

# House\_Price\_Prediction

November 9, 2024

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

```
[2]: data= pd.read_csv("House Price India.csv")
```

```
[3]: data
```

```
[3]:
```

	id	Date	number of bedrooms	number of bathrooms	\
0	6762810145	42491	5	2.50	
1	6762810635	42491	4	2.50	
2	6762810998	42491	5	2.75	
3	6762812605	42491	4	2.50	
4	6762812919	42491	3	2.00	
...	...	...	...	...	
14615	6762830250	42734	2	1.50	
14616	6762830339	42734	3	2.00	
14617	6762830618	42734	2	1.00	
14618	6762830709	42734	4	1.00	
14619	6762831463	42734	3	1.00	

	living area	lot area	number of floors	waterfront present	\
0	3650	9050	2.0	0	
1	2920	4000	1.5	0	
2	2910	9480	1.5	0	
3	3310	42998	2.0	0	
4	2710	4500	1.5	0	
...	...	...	...	...	
14615	1556	20000	1.0	0	
14616	1680	7000	1.5	0	
14617	1070	6120	1.0	0	
14618	1030	6621	1.0	0	
14619	900	4770	1.0	0	

	number of views	condition of the house	...	Built Year	\
0	4	5	...	1921	
1	0	5	...	1909	

2	0	3	...	1939
3	0	3	...	2001
4	0	4	...	1929
...	...	...	...	...
14615	0	4	...	1957
14616	0	4	...	1968
14617	0	3	...	1962
14618	0	4	...	1955
14619	0	3	...	1969

	Renovation Year	Postal Code	Lattitude	Longitude	living_area_renov \
0	0	122003	52.8645	-114.557	2880
1	0	122004	52.8878	-114.470	2470
2	0	122004	52.8852	-114.468	2940
3	0	122005	52.9532	-114.321	3350
4	0	122006	52.9047	-114.485	2060
...	...	...	...	...	...
14615	0	122066	52.6191	-114.472	2250
14616	0	122072	52.5075	-114.393	1540
14617	0	122056	52.7289	-114.507	1130
14618	0	122042	52.7157	-114.411	1420
14619	2009	122018	52.5338	-114.552	900

	lot_area_renov	Number of schools nearby	Distance from the airport \
0	5400	2	58
1	4000	2	51
2	6600	1	53
3	42847	3	76
4	4500	1	51
...	...	...	...
14615	17286	3	76
14616	7480	3	59
14617	6120	2	64
14618	6631	3	54
14619	3480	2	55

	Price
0	2380000
1	1400000
2	1200000
3	838000
4	805000
...	...
14615	221700
14616	219200
14617	209000
14618	205000

14619 146000

[14620 rows x 23 columns]

```
[4]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14620 entries, 0 to 14619
Data columns (total 23 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   id                                    14620 non-null  int64
1   Date                                 14620 non-null  int64
2   number of bedrooms                  14620 non-null  int64
3   number of bathrooms                 14620 non-null  float64
4   living area                         14620 non-null  int64
5   lot area                           14620 non-null  int64
6   number of floors                    14620 non-null  float64
7   waterfront present                  14620 non-null  int64
8   number of views                     14620 non-null  int64
9   condition of the house              14620 non-null  int64
10  grade of the house                  14620 non-null  int64
11  Area of the house(excluding basement) 14620 non-null  int64
12  Area of the basement                 14620 non-null  int64
13  Built Year                           14620 non-null  int64
14  Renovation Year                     14620 non-null  int64
15  Postal Code                         14620 non-null  int64
16  Lattitude                           14620 non-null  float64
17  Longitude                           14620 non-null  float64
18  living_area_renov                   14620 non-null  int64
19  lot_area_renov                      14620 non-null  int64
20  Number of schools nearby             14620 non-null  int64
21  Distance from the airport            14620 non-null  int64
22  Price                               14620 non-null  int64
dtypes: float64(4), int64(19)
memory usage: 2.6 MB
```

```
[5]: data.dropna(inplace=True)
```

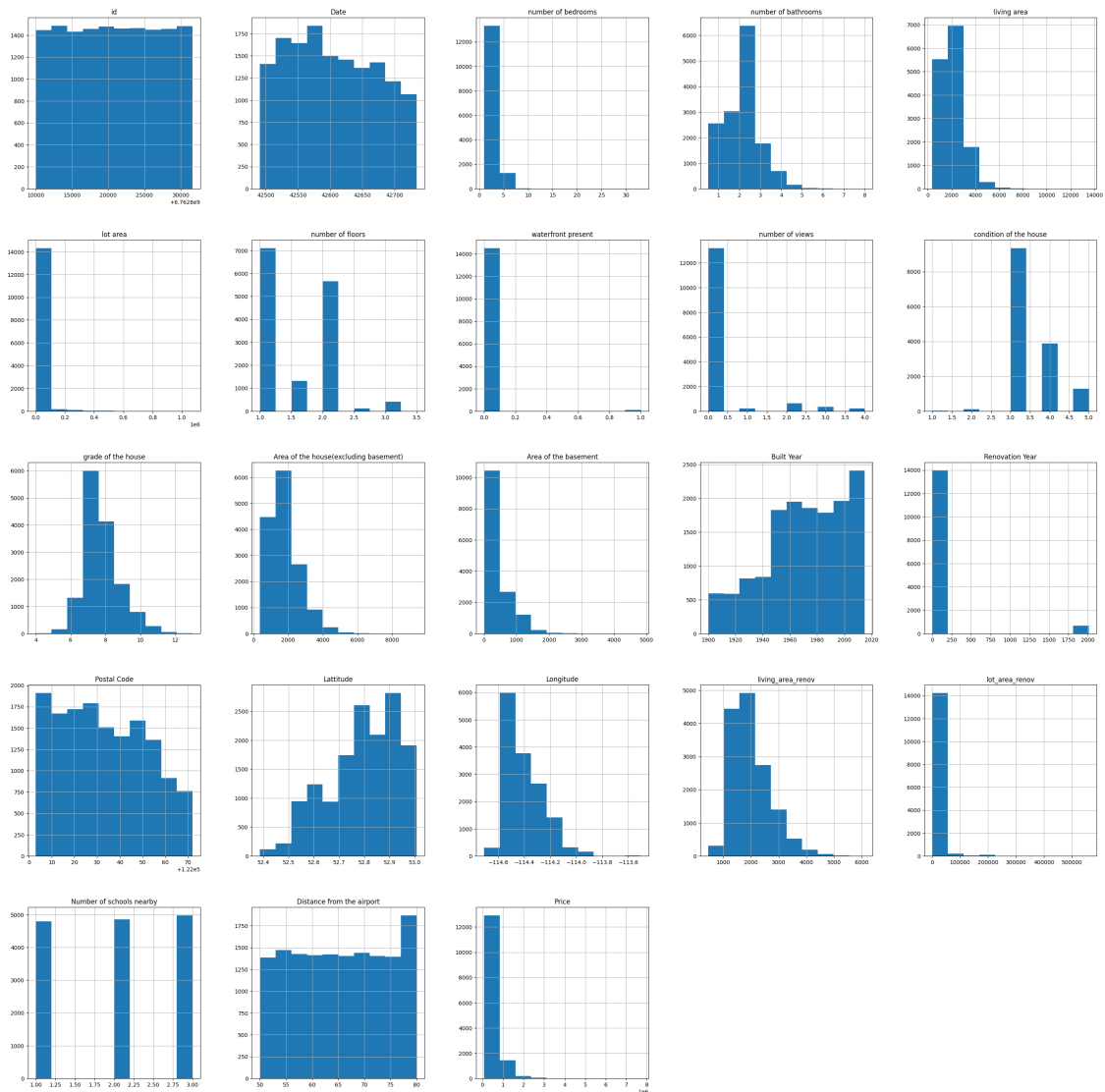
```
[6]: data.hist(figsize=(35, 35))
```

```
[6]: array([[<Axes: title={'center': 'id'}>, <Axes: title={'center': 'Date'}>,
          <Axes: title={'center': 'number of bedrooms'}>,
          <Axes: title={'center': 'number of bathrooms'}>,
          <Axes: title={'center': 'living area'}>],
          [<Axes: title={'center': 'lot area'}>,
          <Axes: title={'center': 'number of floors'}>,
          <Axes: title={'center': 'waterfront present'}>],
          ...])
```

```

    <Axes: title={'center': 'number of views'}>,
    <Axes: title={'center': 'condition of the house'}>],
[<Axes: title={'center': 'grade of the house'}>,
 <Axes: title={'center': 'Area of the house(excluding basement)'}>,
 <Axes: title={'center': 'Area of the basement'}>,
 <Axes: title={'center': 'Built Year'}>,
 <Axes: title={'center': 'Renovation Year'}>],
[<Axes: title={'center': 'Postal Code'}>,
 <Axes: title={'center': 'Latitude'}>,
 <Axes: title={'center': 'Longitude'}>,
 <Axes: title={'center': 'living_area_renov'}>,
 <Axes: title={'center': 'lot_area_renov'}>],
[<Axes: title={'center': 'Number of schools nearby'}>,
 <Axes: title={'center': 'Distance from the airport'}>,
 <Axes: title={'center': 'Price'}>, <Axes: >, <Axes: >]],
dtype=object)

```



```
[7]: data.corr()
```

```
[7]:
```

	id	Date	number of bedrooms \
id	1.000000	0.045966	-0.329034
Date	0.045966	1.000000	-0.015663
number of bedrooms	-0.329034	-0.015663	1.000000
number of bathrooms	-0.516909	-0.026485	0.509784
living area	-0.648127	-0.021958	0.570526
lot area	-0.100269	0.004392	0.034416
number of floors	-0.312305	-0.010335	0.177294
waterfront present	-0.112937	0.012006	-0.006257
number of views	-0.293004	-0.004782	0.078665
condition of the house	-0.045061	-0.027402	0.026597

grade of the house	-0.673448	-0.033097	0.352945
Area of the house(excluding basement)	-0.565116	-0.015994	0.473599
Area of the basement	-0.290806	-0.015711	0.300332
Built Year	-0.068645	-0.005869	0.152954
Renovation Year	-0.109155	-0.011636	0.016132
Postal Code	0.294709	0.018243	-0.044156
Lattitude	-0.479334	-0.023327	-0.013163
Longitude	-0.070841	-0.018231	0.135712
living_area_renov	-0.599900	-0.032495	0.389855
lot_area_renov	-0.089604	-0.000050	0.029400
Number of schools nearby	-0.004821	-0.004071	0.003397
Distance from the airport	-0.004542	0.011457	-0.006157
Price	-0.773114	-0.027919	0.308460

	number of bathrooms	living area \
id	-0.516909	-0.648127
Date	-0.026485	-0.021958
number of bedrooms	0.509784	0.570526
number of bathrooms	1.000000	0.753517
living area	0.753517	1.000000
lot area	0.080806	0.174420
number of floors	0.502924	0.354743
waterfront present	0.060104	0.105837
number of views	0.183789	0.287728
condition of the house	-0.128232	-0.063358
grade of the house	0.663054	0.761835
Area of the house(excluding basement)	0.684391	0.875793
Area of the basement	0.287190	0.441491
Built Year	0.498127	0.309602
Renovation Year	0.049669	0.059400
Postal Code	-0.105546	-0.080303
Lattitude	0.031156	0.054518
Longitude	0.223904	0.240208
living_area_renov	0.570530	0.757571
lot_area_renov	0.078627	0.180312
Number of schools nearby	0.002180	0.002370
Distance from the airport	0.009206	0.002511
Price	0.531735	0.712169

	lot area	number of floors \
id	-0.100269	-0.312305
Date	0.004392	-0.010335
number of bedrooms	0.034416	0.177294
number of bathrooms	0.080806	0.502924
living area	0.174420	0.354743
lot area	1.000000	-0.004138
number of floors	-0.004138	1.000000

waterfront present	0.026282	0.016316
number of views	0.078308	0.020153
condition of the house	-0.008548	-0.269928
grade of the house	0.110546	0.463082
Area of the house(excluding basement)	0.183553	0.525643
Area of the basement	0.019755	-0.242976
Built Year	0.051615	0.481565
Renovation Year	0.006848	0.006705
Postal Code	0.070131	-0.129788
Lattitude	-0.090983	0.050731
Longitude	0.221432	0.127550
living_area_renov	0.149744	0.285093
lot_area_renov	0.706812	-0.010120
Number of schools nearby	-0.012671	-0.007579
Distance from the airport	0.003291	0.016567
Price	0.081992	0.262732

	waterfront present	number of views \
id	-0.112937	-0.293004
Date	0.012006	-0.004782
number of bedrooms	-0.006257	0.078665
number of bathrooms	0.060104	0.183789
living area	0.105837	0.287728
lot area	0.026282	0.078308
number of floors	0.016316	0.020153
waterfront present	1.000000	0.400206
number of views	0.400206	1.000000
condition of the house	0.018644	0.052533
grade of the house	0.079831	0.254532
Area of the house(excluding basement)	0.071865	0.162672
Area of the basement	0.085441	0.293062
Built Year	-0.024226	-0.055357
Renovation Year	0.085865	0.102944
Postal Code	0.038318	0.039268
Lattitude	-0.021795	-0.004555
Longitude	-0.047791	-0.079706
living_area_renov	0.085743	0.281452
lot_area_renov	0.032055	0.072300
Number of schools nearby	0.001563	0.008004
Distance from the airport	0.001448	-0.001657
Price	0.263687	0.395973

	condition of the house ... \
id	-0.045061 ...
Date	-0.027402 ...
number of bedrooms	0.026597 ...
number of bathrooms	-0.128232 ...

living area	-0.063358	...
lot area	-0.008548	...
number of floors	-0.269928	...
waterfront present	0.018644	...
number of views	0.052533	...
condition of the house	1.000000	...
grade of the house	-0.152530	...
Area of the house(excluding basement)	-0.167695	...
Area of the basement	0.180609	...
Built Year	-0.381718	...
Renovation Year	-0.062126	...
Postal Code	0.045334	...
Lattitude	-0.002998	...
Longitude	-0.121189	...
living_area_renov	-0.099743	...
lot_area_renov	-0.004748	...
Number of schools nearby	-0.006939	...
Distance from the airport	-0.002136	...
Price	0.041376	...

	Built Year	Renovation Year	\
id	-0.068645	-0.109155	
Date	-0.005869	-0.011636	
number of bedrooms	0.152954	0.016132	
number of bathrooms	0.498127	0.049669	
living area	0.309602	0.059400	
lot area	0.051615	0.006848	
number of floors	0.481565	0.006705	
waterfront present	-0.024226	0.085865	
number of views	-0.055357	0.102944	
condition of the house	-0.381718	-0.062126	
grade of the house	0.440358	0.014501	
Area of the house(excluding basement)	0.419369	0.025727	
Area of the basement	-0.138843	0.075104	
Built Year	1.000000	-0.233683	
Renovation Year	-0.233683	1.000000	
Postal Code	-0.062349	0.018006	
Lattitude	-0.143153	0.028908	
Longitude	0.414591	-0.080050	
living_area_renov	0.328625	-0.002601	
lot_area_renov	0.072874	0.005869	
Number of schools nearby	-0.001631	-0.000826	
Distance from the airport	-0.003968	0.005342	
Price	0.050307	0.133173	

	Postal Code	Lattitude	Longitude	\
id	0.294709	-0.479334	-0.070841	



Date	0.018243	-0.023327	-0.018231
number of bedrooms	-0.044156	-0.013163	0.135712
number of bathrooms	-0.105546	0.031156	0.223904
living area	-0.080303	0.054518	0.240208
lot area	0.070131	-0.090983	0.221432
number of floors	-0.129788	0.050731	0.127550
waterfront present	0.038318	-0.021795	-0.047791
number of views	0.039268	-0.004555	-0.079706
condition of the house	0.045334	-0.002998	-0.121189
grade of the house	-0.146342	0.115256	0.203754
Area of the house(excluding basement)	-0.083730	-0.000088	0.345899
Area of the basement	-0.010542	0.112989	-0.145879
Built Year	-0.062349	-0.143153	0.414591
Renovation Year	0.018006	0.028908	-0.080050
Postal Code	1.000000	-0.310172	-0.099003
Lattitude	-0.310172	1.000000	-0.131472
Longitude	-0.099003	-0.131472	1.000000
living_area_renov	-0.108454	0.046148	0.341221
lot_area_renov	0.077483	-0.091622	0.258066
Number of schools nearby	0.010605	0.014949	-0.010163
Distance from the airport	0.011528	0.007193	-0.003100
Price	-0.115908	0.297490	0.024414

	living_area_renov	lot_area_renov \
id	-0.599900	-0.089604
Date	-0.032495	-0.000050
number of bedrooms	0.389855	0.029400
number of bathrooms	0.570530	0.078627
living area	0.757571	0.180312
lot area	0.149744	0.706812
number of floors	0.285093	-0.010120
waterfront present	0.085743	0.032055
number of views	0.281452	0.072300
condition of the house	-0.099743	-0.004748
grade of the house	0.720019	0.116725
Area of the house(excluding basement)	0.737744	0.194670
Area of the basement	0.196403	0.011283
Built Year	0.328625	0.072874
Renovation Year	-0.002601	0.005869
Postal Code	-0.108454	0.077483
Lattitude	0.046148	-0.091622
Longitude	0.341221	0.258066
living_area_renov	1.000000	0.189225
lot_area_renov	0.189225	1.000000
Number of schools nearby	-0.001203	-0.025014
Distance from the airport	-0.005673	-0.014587
Price	0.584924	0.075535

	Number of schools nearby \
id	-0.004821
Date	-0.004071
number of bedrooms	0.003397
number of bathrooms	0.002180
living area	0.002370
lot area	-0.012671
number of floors	-0.007579
waterfront present	0.001563
number of views	0.008004
condition of the house	-0.006939
grade of the house	0.000986
Area of the house(excluding basement)	-0.002894
Area of the basement	0.010284
Built Year	-0.001631
Renovation Year	-0.000826
Postal Code	0.010605
Latitude	0.014949
Longitude	-0.010163
living_area_renov	-0.001203
lot_area_renov	-0.025014
Number of schools nearby	1.000000
Distance from the airport	0.004035
Price	0.009890

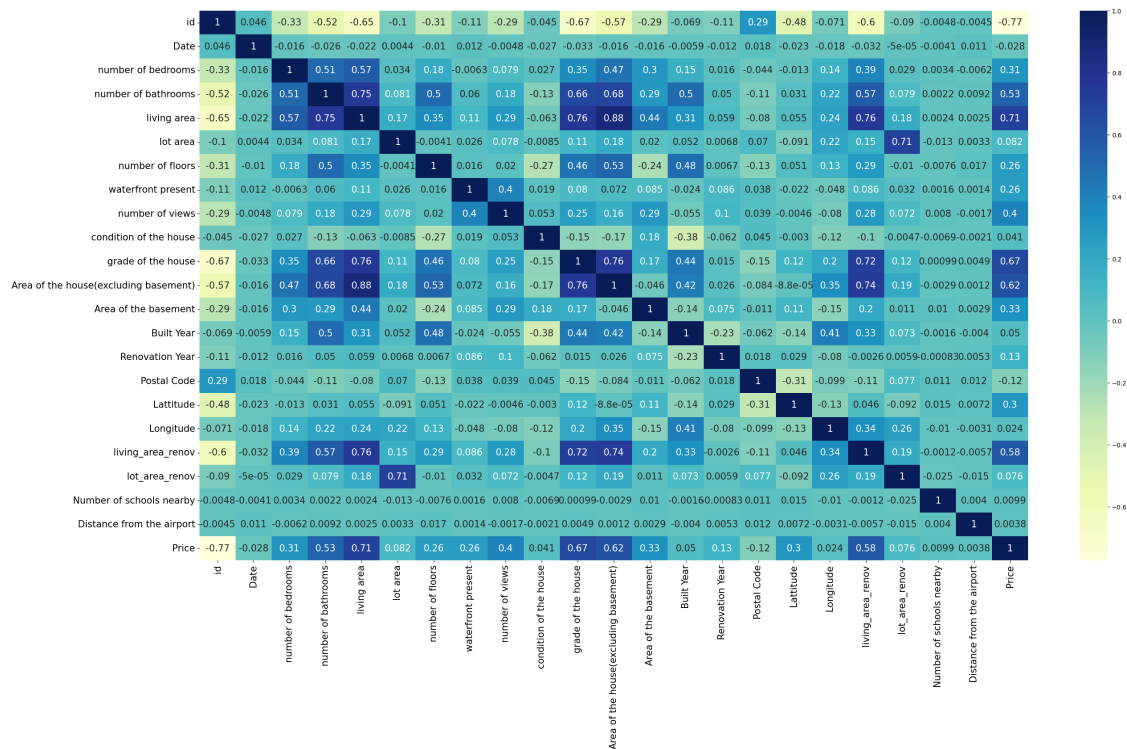
	Distance from the airport	Price
id	-0.004542	-0.773114
Date	0.011457	-0.027919
number of bedrooms	-0.006157	0.308460
number of bathrooms	0.009206	0.531735
living area	0.002511	0.712169
lot area	0.003291	0.081992
number of floors	0.016567	0.262732
waterfront present	0.001448	0.263687
number of views	-0.001657	0.395973
condition of the house	-0.002136	0.041376
grade of the house	0.004940	0.671814
Area of the house(excluding basement)	0.001222	0.615220
Area of the basement	0.002926	0.330202
Built Year	-0.003968	0.050307
Renovation Year	0.005342	0.133173
Postal Code	0.011528	-0.115908
Latitude	0.007193	0.297490
Longitude	-0.003100	0.024414
living_area_renov	-0.005673	0.584924
lot_area_renov	-0.014587	0.075535

Number of schools nearby	0.004035	0.009890
Distance from the airport	1.000000	0.003804
Price	0.003804	1.000000

[23 rows x 23 columns]

```
[8]: plt.figure(figsize=(30,16))
sns.heatmap(data.corr(),annot=True,cmap="YlGnBu",annot_kws={"size": 15},)
plt.xticks(rotation=90, fontsize=15)
plt.yticks(rotation=0, fontsize=15)
```

```
[8]: (array([ 0.5,  1.5,  2.5,  3.5,  4.5,  5.5,  6.5,  7.5,  8.5,  9.5, 10.5,
            11.5, 12.5, 13.5, 14.5, 15.5, 16.5, 17.5, 18.5, 19.5, 20.5, 21.5,
            22.5])),
[Text(0, 0.5, 'id'),
 Text(0, 1.5, 'Date'),
 Text(0, 2.5, 'number of bedrooms'),
 Text(0, 3.5, 'number of bathrooms'),
 Text(0, 4.5, 'living area'),
 Text(0, 5.5, 'lot area'),
 Text(0, 6.5, 'number of floors'),
 Text(0, 7.5, 'waterfront present'),
 Text(0, 8.5, 'number of views'),
 Text(0, 9.5, 'condition of the house'),
 Text(0, 10.5, 'grade of the house'),
 Text(0, 11.5, 'Area of the house(excluding basement)'),
 Text(0, 12.5, 'Area of the basement'),
 Text(0, 13.5, 'Built Year'),
 Text(0, 14.5, 'Renovation Year'),
 Text(0, 15.5, 'Postal Code'),
 Text(0, 16.5, 'Latitude'),
 Text(0, 17.5, 'Longitude'),
 Text(0, 18.5, 'living_area_renov'),
 Text(0, 19.5, 'lot_area_renov'),
 Text(0, 20.5, 'Number of schools nearby'),
 Text(0, 21.5, 'Distance from the airport'),
 Text(0, 22.5, 'Price')])
```



```
[9]: # Calculate Q1 (25th percentile) and Q3 (75th percentile) for the 'Price' column
Q1 = data['Price'].quantile(0.25)
Q3 = data['Price'].quantile(0.75)
IQR = Q3 - Q1
```

```
# Define the lower and upper bounds
```

```
lower_bound = Q1 - 1.5 * IQR
```

```
upper_bound = Q3 + 1.5 * IQR
```

```
# Remove outliers
```

```
data= data[(data['Price'] >= lower_bound) & (data['Price'] <= upper_bound)]
```

```
[10]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
Index: 13859 entries, 3 to 14619
```

```
Data columns (total 23 columns):
```

#	Column	Non-Null Count	Dtype
0	id	13859 non-null	int64
1	Date	13859 non-null	int64
2	number of bedrooms	13859 non-null	int64
3	number of bathrooms	13859 non-null	float64
4	living area	13859 non-null	int64

```

5    lot area                13859 non-null  int64
6    number of floors        13859 non-null  float64
7    waterfront present      13859 non-null  int64
8    number of views         13859 non-null  int64
9    condition of the house  13859 non-null  int64
10   grade of the house      13859 non-null  int64
11   Area of the house(excluding basement) 13859 non-null  int64
12   Area of the basement    13859 non-null  int64
13   Built Year              13859 non-null  int64
14   Renovation Year         13859 non-null  int64
15   Postal Code             13859 non-null  int64
16   Lattitude              13859 non-null  float64
17   Longitude              13859 non-null  float64
18   living_area_renov       13859 non-null  int64
19   lot_area_renov          13859 non-null  int64
20   Number of schools nearby 13859 non-null  int64
21   Distance from the airport 13859 non-null  int64
22   Price                  13859 non-null  int64
dtypes: float64(4), int64(19)
memory usage: 2.5 MB

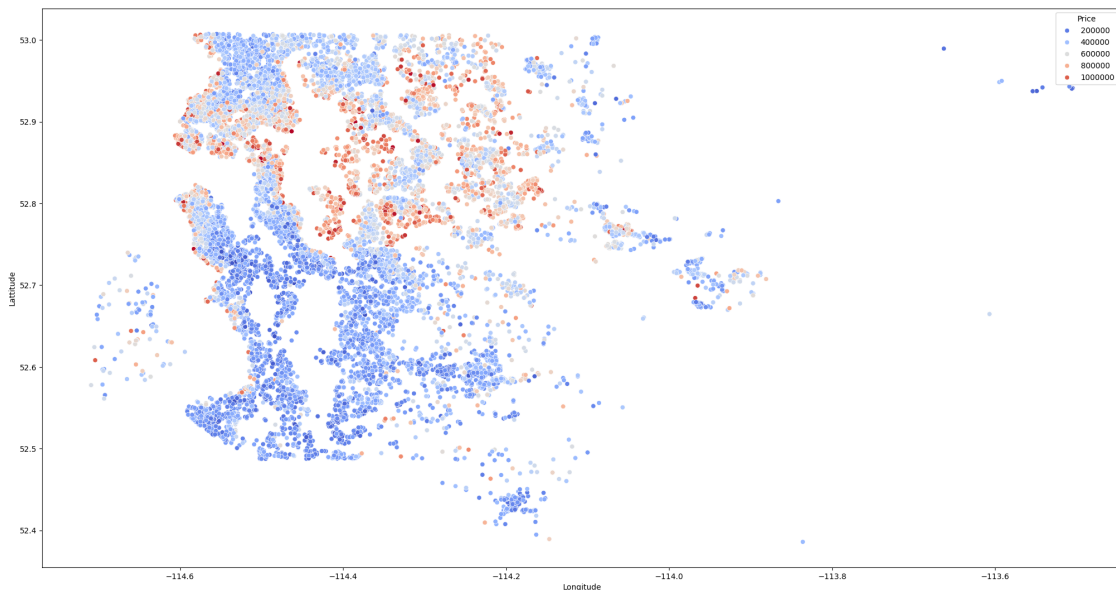
```

```

[11]: plt.figure(figsize=(25,13))
      sns.
      ↪scatterplot(x='Longitude',y='Latitude',data=data,hue='Price',palette='coolwarm')

[11]: <Axes: xlabel='Longitude', ylabel='Latitude'>

```



```

[12]: from sklearn.model_selection import train_test_split

```

```
[13]: x = data.drop(['Price'], axis=1) # Drop the 'Price' column from the dataframe
      ↪to use the rest as features
      y = data['Price']
```

```
[14]: x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2)
```

```
[15]: from sklearn.linear_model import LinearRegression
      from sklearn.preprocessing import StandardScaler
      from sklearn.pipeline import Pipeline

      pipe=Pipeline([
          ('scale',StandardScaler()),
          ('model',LinearRegression())
      ])
      #mod = LinearRegression()

      pipe.fit(x_train, y_train)
```

```
[15]: Pipeline(steps=[('scale', StandardScaler()), ('model', LinearRegression())])
```

```
[16]: pipe.predict(x_test) # Predicting the target values
```

```
[16]: array([568176.4472549 , 573986.47513395, 212987.23244887, ...,
          296507.17230239, 450129.31341638, 461056.23040878])
```

```
[28]: pred = pipe.predict(x_test)
      pipe.score(x_test, y_test)
```

```
[28]: 0.943424082250265
```

```
[33]: from sklearn.metrics import mean_absolute_error, root_mean_squared_error
      mae = mean_absolute_error(y_test, pred)
      rmse = root_mean_squared_error(y_test, pred)
      r2_score=pipe.score(x_test, y_test)

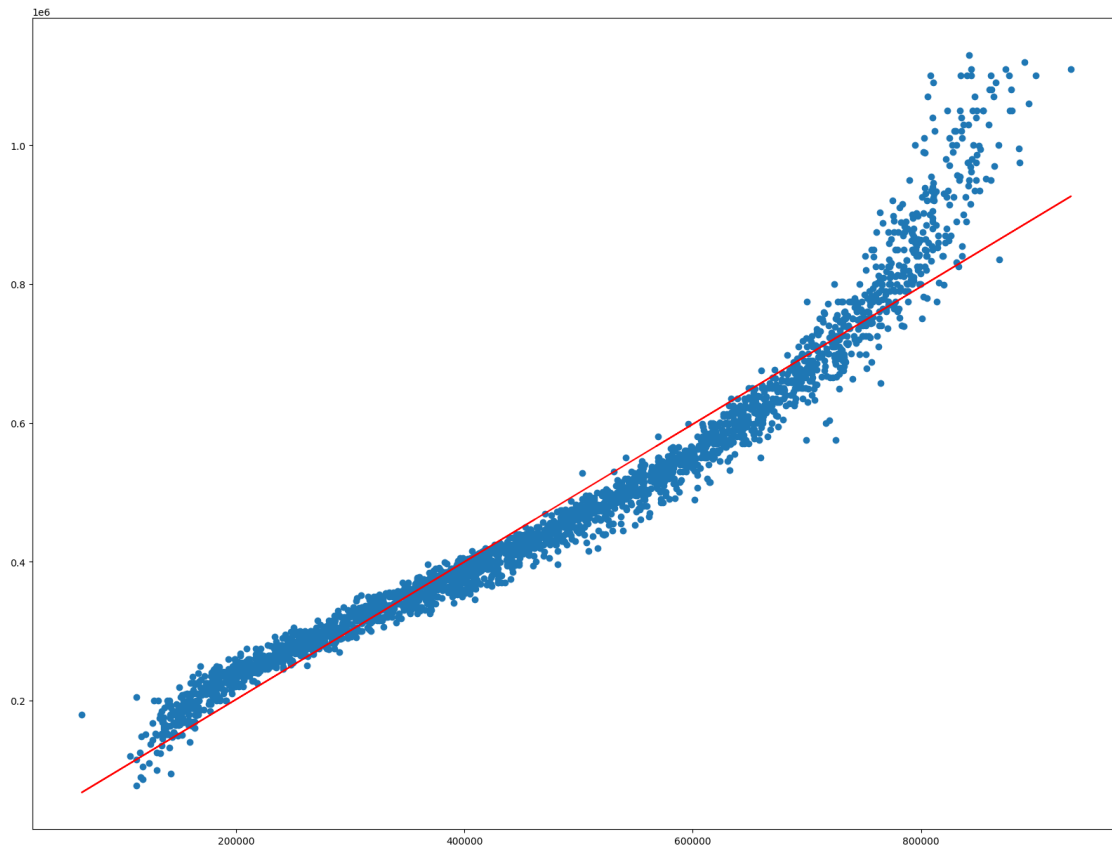
      print(f"Pipeline Model Evaluation:")
      print(f"- R2 Score: {r2_score:.2f}")
      print(f"- Mean Absolute Error (MAE): {mae:.2f}")
      print(f"- Root Mean Squared Error (RMSE): {rmse:.2f}")
```

```
Pipeline Model Evaluation:
- R2 Score: 0.94
- Mean Absolute Error (MAE): 35611.97
- Root Mean Squared Error (RMSE): 48895.75
```

```
[18]: plt.figure(figsize=(20,15))
      plt.scatter(pred,y_test)
      slope,intercept=np.polyfit(pred,y_test,1)
```

```
regression_line = slope * pred + intercept
plt.plot(pred, regression_line, color='red', label='Regression Line')
```

[18]: [<matplotlib.lines.Line2D at 0x22ed5295d10>]



```
[19]: from sklearn.neighbors import KNeighborsRegressor

knn = Pipeline([
    ('scale', StandardScaler()), # Feature scaling
    ('mod', KNeighborsRegressor()) # KNN model
])

# Fit the pipeline with the training data
knn.fit(x_train, y_train)
```

[19]: Pipeline(steps=[('scale', StandardScaler()), ('mod', KNeighborsRegressor())])

```
[34]: Knnpred = knn.predict(x_test) # Predicting the target values

mae = mean_absolute_error(y_test, Knnpred)
```

```

rmse = root_mean_squared_error(y_test, Knnpred)
r2_score=knn.score(x_test, y_test)

print(f"Pipeline Model Evaluation:")
print(f"- R2 Score: {r2_score:.2f}")
print(f"- Mean Absolute Error (MAE): {mae:.2f}")
print(f"- Root Mean Squared Error (RMSE): {rmse:.2f}")

```

Pipeline Model Evaluation:

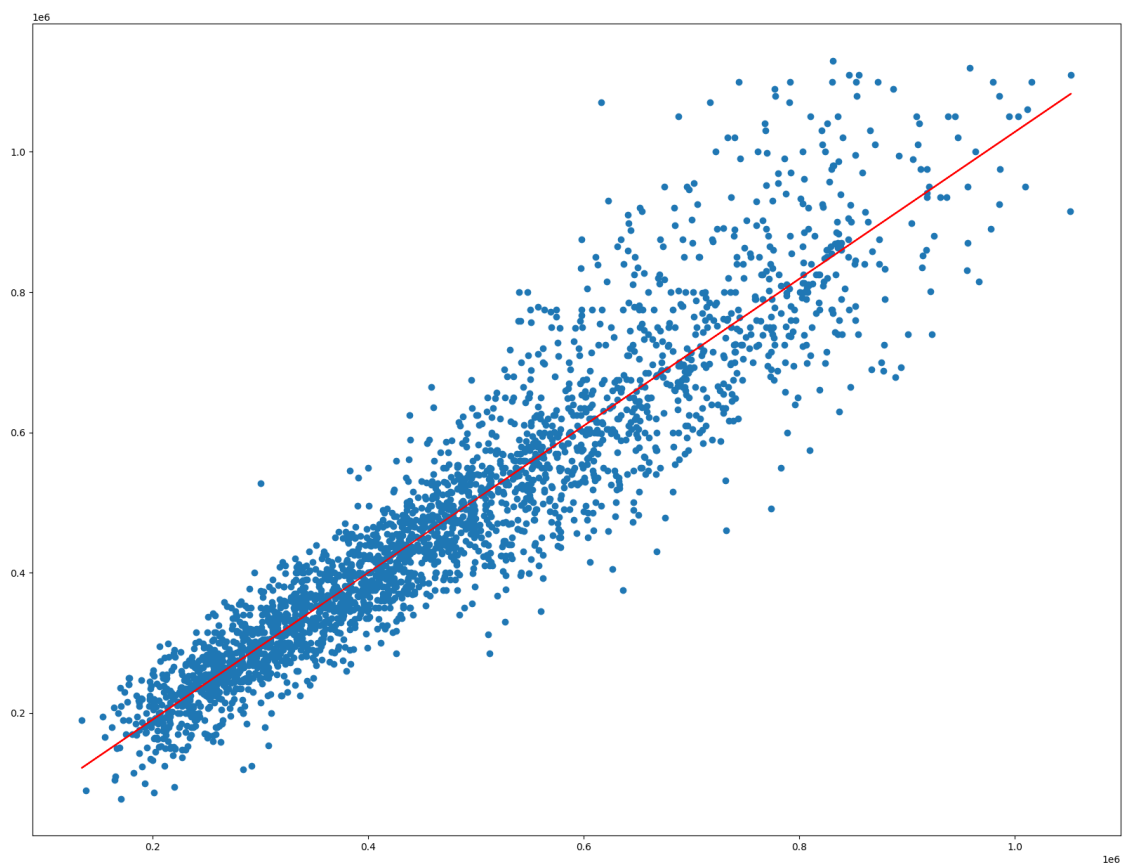
- R<sup>2</sup> Score: 0.87
- Mean Absolute Error (MAE): 51398.76
- Root Mean Squared Error (RMSE): 73307.49

```

[21]: plt.figure(figsize=(20,15))
plt.scatter(Knnpred,y_test)
slope,intercept=np.polyfit(Knnpred,y_test,1)
regression_line = slope * Knnpred + intercept
plt.plot(Knnpred, regression_line, color='red', label='Regression Line')

```

[21]: [





```
[22]: knn.get_params()
```

```
[22]: {'memory': None,
      'steps': [('scale', StandardScaler()), ('mod', KNeighborsRegressor())],
      'verbose': False,
      'scale': StandardScaler(),
      'mod': KNeighborsRegressor(),
      'scale__copy': True,
      'scale__with_mean': True,
      'scale__with_std': True,
      'mod__algorithm': 'auto',
      'mod__leaf_size': 30,
      'mod__metric': 'minkowski',
      'mod__metric_params': None,
      'mod__n_jobs': None,
      'mod__n_neighbors': 5,
      'mod__p': 2,
      'mod__weights': 'uniform'}
```

```
[23]: from sklearn.model_selection import GridSearchCV
      gridknn= GridSearchCV(estimator= knn,
                           param_grid={'mod__n_neighbors': [1,2,3,4,5,6,7,8,9,10]},
                           cv=3)
```

```
[24]: gridknn.fit(x_train,y_train)
      best_score = gridknn.best_score_

      print(f"Best k value: {best_score}")
```

Best k value: 0.8619226424775815

```
[35]: gridknn.score(x_test,y_test)

      gridknnpred = gridknn.predict(x_test) # Predicting the target values

      mae = mean_absolute_error(y_test, gridknnpred)
      rmse = root_mean_squared_error(y_test, gridknnpred)
      r2_score=gridknn.score(x_test, y_test)

      print(f"Pipeline Model Evaluation:")
      print(f"- R2 Score: {r2_score:.2f}")
      print(f"- Mean Absolute Error (MAE): {mae:.2f}")
      print(f"- Root Mean Squared Error (RMSE): {rmse:.2f}")
```

Pipeline Model Evaluation:

- R<sup>2</sup> Score: 0.88
- Mean Absolute Error (MAE): 50243.29
- Root Mean Squared Error (RMSE): 72401.31

```
[26]: from sklearn.ensemble import RandomForestRegressor
      rf = Pipeline([
          ('scale', StandardScaler()),
          ('rf', RandomForestRegressor())
      ])

      rf.fit(x_train, y_train)
      rfpred=rf.predict(x_test)
      rf.score(x_test, y_test)
```

[26]: 0.9999990391404829

```
[37]: mae = mean_absolute_error(y_test, rfpred)
      rmse = root_mean_squared_error(y_test, rfpred)
      r2_score=rf.score(x_test, y_test)

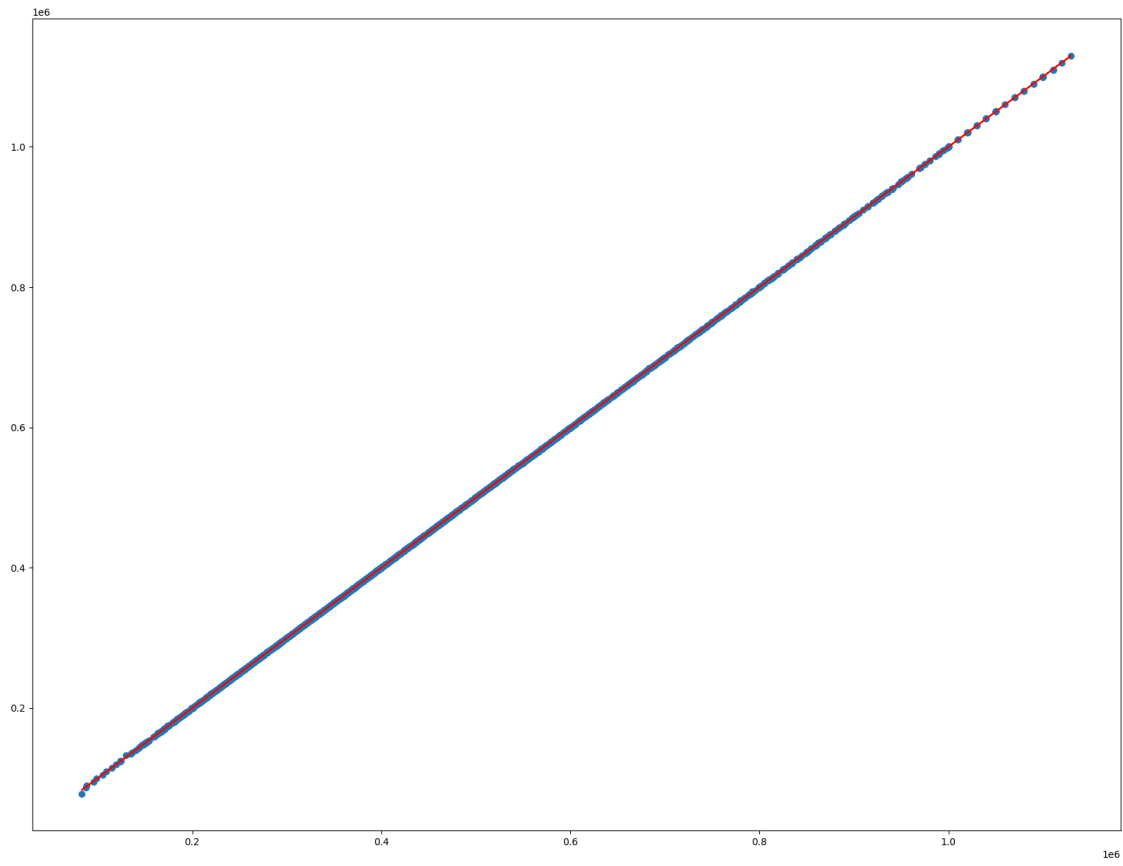
      print(f"Pipeline Model Evaluation:")
      print(f"- R2 Score: {r2_score:.9f}")
      print(f"- Mean Absolute Error (MAE): {mae:.2f}")
      print(f"- Root Mean Squared Error (RMSE): {rmse:.2f}")
```

Pipeline Model Evaluation:

- R<sup>2</sup> Score: 0.999999039
- Mean Absolute Error (MAE): 77.56
- Root Mean Squared Error (RMSE): 201.50

```
[38]: plt.figure(figsize=(20,15))
      plt.scatter(rfpred,y_test)
      slope,intercept=np.polyfit(rfpred,y_test,1)
      regression_line = slope * rfpred + intercept
      plt.plot(rfpred, regression_line, color='red', label='Regression Line')
```

[38]: [[matplotlib.lines.Line2D](#) at 0x22ee872c410>]



[ ]: