# **HOUSE PRICE PREDICTION**



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HOUSE PRICE PREDICTION

MITALI SAINI

### Introduction:

Increasing population in the world people looking to buy a new house as per their budget seem to be conservative and need more market strategy for house agents. As house price increase dramatically every year, there should a system to predict new house price according to the demand of people for house size, Bedroom size and location. This could really help real estate agents to decide house price for their clients. There are several methods proposed to determine house price ranges.

In the new technologically advanced world, there are several proposed methodologies used to predict price. It has been seen that machine learning is the reliable method to achieve this project. It aims to estimate the value of residential properties based on the dataset used which includes Bedrooms, Bathrooms, Size of the house, Zip Code, etc. Linear Regression and its techniques have been used which includes several steps to match needs and can give perfect prediction for the model.

### **Problem Statement:**

The problem statement for the project involves developing model that can accurately estimate the selling price. The goal is to create a reliable tool that can assist homeowners, buyerseal estate agents and investors in making informed decisions about buying, selling or investing in properties.

## **Tools used:**

**O Python**: modules: numpy, pandas, matplotlib, seaborn, scikit-learn, pickle, etc.

framework: Flask

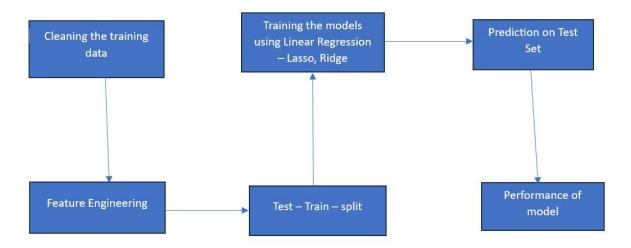
**O** Web Development tools:

Html, css, javascript

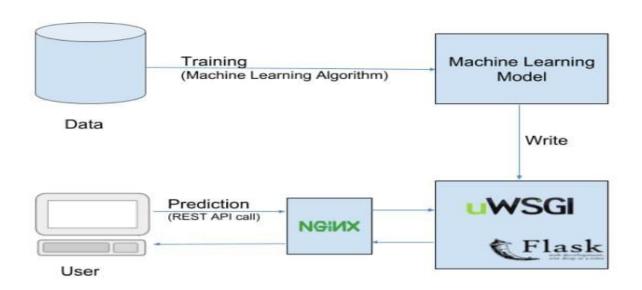
O Machine Learning Techniques:

Regression: Linear Regression, Lasso, Ridge

## **System Architecture:**



## **System Deployment Approach:**



### **Code and Analysis:**

### **Data Loading:**

```
: import numpy as np
  import pandas as pd
data = pd.read_csv("train.csv")
  data.head()
     beds baths
                   size size_units lot_size lot_size_units zip_code
             2.5 2590.0
  0
                              sqft 6000.00
                                                          98144 795000.0
                                                   sqft
             2.0 2240.0
                                      0.31
                                                           98106
                                                                  915000.0
                                                   acre
             3.0 2040.0
                              sqft 3783.00
                                                   sqft
                                                           98107
                                                                  950000.0
             3.0 3800.0
                              sqft 5175.00
                                                          98199 1950000.0
                                                   sqft
                                                                  950000.0
             2.0 1042.0
                              sqft
                                     NaN
                                                   NaN
                                                          98102
: data.shape
: (2016, 8)
```

### EDA:

Data Preprocessing and EDA

```
for column in data.columns:
   print(data[column].value_counts())
   print("*"*20)
beds
3
     645
2
     560
   398
4
   256
5
    123
     22
6
9
      5
7
       3
8
15
       1
Name: count, dtype: int64
************
baths
      627
2.0
1.0
      493
2.5
      282
```

```
data.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2016 entries, 0 to 2015
Data columns (total 8 columns):
 # Column
                 Non-Null Count Dtype
                  2016 non-null int64
2016 non-null float64
2016 non-null float64
0 beds
1 baths
 2
    size
3 size_units 2016 non-null object
                   1669 non-null float64
 4 lot_size
 5 lot_size_units 1669 non-null
                                  object
 6 zip_code 2016 non-null int64
                    2016 non-null float64
 7 price
dtypes: float64(4), int64(2), object(2)
memory usage: 126.1+ KB
data.isna().sum()
beds
                   0
baths
                   0
size
                  0
size units
                  0
lot_size
                 347
lot_size_units
                 347
zip_code
                  0
price
                   0
dtype: int64
data.drop(columns=['lot_size', 'lot_size_units'],inplace=True)
```

#### data.describe()

	beds	baths	size	zip_code	price
ount	2016.000000	2016.000000	2016.000000	2016.000000	2.016000e+03
nean	2.857639	2.159970	1735.740575	98123.638889	9.636252e+05
std	1.255092	1.002023	920.132591	22.650819	9.440954e+05
min	1.000000	0.500000	250.000000	98101.000000	1.590000e+05
25%	2.000000	1.500000	1068.750000	98108.000000	6.017500e+05
50%	3.000000	2.000000	1560.000000	98117.000000	8.000000e+05
<b>75</b> %	4.000000	2.500000	2222.500000	98126.000000	1.105250e+06
max	15.000000	9.000000	11010.000000	98199.000000	2.500000e+07

#### data.info()

```
RangeIndex: 2016 entries, 0 to 2015

Data columns (total 6 columns):

# Column Non-Null Count Dtype
-----
0 beds 2016 non-null int64
1 baths 2016 non-null float64
2 size 2016 non-null float64
3 size_units 2016 non-null object
4 zip_code 2016 non-null int64
5 price 2016 non-null float64
dtypes: float64(3), int64(2), object(1)
memory usage: 94.6+ KB
```

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

#### data.head()

	beds	baths	size	size_units	zip_code	price
0	3	2.5	2590.0	sqft	98144	795000.0
1	4	2.0	2240.0	sqft	98106	915000.0
2	4	3.0	2040.0	sqft	98107	950000.0
3	4	3.0	3800.0	sqft	98199	1950000.0
4	2	2.0	1042.0	saft	98102	950000.0

#### # Price per sq feet

```
data['price_per_sqft'] = data['price']*100000 / data['size']
```

#### data['price\_per\_sqft']

```
0 3.069498e+07
1 4.084821e+07
2 4.656863e+07
3 5.131579e+07
4 9.117083e+07
...
2011 6.642336e+07
2012 6.186727e+07
2013 5.373832e+07
2014 7.421384e+07
2015 3.853801e+07
```

Name: price\_per\_sqft, Length: 2016, dtype: float64

#### data.describe()

	beds	baths	size	zip_code	price	price_per_sqft
count	2016.000000	2016.000000	2016.000000	2016.000000	2.016000e+03	2.016000e+03
mean	2.857639	2.159970	1735.740575	98123.638889	9.636252e+05	5.915851e+07
std	1.255092	1.002023	920.132591	22.650819	9.440954e+05	8.327952e+07
min	1.000000	0.500000	250.000000	98101.000000	1.590000e+05	6.796117e+06
25%	2.000000	1.500000	1068.750000	98108.000000	6.017500e+05	4.452221e+07
50%	3.000000	2.000000	1560.000000	98117.000000	8.000000e+05	5.529762e+07
75%	4.000000	2.500000	2222.500000	98126.000000	1.105250e+06	6.595389e+07
max	15.000000	9.000000	11010.000000	98199.000000	2.500000e+07	3.424658e+09

#### data.shape

(2016, 7)

data

	beds	baths	size	size_units	zip_code	price	price_per_sqft
0	3	2.5	2590.0	sqft	98144	795000.0	3.069498e+07
1	4	2.0	2240.0	sqft	98106	915000.0	4.084821e+07
2	4	3.0	2040.0	sqft	98107	950000.0	4.656863e+07
3	4	3.0	3800.0	sqft	98199	1950000.0	5.131579e+07
4	2	2.0	1042.0	sqft	98102	950000.0	9.117083e+07

```
data.drop(columns=['size_units'],inplace=True)

data.drop(columns=['price_per_sqft'],inplace=True)

data.head()

beds baths size zip_code price
```

	beds	baths	size	zip_code	price
0	3	2.5	2590.0	98144	795000.0
1	4	2.0	2240.0	98106	915000.0
2	4	3.0	2040.0	98107	950000.0
3	4	3.0	3800.0	98199	1950000.0
4	2	2.0	1042.0	98102	950000.0

```
data.to_csv("final_dataset.csv")
```

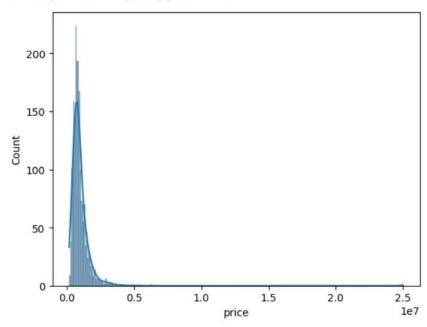
```
one_hot_encoded = pd.get_dummies(data['beds'], prefix='beds')
data_encoded = pd.concat([data, one_hot_encoded], axis=1)
print(data_encoded)
```

```
beds baths
                  size zip_code
                                     price beds_1 beds_2 beds_3 \
           2.5 2590.0
                           98144 795000.0
                                             False
                                                    False
                                                             True
            2.0 2240.0
                           98106
                                   915000.0
1
        4
                                             False
                                                    False
                                                            False
2
        4
            3.0 2040.0
                           98107
                                   950000.0
                                             False
                                                    False
                                                            False
            3.0 3800.0
                           98199 1950000.0
                                             False
                                                    False
                                                            False
4
            2.0 1042.0
                           98102
                                  950000.0
                                             False
                                                     True
                                                           False
                            ....
                                             False
            2.0 1370.0
                                  910000.0
                                                            True
2011
       3
                           98112
                                                    False
2012
       1
            1.0
                 889.0
                           98121
                                   550000.0
                                              True
                                                    False
                                                            False
2013
        4
            2.0 2140.0
                           98199 1150000.0
                                             False
                                                    False
                                                            False
2014
            2.0
                 795.0
                           98103
                                   590000.0
                                             False
                                                     True
                                                           False
            2.0 1710.0
                                             False
2015
                           98133
                                  659000.0
                                                    False
                                                            True
```

```
: import matplotlib.pyplot as plt
import seaborn as sns
```

```
sns.histplot(data['price'], kde=True)
```

```
: <AxesSubplot: xlabel='price', ylabel='Count'>
```

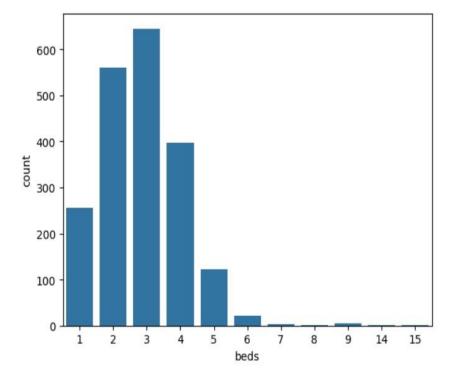




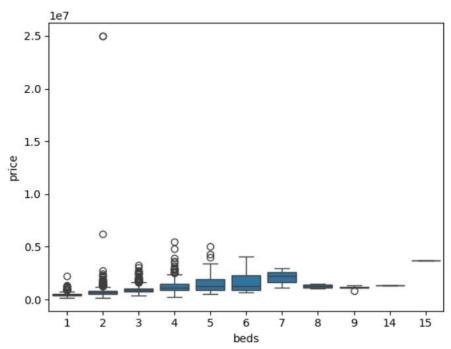


sns.countplot(x='beds', data=data)

: <AxesSubplot: xlabel='beds', ylabel='count'>



```
sns.boxplot(x='beds', y='price', data=data)
plt.show()
```



### **Modeling:**

```
X = data.drop(columns=['price'])
y = data['price']
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression,Lasso,Ridge
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import make_column_transformer
from sklearn.pipeline import make_pipeline
from sklearn.metrics import r2_score
X_train,X_test,y_train,y_test = train_test_split(X,y, test_size=0.2, random_state=0)
print(X_train.shape)
print(y_train.shape)
(1612, 4)
(1612,)
column_trans = make_column_transformer((OneHotEncoder(), ['beds']), remainder='passthrough')
scaler = StandardScaler()
lr = LinearRegression()
from sklearn.linear_model import LinearRegression
lr = LinearRegression()
```

```
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
# X being feature matrix
scaler = StandardScaler(with_mean=False)
X_scaled = scaler.fit_transform(X)
lr = LinearRegression()
lr.fit(X_scaled, y)

    LinearRegression

LinearRegression()
pipe = make_pipeline(column_trans,scaler, lr)
pipe.fit(X_train,y_train,)
                    Pipeline
    ▶ columntransformer: ColumnTransformer ②
         onehotencoder
                                  remainder
      ▶ OneHotEncoder
                               ▶ passthrough
                StandardScaler

    LinearRegression

y_pred_lr = pipe.predict(X_test)
r2_score(y_test,y_pred_lr)
0.5746822864697891
using Lasso
lasso = Lasso()
pipe = make_pipeline(column_trans,scaler, lasso)
pipe.fit(X_train,y_train)
                    Pipeline
    columntransformer: ColumnTransformer
         onehotencoder
                                 remainder
      ▶ OneHotEncoder
                               ▶ passthrough
               ▶ StandardScaler
                    ► Lasso
```

```
y_pred_lasso = pipe.predict(X_test)
r2_score(y_test,y_pred_lasso)
0.5746817917321105
using Ridge
ridge = Ridge()
pipe = make_pipeline(column_trans,scaler, ridge)
pipe.fit(X_train,y_train)
                    Pipeline
    columntransformer: ColumnTransformer
          onehotencoder
                                 remainder
      ▶ OneHotEncoder
                                ▶ passthrough
                StandardScaler
                    ► Ridge
y_pred_ridge = pipe.predict(X_test)
r2_score(y_test,y_pred_ridge)
0.5746891139050041
print("No Regularization: ", r2_score(y_test,y_pred_lr))
print("Lasso: ", r2_score(y_test,y_pred_lasso))
print("Ridge: ", r2_score(y_test,y_pred_ridge))
No Regularization: 0.5746822864697891
Lasso: 0.5746817917321105
Ridge: 0.5746891139050041
import pickle
pickle.dump(pipe, open('RidgeModel.pkl','wb'))
```

### Html code:

```
1
    <!DOCTYPE html>
 2
    <html lang="en">
3
    <head>
4
        <meta charset="UTF-8">
5
         <meta name="viewport" content="width=device-width, initial-scale=1.0">
 6
        <title>House Price Prediction</title>
 7
         <style>
 8
            body{
 9
                 font-family: Arial, sans-serif;
10
                margin: 0;
                padding: 0;
11
                background-color: □#f4f4;
12
13
14
             header{
15
                background-color: ■#333;
16
                color: □#fff;
17
                padding: 10px;
18
                text-align: center;
19
20
             main{
                max-width: 800px;
21
                margin: 20px auto;
22
23
                padding: 20px;
24
                background-color: □#fff;
                box-shadow: 0 0 10px ☐rgba(0, 0, 0, 0.1);
25
26
27
             footer{
28
                text-align: center;
29
                padding: 10px;
30
                background-color: #333;
31
                color: □#fff;
32
                position: fixed;
33
                bottom: 0;
34
                width: 100px;
35
36
             form{
37
                margin-top: 20px;
38
39
             label{
40
                display: block;
41
                margin-bottom: 16px;
42
             --1--+1
```

```
43
             select{
44
                 width: 100%;
45
                 padding: 8px;
46
                 margin-bottom: 16px;
47
48
             button{
49
                 background-color: #333;
50
                 color: □#fff;
51
                 padding: 10px;
52
                 border: none;
53
                 cursor: pointer;
54
55
             #predictedPrice{
56
                 margin-top: 20px;
57
                 font-weight: bold;
58
59
         </style>
60
     </head>
61
     <body>
62
         <header>
63
             <h1>House Price Prediction</h1>
64
         </header>
65
         <main>
             Welcome to House Price Prediction
66
67
     <form id="predictionForm">
68
        <label for="beds">Beds:</label>
69
         <select id="beds" name="beds">
             <option value"" disabled selected>Select no of bedrooms
70
71
             {% for bedroom in bedrooms %}
                 <option value="{{ bedroom }}">{{ bedroom }}</option>
72
73
             {% endfor %}
74
         </select>
75
         <label for="baths">Baths:</label>
76
         <select id="baths" name="baths">
77
             <option value"" disabled selected>Select no of bathrooms
78
             {% for bathroom in bathrooms %}
79
                 <option value="{{ bathroom }}">{{ bathroom }}</option>
80
             {% endfor %}
81
         </select>
         <label for="size">Size:</label>
82
```

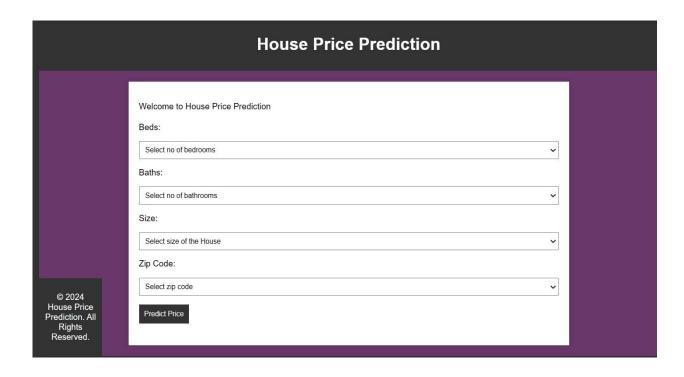
```
83
          <select id="size" name="size">
              <option value"" disabled selected>Select size of the House
 85
              {% for house_size in sizes %}
 86
                  <option value="{{ house_size }}">{{ house_size }}</option>
 87
              {% endfor %}
 88
          </select>
 89
          <label for="zip_code">Zip Code:</label>
 90
          <select id="zip_code" name="zip_code">
 91
              <option value"" disabled selected>Select zip code</option>
 92
              {% for zip_code in zip_codes %}
                  <option value="{{ zip_code }}">{{ zip_code }}</option>
 93
 94
              {% endfor %}
 95
          </select>
 96
          <button type="button" onclick="sendData()">Predict Price</button>
 97
          <div id="predictedPrice"></div>
 98
      </form>
99
          </main>
100
          <footer>
101
              © 2024 House Price Prediction. All Rights Reserved.
102
          </footer>
103
          <script>
104
              function fetchOptions(endpoint, dropdownId){
105
                   fetch(endpoint)
106
                       .then(response => response.json())
107
                       .then(data => {
                           const dropdown = document.getElementById(dropdownId);
108
109
                           dropdown.innerHTML = '<option value="" disabled selected>Select an option/;
110
                           data.forEach(option => {
111
                               const optionElement = document.createElement('option');
112
                               optionElement.value = option;
113
                               optionElement.textContent = option;
114
                               dropdown.appendChild(optionElement);
115
                          });
116
                      });
117
118
              window.onload = function(){
                  fetchOptions('/bedrooms', 'beds');
119
120
                  fetchOptions('/bathrooms', 'baths');
121
                  fetchOptions('/sizes', 'size');
122
                  fetchOptions('/zip_codes', 'zip_code');
 122
                   fetchOptions('/zip_codes', 'zip_code');
 123
               };
 124
               function sendData() {
 125
                   const form = document.getElementById('predictionForm');
 126
                   const formData = new FormData(form);
 127
                   fetch('/predict', {
                       method: 'POST',
 128
 129
                       body: formData
 130
 131
                   .then(response => response.text())
 132
                   .then(price => {
                       document.getElementById("predictedPrice").innerHTML = "Price: INR " + price;
 133
 134
                   });
 135
 136
           </script>
 137
       </body>
 138
       </html>--
```

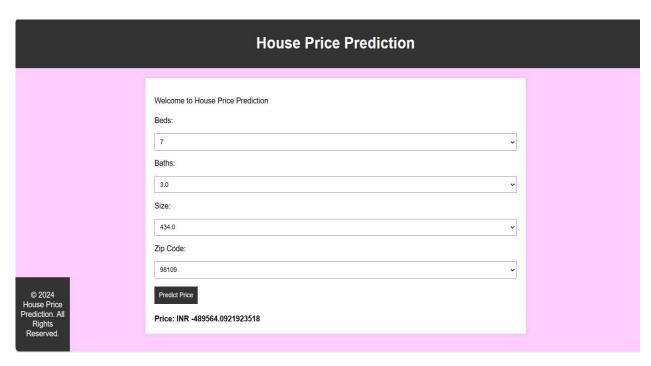
### Main file:

```
from flask import Flask, render_template, request, jsonify
import pandas as pd
import pickle
app = Flask(__name__, template_folder='templates')
data = pd.read_csv('final_dataset.csv')
pipe = pickle.load(open("RidgeModel.pkl", 'rb'))
@app.route('/index')
def index():
   bedrooms = sorted(data['beds'].unique())
    bathrooms = sorted(data['baths'].unique())
   sizes = sorted(data['size'].unique())
   zip_codes = sorted(data['zip_code'].unique())
   return render_template('house.html', bedrooms=bedrooms, bathrooms=bathrooms, sizes=sizes, zip_codes=zip_codes)
@app.route('/predict',methods=['POST'])
def predict():
   bedrooms = request.form.get('beds')
    bathrooms = request.form.get('baths')
   size = request.form.get('size')
   zipcode = request.form.get('zip_code')
    #create a dataframe with input data
    input_data = pd.DataFrame([[bedrooms, bathrooms, size, zipcode]], columns=['beds', 'baths', 'size', 'zip_code'])
    print("Input data: ")
   print(input_data)
    # Handle unknown categories in the input data
    for column in input data.columns:
       unknown_categories = set(input_data[column]) - set(data[column].unique())
       if unknown_categories:
           input_data[column] = input_data[column].replace(unknown_categories, data[column].mode()[0])
    print("Preprocessed Input Data: ")
    print(input_data)
    # predict the price
    prediction = pipe.predict(input_data)[0]
    return str(prediction)
from flask import Flask, render_template, request, jsonify
import pandas as pd
```

```
app = Flask(__name__)
data = pd.read_csv('final_dataset.csv')
pipe = pickle.load(open("RidgeModel.pkl", 'rb'))
@app.route('/')
def index():
   bedrooms = sorted(data['beds'].unique())
   bathrooms = sorted(data['baths'].unique())
    sizes = sorted(data['size'].unique())
   zip_codes = sorted(data['zip_code'].unique())
    return render_template('house.html', bedrooms=bedrooms, bathrooms=bathrooms, sizes=sizes, zip_codes=zip_codes)
@app.route('/predict',methods=['POST'])
def predict():
   bedrooms = request.form.get('beds')
    bathrooms = request.form.get('baths')
    size = request.form.get('size')
   zipcode = request.form.get('zip_code')
    #create a dataframe with input data
   input_data = pd.DataFrame([[bedrooms, bathrooms, size, zipcode]], columns=['beds', 'baths', 'size', 'zip_code'])
   print("Input data: ")
   print(input_data)
    # convert 'baths' column to numeric with errors='coerce'
    input_data['baths'] = pd.to_numeric(input_data['baths'], errors='coerce')
    # convert input data to numeric types
    input_data = input_data.astype({'beds': int, 'baths': float, 'size': float, 'zip_code': int})
    # Handle unknown categories in the input data
    for column in input_data.columns:
        unknown_categories = set(input_data[column]) - set(data[column].unique())
        if unknown categories:
            print(f"Unknown categories in {column}: {unknown_categories}")
            input\_data[column] = input\_data[column].replace(unknown\_categories, \ data[column].mode()[\emptyset])
    print("Preprocessed Input Data: ")
    print(input_data)
    # predict the price
    prediction = pipe.predict(input_data)[0]
   return str(prediction)
if __name__ == "__main__":
   app.run(debug=True)
if __name__ == "__main__":
   app.run(debug=True)
```

## **Result:**





### **Conclusion:**

The results have shown the predicted price of a house with a particular zip code, number of bedrooms, no of bathrooms and size of house.

### **Future Scope:**

- Geospatial Analysis and Visualization
- O Integration with Blockchain Technology
- Fine-Tuning of models with Time Series
- O Integration of External APIs
- Expansion of International Markets