melbourne-house-pricing

February 9, 2024

1 House Pricing

1.1 Introduction

In this project, we will train regression models and compare their results over a Kaggle dataset. We will try to get the best performance in predicting the house prices.

1.2 Data

We will work with house pricing datasets open-source on Kaggle. This dataset contains 18 features and 4551 data rows.
The 18 features are:

1. date
2. price
3. bedrooms
4. bathrooms
5. sqft_living
6. sqft_lot
7. floors
8. waterfront
9. view
10. condition
11. sqft_above
12. sqft_basement
13. yr_built
14. yr_renovated
15. street
16. city
17. statezip
18. country

For details abour the data, visit: https://www.kaggle.com/datasets/shree1992/housedata/data

1.3 Data analysis

1.3.1 Importing the required libraries

[72]:
```
#for data manipulation
import numpy as np
import pandas as pd
import datetime
from IPython.display import display, HTML, display_html
from itertools import chain,cycle

#for data visualization
import seaborn as sns
import matplotlib.pyplot as pl
import plotly.express as px
import plotly.graph_objects as go
import matplotlib.cm as cm
import matplotlib.colors as colors

#for requesting additional data
import requests
from io import StringIO
import json
from urllib.request import urlopen

#for geo information
from geopy.geocoders import Nominatim
import folium

#for data modelling
from sklearn.metrics import accuracy_score, mean_squared_error,␣
↪mean_absolute_error, r2_score
from sklearn.model_selection import train_test_split

import xgboost as xgb
from catboost import CatBoostRegressor, Pool
import lightgbm as ltb

import warnings
def fxn():
    warnings.warn("deprecated", DeprecationWarning)

with warnings.catch_warnings(action="ignore"):
    fxn()
```

1.3.2 Data cleaning

[73]:
```
data = pd.read_csv("data.csv")
data = data.drop(columns=['country', 'street', 'date']) # drop the unimportant␣
↪columns
data = data.loc[data['price'] != 0]
data = data.dropna()
data = data.drop_duplicates()

data['yr_built'] = pd.DatetimeIndex(data['yr_built']).year
data['yr_renovated'] = pd.DatetimeIndex(data['yr_renovated']).year

data.head()
```

[73]:
```
       price  bedrooms  bathrooms  sqft_living  sqft_lot  floors  waterfront  \
0   313000.0       3.0       1.50         1340      7912     1.5           0
1  2384000.0       5.0       2.50         3650      9050     2.0           0
2   342000.0       3.0       2.00         1930     11947     1.0           0
3   420000.0       3.0       2.25         2000      8030     1.0           0
4   550000.0       4.0       2.50         1940     10500     1.0           0

   view  condition  sqft_above  sqft_basement  yr_built  yr_renovated  \
0     0          3        1340              0      1970          1970
1     4          5        3370            280      1970          1970
2     0          4        1930              0      1970          1970
3     0          4        1000           1000      1970          1970
4     0          4        1140            800      1970          1970

        city  statezip
0  Shoreline  WA 98133
1    Seattle  WA 98119
2       Kent  WA 98042
3   Bellevue  WA 98008
4    Redmond  WA 98052
```

[74]:
```
print("Original data size: (4551, 18) \n New data set size: {}".format(data.
↪shape))
```

```
Original data size: (4551, 18)
 New data set size: (4551, 15)
```

1.3.3 Adding latitude and longitude data

[75]:
```
headers = {
    'authority': 'gist.githubusercontent.com',
    'accept': 'text/html,application/xhtml+xml,application/xml;q=0.9,image/
↪avif,image/webp,image/apng,*/*;q=0.8,application/signed-exchange;v=b3;q=0.7',
```

```
    'accept-language': 'en-GB,en;q=0.9',
    'cache-control': 'max-age=0',
    'sec-ch-ua': '"Not A(Brand";v="99", "Google Chrome";v="121", "Chromium";
 ↪v="121"',
    'sec-ch-ua-mobile': '?0',
    'sec-ch-ua-platform': '"Windows"',
    'sec-fetch-dest': 'document',
    'sec-fetch-mode': 'navigate',
    'sec-fetch-site': 'none',
    'sec-fetch-user': '?1',
    'upgrade-insecure-requests': '1',
    'user-agent': 'Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36␣
 ↪(KHTML, like Gecko) Chrome/121.0.0.0 Safari/537.36',
}

response = requests.get(
    'https://gist.githubusercontent.com/erichurst/7882666/raw/
 ↪5bdc46db47d9515269ab12ed6fb2850377fd869e/
 ↪US%2520Zip%2520Codes%2520from%25202013%2520Government%2520Data',
    headers=headers,
)

content = response.content.decode()
StringL = StringIO(content)
LatLon_data = pd.read_csv(StringL, sep = ',')

data[['State', 'ZIP']] = data['statezip'].str.split(' ', expand= True)
data = data.drop(columns= ['statezip', 'State'])
data['ZIP'] = data['ZIP'].astype(int)
data = data.merge(LatLon_data, how= 'inner', on='ZIP')
```

[76]:
```
data.head()
```

[76]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	\
0	313000.0	3.0	1.50	1340	7912	1.5	0	
1	2384000.0	5.0	2.50	3650	9050	2.0	0	
2	342000.0	3.0	2.00	1930	11947	1.0	0	
3	420000.0	3.0	2.25	2000	8030	1.0	0	
4	550000.0	4.0	2.50	1940	10500	1.0	0	

	view	condition	sqft_above	sqft_basement	yr_built	yr_renovated	\
0	0	3	1340	0	1970	1970	
1	4	5	3370	280	1970	1970	
2	0	4	1930	0	1970	1970	
3	0	4	1000	1000	1970	1970	
4	0	4	1140	800	1970	1970	

```
        city    ZIP        LAT         LNG
0  Shoreline  98133  47.740485 -122.342826
1    Seattle  98119  47.638679 -122.370946
2       Kent  98042  47.367737 -122.117029
3   Bellevue  98008  47.605797 -122.099118
4    Redmond  98052  47.680990 -122.120531
```

1.3.4 Some general information about the data

[77]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4551 entries, 0 to 4550
Data columns (total 17 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   price          4551 non-null   float64
 1   bedrooms       4551 non-null   float64
 2   bathrooms      4551 non-null   float64
 3   sqft_living    4551 non-null   int64
 4   sqft_lot       4551 non-null   int64
 5   floors         4551 non-null   float64
 6   waterfront     4551 non-null   int64
 7   view           4551 non-null   int64
 8   condition      4551 non-null   int64
 9   sqft_above     4551 non-null   int64
 10  sqft_basement  4551 non-null   int64
 11  yr_built       4551 non-null   int32
 12  yr_renovated   4551 non-null   int32
 13  city           4551 non-null   object
 14  ZIP            4551 non-null   int32
 15  LAT            4551 non-null   float64
 16  LNG            4551 non-null   float64
dtypes: float64(6), int32(3), int64(7), object(1)
memory usage: 551.2+ KB
```

[78]:
```python
data.describe()
```

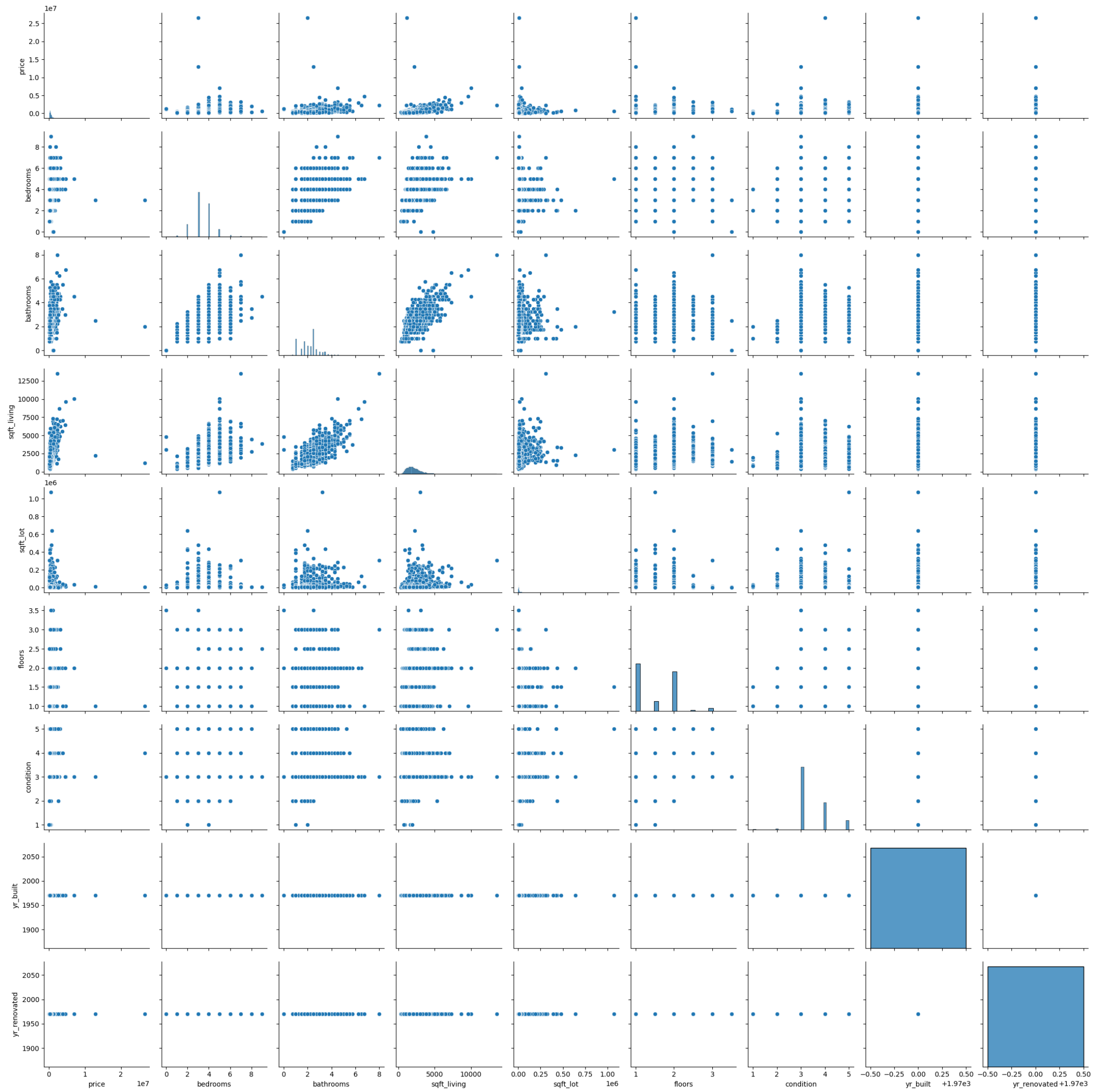
[78]:
```
              price     bedrooms    bathrooms   sqft_living      sqft_lot  \
count  4.551000e+03  4551.000000  4551.000000   4551.000000  4.551000e+03
mean   5.579059e+05     3.394639     2.155021   2132.372226  1.483528e+04
std    5.639299e+05     0.904595     0.776351    955.949708  3.596408e+04
min    7.800000e+03     0.000000     0.000000    370.000000  6.380000e+02
25%    3.262643e+05     3.000000     1.750000   1460.000000  5.000000e+03
50%    4.650000e+05     3.000000     2.250000   1970.000000  7.680000e+03
75%    6.575000e+05     4.000000     2.500000   2610.000000  1.097800e+04
max    2.659000e+07     9.000000     8.000000  13540.000000  1.074218e+06
```

```
          floors   waterfront         view    condition   sqft_above  \
count  4551.000000  4551.000000  4551.000000  4551.000000  4551.000000
mean      1.512195     0.006592     0.234674     3.449352  1822.221710
std       0.538531     0.080932     0.765373     0.675160   854.452888
min       1.000000     0.000000     0.000000     1.000000   370.000000
25%       1.000000     0.000000     0.000000     3.000000  1190.000000
50%       1.500000     0.000000     0.000000     3.000000  1590.000000
75%       2.000000     0.000000     0.000000     4.000000  2300.000000
max       3.500000     1.000000     4.000000     5.000000  9410.000000

       sqft_basement  yr_built  yr_renovated           ZIP          LAT  \
count    4551.000000    4551.0        4551.0   4551.000000  4551.000000
mean      310.150516    1970.0        1970.0  98079.397056    47.567688
std       461.987629       0.0           0.0     53.048784     0.132885
min         0.000000    1970.0        1970.0  98001.000000    47.216372
25%         0.000000    1970.0        1970.0  98033.000000    47.493732
50%         0.000000    1970.0        1970.0  98072.000000    47.585627
75%       600.000000    1970.0        1970.0  98117.000000    47.678255
max      4820.000000    1970.0        1970.0  98354.000000    47.760785

               LNG
count  4551.000000
mean   -122.204906
std       0.157461
min    -122.473322
25%    -122.324859
50%    -122.232795
75%    -122.117029
max    -121.278786
```

[79]:
```python
features = ['price', 'bedrooms','bathrooms', 'sqft_living', 'sqft_lot',␣
 ↪'floors', 'condition', 'yr_built', 'yr_renovated']

pl.figure(figsize=(6,6))
sns.pairplot(data[features])
```

[79]: <seaborn.axisgrid.PairGrid at 0x14609d67bd0>

<Figure size 600x600 with 0 Axes>



As visually as in the data description, we can infer that the features "yr_renovated" and "yr_bulit" have almost the same values for every point of information; hence, we will get rid of them for our project.

[80]:
```
data = data.drop(columns= ['yr_built', 'yr_renovated'])
```

Now we are going to generate some graphs about the average house prices in every postal location

[81]:
```
mean_prices_data = data.copy()
mean_prices_data = mean_prices_data[['ZIP', 'LAT', 'LNG', 'price']]
# mean_prices_data['ZIP-city'] = mean_prices_data['ZIP'].astype(str) + ", " +␣
 ↪mean_prices_data['city'].astype(str)
# mean_prices_data = mean_prices_data.drop(columns= ['ZIP', 'city'])
```

```
a = mean_prices_data.groupby(['ZIP'], as_index= False)[['price', 'LAT', 'LNG']].
 ↪size()
b = mean_prices_data.groupby(['ZIP'], as_index= False)[['price', 'LAT', 'LNG']].
 ↪mean()

mean_prices_data = a.merge(b, how= 'inner', on= 'ZIP')
mean_prices_data = mean_prices_data.rename(columns = {'price': 'Mean Price',␣
 ↪'size': 'Number of houses'})
mean_prices_data.head()
```

[81]:

	ZIP	Number of houses	Mean Price	LAT	LNG
0	98001	66	2.616399e+05	47.310617	-122.263291
1	98002	35	2.299344e+05	47.308286	-122.216812
2	98003	48	2.994256e+05	47.304801	-122.316969
3	98004	71	1.372758e+06	47.618337	-122.205341
4	98005	29	7.787792e+05	47.614533	-122.168798

[82]:
```
fig = px.scatter_mapbox(mean_prices_data, lat= 'LAT', lon= 'LNG', size = 'Mean␣
 ↪Price', color= 'Number of houses')

fig.update_layout(mapbox_style="open-street-map", height= 600, width = 1000)
fig.update_layout(margin={"r": 0, "t": 0, "l": 0, "b": 0})

fig.show()
```

In the image above the circle size indicates the mean prices while the color indicates the number of houses in every Postal location, by pointing at every city we can additionally see the mean price of the Zip code. We then compared the highest and lowest average house prices by zip location.

[83]:
```
def display_side_by_side(*args,titles=cycle([''])):
    html_str=''
    for df,title in zip(args, chain(titles,cycle(['</br>'])) ):
        html_str+='<th style="text-align:center"><td style="vertical-align:
 ↪top">'
        html_str+=f'<h2 style="text-align: left;">{title}</h2>'
        html_str+=df.to_html().replace('table','table style="display:inline"')
        html_str+='</td></th>'
    display_html(html_str,raw=True)

mean_prices_data_highest = mean_prices_data.sort_values(by= 'Mean Price',␣
 ↪ascending= False).iloc[:5, :]
mean_prices_data_highest = mean_prices_data_highest.reset_index()
mean_prices_data_highest = mean_prices_data_highest.drop(columns= ['index'])

mean_prices_data_lowest = mean_prices_data.sort_values(by= 'Mean Price',␣
 ↪ascending= True).iloc[:5, :]
```

```
mean_prices_data_lowest = mean_prices_data_lowest.reset_index()
mean_prices_data_lowest = mean_prices_data_lowest.drop(columns= ['index'])

display_side_by_side(mean_prices_data_highest, mean_prices_data_lowest, titles=␣
↪['Highest average house price ', 'Lowest average house price'])
```

[84]:
```
most_mean_expensive_houses = mean_prices_data_highest['ZIP'].values.tolist()

y = []
for i in range(5):
    y0 = np.array(data.loc[data['ZIP'] ==␣
↪most_mean_expensive_houses[i]]['price'])
    y.append(y0)

fig = go.Figure()

colors = ['rgba(93, 164, 214, 0.5)', 'rgba(255, 144, 14, 0.5)', 'rgba(44, 160,␣
↪101, 0.5)',
          'rgba(255, 65, 54, 0.5)', 'rgba(207, 114, 255, 0.5)']

for xd, yd, cls in zip(most_mean_expensive_houses, y, colors):
        fig.add_trace(go.Box(
            y=yd,
            name=xd,
            boxpoints='all',
            jitter=0.5,
            whiskerwidth=0.2,
            fillcolor=cls,
            marker_size=2,
            line_width=1,
            boxmean= 'sd')
        )

fig.update_layout(
    title='Dispersion of houses prices for the most 5 expensive cities',
    yaxis=dict(
        autorange=True,
        showgrid=True,
        zeroline=True,
        dtick=1000000,
        gridcolor='rgb(255, 255, 255)',
        gridwidth=1,
        zerolinecolor='rgb(255, 255, 255)',
        zerolinewidth=2,
    ),
    margin=dict(
        l=40,
```

```
        r=30,
        b=80,
        t=100,
    ),
    paper_bgcolor='rgb(243, 243, 243)',
    plot_bgcolor='rgb(243, 243, 243)',
    showlegend=False
)

fig.show()
```

[85]:
```
least_mean_expensive_houses = mean_prices_data_lowest['ZIP'].values.tolist()

y = []
for i in range(5):
    y0 = np.array(data.loc[data['ZIP'] ==␣
 ↪least_mean_expensive_houses[i]]['price'])
    y.append(y0)

fig = go.Figure()

colors = ['rgba(93, 164, 214, 0.5)', 'rgba(255, 144, 14, 0.5)', 'rgba(44, 160,␣
 ↪101, 0.5)',
          'rgba(255, 65, 54, 0.5)', 'rgba(207, 114, 255, 0.5)']

for xd, yd, cls in zip(least_mean_expensive_houses, y, colors):
        fig.add_trace(go.Box(
            y=yd,
            name=xd,
            boxpoints='all',
            jitter=0.5,
            whiskerwidth=0.2,
            fillcolor=cls,
            marker_size=2,
            line_width=1,
            boxmean= 'sd')
        )

fig.update_layout(
    title='Dispersion of houses prices for the most 5 expensive cities',
    yaxis=dict(
        autorange=True,
        showgrid=True,
        zeroline=True,
        dtick=500000,
        gridcolor='rgb(255, 255, 255)',
        gridwidth=250000,
```

```
        zerolinecolor='rgb(255, 255, 255)',
        zerolinewidth=2,
    ),
    margin=dict(
        l=40,
        r=30,
        b=80,
        t=100,
    ),
    paper_bgcolor='rgb(243, 243, 243)',
    plot_bgcolor='rgb(243, 243, 243)',
    showlegend=False
)

fig.show()
```

As we can see there are many outliers concerning the house prices. We can set some limits on the data to have a more tractable one.

[86]:
```
data = data.loc[(data['price'] <= 1000000) &
                (data['bedrooms'] < 8) &
                (data['bathrooms'] < 6) &
                (data['sqft_living'] < 7500) &
                (data['condition'] > 1) &
                (data['bedrooms'] > 1) &
                (data['view'] < 3)]
data.shape
```

[86]:
```
(4075, 15)
```

1.4 Model training

1.4.1 Data split

[87]:
```
train = data.copy()
cat_col = train.select_dtypes(include='object').columns.to_list()
# train = train.drop(columns= ['city', 'ZIP'])
X = train.drop(columns='price')
y = train['price']

for c in X.columns:
    col_type = X[c].dtype
    if col_type == 'object' or col_type.name == 'category':
        X[c] = X[c].astype('category')

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=0)
```

1.4.2 GBM Model

[88]:
```python
model_params = {'boosting_type': 'gbdt',
                'colsample_bytree': 0.6,
                'learning_rate': 0.05,
                'max_depth': -1,
                'min_child_samples': 13,
                'min_child_weight': 0.01,
                'min_split_gain': 0.25,
                'n_jobs': -1,
                'num_leaves': 80,
                'objective': 'regression',
                'random_state': 0,
                'seed': 0,
                'reg_alpha': 1.0559559479313415,
                'reg_lambda': 1.0949294490500017e-06,
                'subsample': 0.96,
                'subsample_for_bin': 200000,
                'subsample_freq': 4,
                'verbose': -1,
                'metric': 'rmse',
            }

gmb_model = ltb.LGBMRegressor(**model_params)
gmb_model.fit(X_train, y_train)
```

[88]:
```
LGBMRegressor(colsample_bytree=0.6, learning_rate=0.05, metric='rmse',
              min_child_samples=13, min_child_weight=0.01, min_split_gain=0.25,
              n_jobs=-1, num_leaves=80, objective='regression', random_state=0,
              reg_alpha=1.0559559479313414, reg_lambda=1.0949294490500017e-06,
              seed=0, subsample=0.96, subsample_freq=4, verbose=-1)
```

[89]:
```python
y_pred1 = gmb_model.predict(X_test)

mse1 = mean_squared_error(y_test, y_pred1)
mae1 = mean_absolute_error(y_test, y_pred1)
r21 = r2_score(y_test, y_pred1)

print(f'Mean Squared Error (MSE): {mse1:.4f}')
print(f'Mean Absolute Error (MAE): {mae1:.4f}')
print(f'R-squared (R2): {r21:.4f}')
```

```
Mean Squared Error (MSE): 7924939038.9410
Mean Absolute Error (MAE): 60860.8937
R-squared (R2): 0.7928
```

1.4.3 XGB model

[90]:
```
XGB_model = xgb.XGBRegressor(objective ='reg:linear', n_estimators = 10, seed =
↪123, enable_categorical=True)
XGB_model.fit(X_train, y_train)
```

```
c:\Users\bsar_\Venv\Py3.11BDA\Lib\site-packages\xgboost\core.py:160:
UserWarning:

[00:29:40] WARNING: C:\buildkite-agent\builds\buildkite-windows-cpu-autoscaling-
group-i-0b3782d1791676daf-1\xgboost\xgboost-ci-
windows\src\objective\regression_obj.cu:209: reg:linear is now deprecated in
favor of reg:squarederror.
```

[90]:
```
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=True, eval_metric=None, feature_types=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=10, n_jobs=None,
             num_parallel_tree=None, objective='reg:linear', …)
```

[91]:
```
y_pred2 = XGB_model.predict(X_test)

mse2 = mean_squared_error(y_test, y_pred2)
mae2 = mean_absolute_error(y_test, y_pred2)
r22 = r2_score(y_test, y_pred2)

print(f'Mean Squared Error (MSE): {mse2:.4f}')
print(f'Mean Absolute Error (MAE): {mae2:.4f}')
print(f'R-squared (R2): {r22:.4f}')
```

```
Mean Squared Error (MSE): 8151269994.5435
Mean Absolute Error (MAE): 62288.0240
R-squared (R2): 0.7868
```

1.4.4 Catboost Model

[92]:
```
model = CatBoostRegressor(cat_features=cat_col,
                          n_estimators=1000,
                          random_seed=12,
                          verbose=100)
```

```
model.fit(X_train, y_train)
```

```
Learning rate set to 0.049348
0:      learn: 189890.5360140   total: 29.2ms   remaining: 29.1s
100:    learn: 87726.0636300    total: 2.42s    remaining: 21.5s
200:    learn: 78768.9504177    total: 4.8s     remaining: 19.1s
300:    learn: 73462.6650734    total: 6.91s    remaining: 16.1s
400:    learn: 68914.9080758    total: 9.43s    remaining: 14.1s
500:    learn: 65383.7329301    total: 12.3s    remaining: 12.3s
600:    learn: 62733.0220863    total: 15.1s    remaining: 10s
700:    learn: 60297.5505604    total: 18s      remaining: 7.67s
800:    learn: 58313.4185587    total: 20.7s    remaining: 5.14s
900:    learn: 56428.4918336    total: 23.5s    remaining: 2.59s
999:    learn: 54649.1459017    total: 26.4s    remaining: 0us
```

[92]: <catboost.core.CatBoostRegressor at 0x14611362a90>

[93]:
```
y_pred3 = model.predict(X_test)

mse3 = mean_squared_error(y_test, y_pred3)
mae3 = mean_absolute_error(y_test, y_pred3)
r23 = r2_score(y_test, y_pred3)

print(f'Mean Squared Error (MSE): {mse3:.4f}')
print(f'Mean Absolute Error (MAE): {mae3:.4f}')
print(f'R-squared (R2): {r23:.4f}')
```

```
Mean Squared Error (MSE): 7837530225.0531
Mean Absolute Error (MAE): 60562.0719
R-squared (R2): 0.7951
```

1.4.5 Comparison of the models presented

[94]:
```
y_test = pd.DataFrame(y_test).reset_index(drop = True).rename(columns={'price':
 ↪'Actual Price'})
y_pred1 = pd.DataFrame(y_pred1, columns = ['Prediction by GBM'])
y_pred2 = pd.DataFrame(y_pred2, columns = ['Prediction by XGB'])
y_pred3 = pd.DataFrame(y_pred3, columns = ['Prediction by Catboost'])
```

[95]:
```
y_pred = [y_test, y_pred1, y_pred2, y_pred3]
y_pred = pd.concat(y_pred, axis = 1)
y_pred.head()
```

[95]:

	Actual Price	Prediction by GBM	Prediction by XGB	Prediction by Catboost
0	913888.0	683797.923491	694543.062500	667705.801883
1	660000.0	627339.479547	686967.750000	661691.989389
2	717000.0	507206.938822	488774.281250	505627.420663

3	265000.0	227649.487526	277435.906250	231007.004598
4	187000.0	185594.709444	196884.796875	171448.342241

[96]:
```
fig = px.scatter(y_pred, x= 'Actual Price', y= y_pred.columns[1:4],␣
↪trendline="ols")
fig.show()
```

```
c:\Users\bsar_\Venv\Py3.11BDA\Lib\site-packages\plotly\express\_core.py:2065:
FutureWarning:

When grouping with a length-1 list-like, you will need to pass a length-1 tuple
to get_group in a future version of pandas. Pass `(name,)` instead of `name` to
silence this warning.
```

[100]:
```
pd.DataFrame({'Mean Squared Error (MSE)': [f'{mse1:.4f}', f'{mse2:.4f}',␣
↪f'{mse3:.4f}'],
              'Mean Absolute Error (MAE)': [f'{mae1:.4f}', f'{mae2:.4f}',␣
↪f'{mae3:.4f}'],
              'R-squared (R2)': [f'{r21:.4f}', f'{r22:.4f}', f'{r23:.4f}']}).
↪rename(index= {0: 'GBM Model', 1: 'XGB Model', 2: 'Catboost'})
```

[100]:

	Mean Squared Error (MSE)	Mean Absolute Error (MAE)	R-squared (R2)
GBM Model	7924939038.9410	60860.8937	0.7928
XGB Model	8151269994.5435	62288.0240	0.7868
Catboost	7837530225.0531	60562.0719	0.7951

1.5 Conclusion

Overall, we can see the three models produce good R squared values, all around 80% which can be considered adequate but not excellent for the predictions. In future projects, we can train other models to see how they react to the dataset used and try to get a better performance