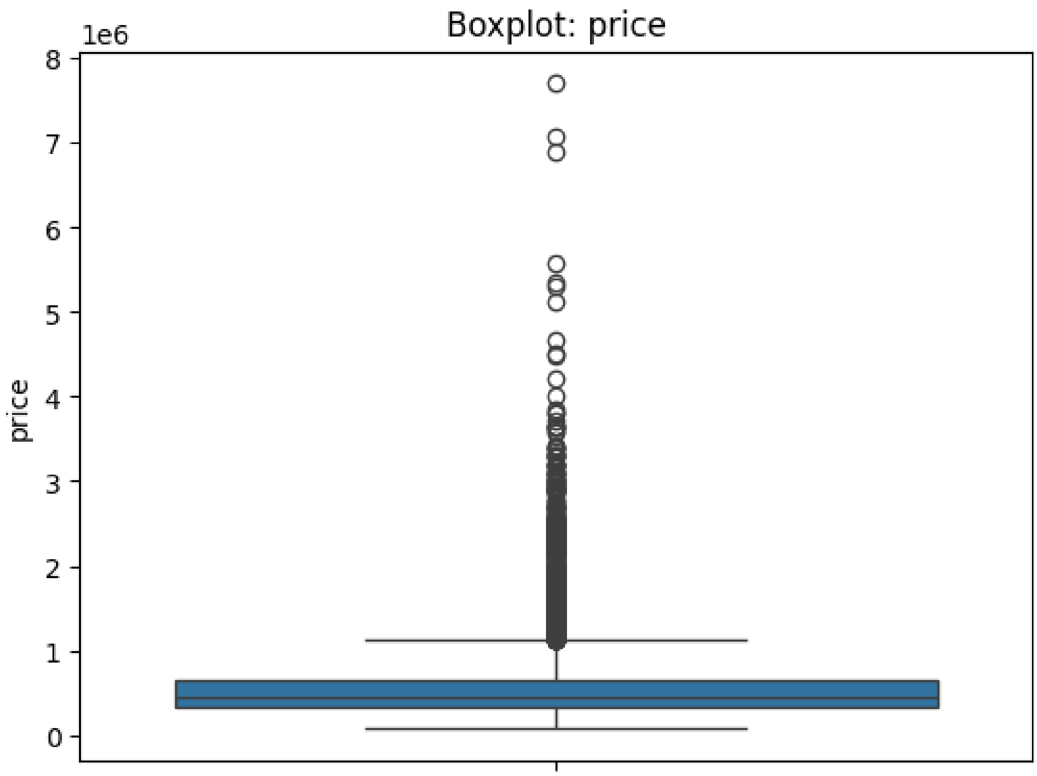
[4]:
```python
sns.histplot(df_clean.price)
plt.title("Histogram: price")
```

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



[5]:
```
sns.boxplot(df_clean.price)
plt.title("Boxplot: price")
```

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



[6]:
```
df_clean["price"].describe()
```

[6]:
```
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
```

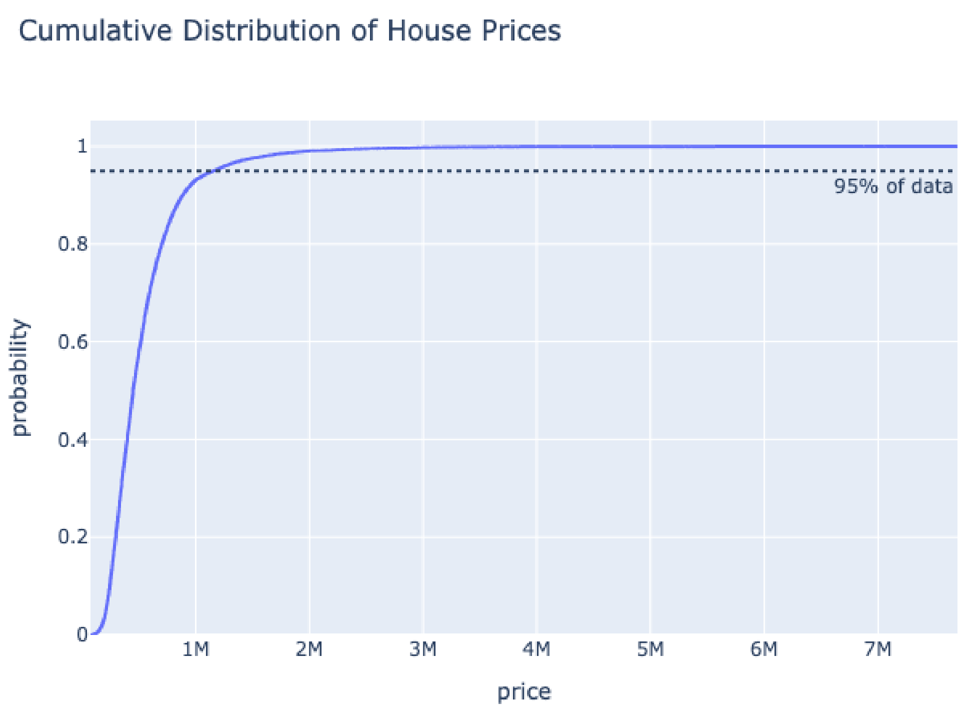
[7]:
```
# 11 houses over 4 million
df_clean[df_clean.price > 4e6]
```

[7]:
```
          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?

[8]:
```
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()
```



[9]:
```
# 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
```

[10]:
```python
# 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()
```

[10]:
```
      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]
```

[11]:
```python
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)

[12]:
```python
metrics_df = create_metrics_df()
```

1.5.1 Random Forest flagging the outliers

[13]:
```python
# Split into train and test
seed = 13
# The price is the target variable
y = df_clean["price"]
```

```python
# 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)
```

[14]:
```python
X_train
```

[14]:
```
       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]
```

[15]:
```
# most common hyperparameters or the default ones

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.")
```

[16]:
```
metrics_df
```

[16]:
```
                   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

[17]:
```
# 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)
```

[18]:
```
X_train
```

[18]:
```
       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]
```

[19]:

```
# most common hyperparameters or the default ones

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.")
```

[20]:

```
metrics_df
```

[20]:

```
                   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

         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.
```

1.5.3 Random Forest removing top 5% outliers

[21]:
```
# 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)
```

[22]:
```
X_train
```

[22]:
```
       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]
```

[23]:

```
# most common hyperparameters or the default ones

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.")
```

[24]:

```
metrics_df
```

[24]:

```
                   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

         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.
```

1.5.4 XGBoost flagging the outliers

[25]:
```python
# 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)
```

[26]:
```python
xgb_clf = xgb.XGBRegressor(seed = seed)
xgb_clf.fit(X_train, y_train)
```

[26]:
```
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, …)
```

[27]:
```python
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.")
```

[28]:
```
metrics_df
```

[28]:
```
                   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%

[29]:
```
# 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)
```

[30]:
```
X_train
```

[30]:
```
       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]
```

[31]:
```
xgb_clf = xgb.XGBRegressor(seed = seed)
xgb_clf.fit(X_train, y_train)
```

[31]:
```
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, …)
```

[32]:
```
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.")
```

[33]:
```
metrics_df
```

[33]:

	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
8           XGBRegressor  train  0.9679       0.9679  36410.9174  0.0830
9           XGBRegressor   test  0.8891       0.8885  61265.8381  0.1234

          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.
8   50584.7096    Removing top 1%, no normalization.
9   97618.3705    Removing top 1%, no normalization.
```

1.5.6 XGBoost removing top 5%

[34]:
```
# 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)
```

[35]:
```
xgb_clf = xgb.XGBRegressor(seed = seed)
xgb_clf.fit(X_train, y_train)
```

[35]:
```
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, …)
```

[36]:
```
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.")
```

[37]:

```
metrics_df
```

[37]:

	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
8	XGBRegressor	train	0.9679	0.9679	36410.9174	0.0830
9	XGBRegressor	test	0.8891	0.8885	61265.8381	0.1234
10	XGBRegressor	train	0.9569	0.9568	32103.1211	0.0783
11	XGBRegressor	test	0.8806	0.8800	51602.5277	0.1189

	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.
8	50584.7096	Removing top 1%, no normalization.
9	97618.3705	Removing top 1%, no normalization.
10	43810.9507	Removing top 5%, no normalization.
11	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.

2 Data Leakage Analysis: Outlier Flagging

Our initial approach calculated outlier thresholds using the entire dataset, introducing data leakage by allowing test set information to influence training features. While this is common in exploratory phases, it risks inflating model performance. In this section, we apply hypothesis testing to determine if correcting this leakage results in a statistically significant difference in model predictions.

[38]:
```python
# Apply outlier flagging
def apply_flagging(X, y):
    # quantiles
    quantile_99 = y.quantile(0.99)
    quantile_95 = y.quantile(0.95)

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

    # Flag the datapoints inside each quantiles 99 and 95
    X["q_99"] = (y < quantile_99).astype(int)
    X["q_95"] = (y < quantile_95).astype(int)

    return X
```

2.1 Preparing Datasets

[39]:
```python
# 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)
```

2.1.1 Dataset without Leakage

[40]:
```python
# Data without leakage
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=seed)

# Flagging
X_train = apply_flagging(X_train, y_train)
X_test = apply_flagging(X_test, y_test)
```

```
Quantile 99:  1980000.0
Quantile 95:  1150000.0
Quantile 99:  1945159.9999999944
Quantile 95:  1185000.0
```

2.1.2 Dataset with Leakage

[41]:
```
# Data with leakage

X_leakage = apply_flagging(X, y)

X_train_leak, X_test_leak, y_train_leak, y_test_leak =␣
↪train_test_split(X_leakage, y, test_size=0.2, random_state=seed)
```

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

2.1.3 Experiment metrics df

[42]:
```
# New metrics dataframe

leak_df = create_metrics_df()
leak_df
```

[42]:
```
Empty DataFrame
Columns: [Model, Split, R2, Adjusted_R2, MAE, RMSE, MAPE, Comments]
Index: []
```

2.2 Statistical Significance Test: Random Forest Performance

2.2.1 Without leakage

[43]:
```
# most common hyperparameters or the default ones

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


leak_df = add_new_metrics(leak_df,
                             rf_regressor,
                             X_train,
                             y_train,
                             split = "train",
                             comments="No leakage.")

leak_df = add_new_metrics(leak_df,
                             rf_regressor,
                             X_test,
                             y_test,
                             split = "test",
                             comments="No leakage.")
```

```
leak_df
```

[43]:
```
                    Model  Split      R2  Adjusted_R2         MAE    MAPE  \
0  RandomForestRegressor  train  0.9880       0.9879  22693.7463  0.0455
1  RandomForestRegressor   test  0.9331       0.9327  59616.8735  0.1197

         RMSE     Comments
0  40491.8085  No leakage.
1  92989.3473  No leakage.
```

2.2.2 With leakage

[44]:
```
# most common hyperparameters or the default ones

rf_regressor_leak = RandomForestRegressor(random_state=seed)#default values +
↪random_state = 13
rf_regressor_leak.fit(X_train_leak, y_train_leak)


leak_df = add_new_metrics(leak_df,
                             rf_regressor_leak,
                             X_train_leak,
                             y_train_leak,
                             split = "train",
                             comments="with leakage.")

leak_df = add_new_metrics(leak_df,
                             rf_regressor_leak,
                             X_test_leak,
                             y_test_leak,
                             split = "test",
                             comments="with leakage.")

leak_df
```

[44]:
```
                    Model  Split      R2  Adjusted_R2         MAE    MAPE  \
0  RandomForestRegressor  train  0.9880       0.9879  22693.7463  0.0455
1  RandomForestRegressor   test  0.9331       0.9327  59616.8735  0.1197
2  RandomForestRegressor  train  0.9879       0.9879  22769.7215  0.0456
3  RandomForestRegressor   test  0.9322       0.9319  59863.8409  0.1203

         RMSE       Comments
0  40491.8085    No leakage.
1  92989.3473    No leakage.
2  40566.2303  with leakage.
3  93599.4998  with leakage.
```

[45]:
```python
# Hypothesis testing for the test scores

# Ho: scores_leakage = scores_no_leakage
# Ha: scores_leakage != scores_no_leakage

# Method 1: With leakage
scores_leakage = cross_val_score(rf_regressor_leak, X_test_leak, y_test_leak,
                                  cv=5, scoring='r2')

# Method 2: Without leakage
scores_no_leakage = cross_val_score(rf_regressor, X_test, y_test,
                                     cv=5, scoring='r2')

# Paired t-test (same folds, so paired)
t_stat, p_value = stats.ttest_rel(scores_leakage, scores_no_leakage)

print(f"Mean R² with leakage: {scores_leakage.mean():.4f} ± {scores_leakage.
 ↪std():.4f}")
print(f"Mean R² without leakage: {scores_no_leakage.mean():.4f} ±␣
 ↪{scores_no_leakage.std():.4f}")
print(f"p-value: {p_value:.4f}")

if p_value < 0.05:
    print("Difference is statistically significant. We reject the null␣
 ↪hypothesis.")
else:
    print("Difference is NOT statistically significant. We cannot reject the␣
 ↪null hypothesis.")
```

```
Mean R² with leakage: 0.9049 ± 0.0178
Mean R² without leakage: 0.9061 ± 0.0180
p-value: 0.1119
Difference is NOT statistically significant. We cannot reject the null
hypothesis.
```

[46]:
```python
# Hypothesis testing for the train scores

# Ho: scores_leakage = scores_no_leakage
# Ha: scores_leakage != scores_no_leakage

# Method 1: With leakage
scores_leakage = cross_val_score(rf_regressor_leak, X_train_leak, y_train_leak,
                                  cv=5, scoring='r2')

# Method 2: Without leakage
scores_no_leakage = cross_val_score(rf_regressor, X_train, y_train,
                                     cv=5, scoring='r2')
```

```
# Paired t-test (same folds, so paired)
t_stat, p_value = stats.ttest_rel(scores_leakage, scores_no_leakage)

print(f"Mean R² with leakage: {scores_leakage.mean():.4f} ± {scores_leakage.
↪std():.4f}")
print(f"Mean R² without leakage: {scores_no_leakage.mean():.4f} ±␣
↪{scores_no_leakage.std():.4f}")
print(f"p-value: {p_value:.4f}")

if p_value < 0.05:
    print("Difference is statistically significant. We reject the null␣
↪hypothesis.")
else:
    print("Difference is NOT statistically significant. We cannot reject the␣
↪null hypothesis.")
```

```
Mean R² with leakage: 0.9054 ± 0.0179
Mean R² without leakage: 0.9051 ± 0.0180
p-value: 0.6313
Difference is NOT statistically significant. We cannot reject the null
hypothesis.
```

2.3 Statistical Significance Test: XGBoost Performance

2.3.1 No leakage

[47]:
```
xgb_clf = xgb.XGBRegressor(seed = seed)
xgb_clf.fit(X_train, y_train)

leak_df = add_new_metrics(leak_df,
                          xgb_clf,
                          X_train,
                          y_train,
                          split = "train",
                          comments="No leakage.")

leak_df = add_new_metrics(leak_df,
                          xgb_clf,
                          X_test,
                          y_test,
                          split = "test",
                          comments="No leakage.")

leak_df
```

[47]:
```
                    Model  Split      R2  Adjusted_R2         MAE    MAPE  \
0   RandomForestRegressor  train  0.9880       0.9879  22693.7463  0.0455
```

```
1  RandomForestRegressor   test  0.9331       0.9327  59616.8735  0.1197
2  RandomForestRegressor  train  0.9879       0.9879  22769.7215  0.0456
3  RandomForestRegressor   test  0.9322       0.9319  59863.8409  0.1203
4           XGBRegressor  train  0.9820       0.9820  35896.1715  0.0825
5           XGBRegressor   test  0.9240       0.9236  59986.6293  0.1188

         RMSE       Comments
0  40491.8085    No leakage.
1  92989.3473    No leakage.
2  40566.2303  with leakage.
3  93599.4998  with leakage.
4  49457.6309    No leakage.
5  99079.9228    No leakage.
```

[48]:

```python
xgb_clf_leak = xgb.XGBRegressor(seed = seed)
xgb_clf_leak.fit(X_train_leak, y_train_leak)

leak_df = add_new_metrics(leak_df,
                             xgb_clf_leak,
                             X_train_leak,
                             y_train_leak,
                             split = "train",
                             comments="with leakage.")

leak_df = add_new_metrics(leak_df,
                             xgb_clf_leak,
                             X_test_leak,
                             y_test_leak,
                             split = "test",
                             comments="with leakage.")

leak_df
```

[48]:

```
                   Model  Split      R2  Adjusted_R2         MAE    MAPE  \
0  RandomForestRegressor  train  0.9880       0.9879  22693.7463  0.0455
1  RandomForestRegressor   test  0.9331       0.9327  59616.8735  0.1197
2  RandomForestRegressor  train  0.9879       0.9879  22769.7215  0.0456
3  RandomForestRegressor   test  0.9322       0.9319  59863.8409  0.1203
4           XGBRegressor  train  0.9820       0.9820  35896.1715  0.0825
5           XGBRegressor   test  0.9240       0.9236  59986.6293  0.1188
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  40491.8085    No leakage.
1  92989.3473    No leakage.
2  40566.2303  with leakage.
```

```
3  93599.4998  with leakage.
4  49457.6309    No leakage.
5  99079.9228    No leakage.
6  48751.1351  with leakage.
7  97798.9764  with leakage.
```

[49]:
```python
# Hypothesis testing for the test scores

# Ho: scores_leakage = scores_no_leakage
# Ha: scores_leakage != scores_no_leakage

# Method 1: With leakage
scores_leakage = cross_val_score(xgb_clf_leak, X_test_leak, y_test_leak,
                                  cv=5, scoring='r2')

# Method 2: Without leakage
scores_no_leakage = cross_val_score(xgb_clf, X_test, y_test,
                                     cv=5, scoring='r2')

# Paired t-test (same folds, so paired)
t_stat, p_value = stats.ttest_rel(scores_leakage, scores_no_leakage)

print(f"Mean R² with leakage: {scores_leakage.mean():.4f} ± {scores_leakage.
 ↪std():.4f}")
print(f"Mean R² without leakage: {scores_no_leakage.mean():.4f} ±␣
 ↪{scores_no_leakage.std():.4f}")
print(f"p-value: {p_value:.4f}")

if p_value < 0.05:
    print("Difference is statistically significant. We reject the null␣
 ↪hypothesis.")
else:
    print("Difference is NOT statistically significant. We cannot reject the␣
 ↪null hypothesis.")
```

```
Mean R² with leakage: 0.9073 ± 0.0139
Mean R² without leakage: 0.9064 ± 0.0166
p-value: 0.6127
Difference is NOT statistically significant. We cannot reject the null
hypothesis.
```

[50]:
```python
# Hypothesis testing for the train scores

# Ho: scores_leakage = scores_no_leakage
# Ha: scores_leakage != scores_no_leakage

# Method 1: With leakage
```

```
scores_leakage = cross_val_score(xgb_clf_leak, X_train_leak, y_train_leak,
                                 cv=5, scoring='r2')

# Method 2: Without leakage
scores_no_leakage = cross_val_score(xgb_clf, X_train, y_train,
                                    cv=5, scoring='r2')

# Paired t-test (same folds, so paired)
t_stat, p_value = stats.ttest_rel(scores_leakage, scores_no_leakage)

print(f"Mean R² with leakage: {scores_leakage.mean():.4f} ± {scores_leakage.
 ↪std():.4f}")
print(f"Mean R² without leakage: {scores_no_leakage.mean():.4f} ±␣
 ↪{scores_no_leakage.std():.4f}")
print(f"p-value: {p_value:.4f}")

if p_value < 0.05:
    print("Difference is statistically significant. We reject the null␣
 ↪hypothesis.")
else:
    print("Difference is NOT statistically significant. We cannot reject the␣
 ↪null hypothesis.")
```

```
Mean R² with leakage: 0.9063 ± 0.0137
Mean R² without leakage: 0.9095 ± 0.0149
p-value: 0.5156
Difference is NOT statistically significant. We cannot reject the null
hypothesis.
```

2.4 Conclusion on Leakage

Statistical testing showed no significant difference between the approaches. For the scope of this analysis, we will proceed with the current implementation for simplicity, while acknowledging that a production-grade deployment would require the leakage-free pipeline to ensure strict data isolation.

2.5 Export Dataset and Metrics

[51]:
```
# filename_metrics = "Metrics/outlier_analysis_metrics.csv"

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

[52]:
```
# df_clean
```

[53]:
```
# filename_data = "Data/v1_house_sales.csv"

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