# **HOUSE PRICE PREDICTION**

# **Phase 1:Problem Definition and Design Thinking**

# **Problem Definition:**

The housing market is a pivotal sector that profoundly impacts individuals and families by representing one of the most substantial investments in their lifetimes. Accurate house price prediction is paramount to empower both buyers and sellers with the information they need to make well-informed decisions. This project aims to leverage machine learning techniques to predict house prices based on a comprehensive set of features, including but not limited to location, square footage, number of bedrooms and bathrooms, and other pertinent factors.

# **Design Thinking:**

# Collection Data and Integration:

We will collect and consolidate a diverse dataset comprising historical housing information, encompassing details such as property characteristics, transaction history, and location attributes. This dataset will serve as the foundation for our predictive model.

# Data Preprocessing and Feature Engineering:

Prior to modeling, we will preprocess the data, addressing issues such as missing values, outliers, and feature scaling. Additionally, we will engineer new features to extract valuable insights and relationships from the raw data.

# Model Development:

Employing state-of-the-art machine learning algorithms, including but not limited to linear regression, decision trees, and gradient boosting, we will develop predictive models capable of estimating house prices accurately.

# **Hyperparameter Tuning:**

To optimize model performance, we will conduct hyperparameter tuning using techniques such as grid search or random search, ensuring that our models are fine-tuned to the specific characteristics of the data.

#### Model Evaluation:

We will rigorously evaluate the models using appropriate evaluation metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) to assess their predictive accuracy.

# Validation and Testing:

To measure the model's generalization capabilities, we will validate its performance on a holdout testing dataset, assessing its ability to make accurate predictions on previously unseen data.

# Interpretability and Explainability:

In addition to predictive accuracy, we will aim to make our models interpretable and explainable, enabling stakeholders to understand the rationale behind the price predictions.

#### **Ethical Considerations:**

We will proactively address potential biases in the data to ensure fairness in predictions, avoiding discrimination related to factors such as race, gender, or socioeconomic status

# Privacy and Security:

The handling of sensitive data, including personal information, will strictly adhere to privacy regulations and security best practices.

# Deployment and Integration:

Once a satisfactory model is achieved, we will deploy it in a production environment where it can provide real-time house price predictions, potentially integrated into a user-friendly platform.

#### Continuous Monitoring and Maintenance:

Regular model updates, data refreshes, and performance monitoring will be conducted to ensure the model remains accurate and relevant over time.

# Dataset:

The dataset used in the project is USA\_Hosing. which is downloaded from kaagle. Kaagle is a subsidiary of Google, it is an online community of data scientists and machine learning engineers. Kaggle allows users to find datasets they want to use in building AI models, publish datasets, work with other data scientists and machine learning engineers, and enter competitions to solve data science challenges. The link for the dataset is given below.

Dataset Link: https://www.kaggle.com/datasets/vedavyasv/usa-housing

# Data Preprocessing:

Data preprocessing includes methods like data cleaning, data transformation, data reduction, handling imbalanced data, data visualization etc..

# Model Training:

Feed the training data into the model and use an optimization algorithm (e.g., gradient descent) to update the model's parameters to minimize a loss function. This process involves iteratively adjusting the model's weights to make better predictions.

# Coding:

# **#Predicting House Prices using Machine Learning**

# #Import Modules

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
from sklearn import metrics
from sklearn.model_selection import train_test_split
%matplotlib inline
from sklearn.metrics import r2_score
import warnings
```

#### #Load the housing dataset

```
data=pd.read csv('/content/USA Housing.csv')
data
      Avg. Area Income Avg. Area House Age Avg. Area Number of Rooms
0
          79545.458574
                                    5.682861
                                                                7.009188
          79248.642455
                                    6.002900
                                                                6.730821
          61287.067179
                                                                8.512727
2
                                    5.865890
                                                                5.586729
3
          63345.240046
                                    7.188236
          59982.197226
                                    5.040555
                                                                7.839388
4995
          60567.944140
                                    7.830362
                                                                6.137356
          78491.275435
4996
                                    6.999135
                                                                6.576763
4997
          63390.686886
                                    7.250591
                                                                4.805081
4998
          68001.331235
                                    5.534388
                                                                7.130144
4999
          65510.581804
                                                                6.792336
                                    5.992305
```

```
Avg. Area Number of Bedrooms
                                      Area Population
                                                               Price
0
                               4.09
                                         23086.800503
                                                        1.059034e+06
1
                               3.09
                                         40173.072174
                                                        1.505891e+06
2
                               5.13
                                         36882.159400
                                                        1.058988e+06
3
                               3.26
                                         34310.242831
                                                        1.260617e+06
4
                               4.23
                                         26354.109472
                                                        6.309435e+05
                                 . . .
4995
                                3.46
                                         22837.361035
                                                        1.060194e+06
                                         25616.115489
                                                        1.482618e+06
4996
                               4.02
4997
                               2.13
                                         33266.145490
                                                        1.030730e+06
4998
                               5.44
                                         42625.620156
                                                        1.198657e+06
                               4.07
4999
                                         46501.283803
                                                        1.298950e+06
                                                   Address
      208 Michael Ferry Apt. 674\nLaurabury, NE 3701...
0
1
      188 Johnson Views Suite 079\nLake Kathleen, CA...
2
      9127 Elizabeth Stravenue\nDanieltown, WI 06482...
3
                               USS Barnett\nFP0 AP 44820
4
                              USNS Raymond\nFPO AE 09386
4995
                        USNS Williams\nFPO AP 30153-7653
4996
                   PSC 9258, Box 8489\nAPO AA 42991-3352
4997
      4215 Tracy Garden Suite 076\nJoshualand, VA 01...
                               USS Wallace\nFPO AE 73316
4998
4999
      37778 George Ridges Apt. 509\nEast Holly, NV 2...
[5000 rows \times 7 columns]
```

#### #Preprocess the data

```
data.head()
                      Avg. Area House Age
                                            Avg. Area Number of Rooms
   Avg. Area Income
0
       79545.458574
                                 5.682861
                                                              7.009188
1
       79248.642455
                                 6.002900
                                                              6.730821
2
       61287.067179
                                 5.865890
                                                              8.512727
3
       63345.240046
                                 7.188236
                                                              5.586729
4
       59982.197226
                                 5.040555
                                                              7.839388
   Avg. Area Number of Bedrooms
                                  Area Population
                                                            Price \
0
                            4.09
                                                    1.059034e+06
                                      23086.800503
1
                            3.09
                                      40173.072174
                                                    1.505891e+06
2
                            5.13
                                      36882.159400
                                                    1.058988e+06
3
                            3.26
                                      34310.242831
                                                    1.260617e+06
4
                            4.23
                                      26354.109472
                                                    6.309435e+05
                                               Address
   208 Michael Ferry Apt. 674\nLaurabury, NE 3701...
   188 Johnson Views Suite 079\nLake Kathleen, CA...
  9127 Elizabeth Stravenue\nDanieltown, WI 06482...
```

```
3
                            USS Barnett\nFP0 AP 44820
4
                          USNS Raymond\nFPO AE 09386
data.shape
(5000, 7)
data.columns
Index(['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number of
Rooms',
       'Avg. Area Number of Bedrooms', 'Area Population', 'Price',
'Address'],
      dtype='object')
data.isnull().sum
<bound method NDFrame._add_numeric_operations.<locals>.sum of
Avg. Area Income Avg. Area House Age Avg. Area Number of Rooms
                 False
                                       False
                                                                   False
1
                 False
                                       False
                                                                   False
2
                 False
                                       False
                                                                   False
3
                 False
                                       False
                                                                   False
4
                 False
                                       False
                                                                   False
4995
                 False
                                       False
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4996
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                 False
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4998
                 False
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4999
                 False
                                       False
                                                                   False
                                     Area Population
      Avg. Area Number of Bedrooms
                                                      Price Address
0
                              False
                                               False
                                                      False
                                                                False
1
                              False
                                               False
                                                      False
                                                                False
2
                              False
                                               False
                                                      False
                                                                False
3
                                               False False
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4
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4995
                                                                False
4996
                              False
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                                                      False
                                                                False
4997
                              False
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                                                      False
                                                                False
```

4998 4999		False False	False False		False False			
[5000 rows x 7 columns]>								
data.info								
<pre><bound 0<="" \="" age="" area="" avg.="" dataframe.info="" house="" income="" method="" number="" of="" rooms="" td=""></bound></pre>								
0	79545.458574				7.009188			
1	79248.642455	6.00	2900		6.730821			
2	61287.067179	5.86	5890		8.512727			
3	63345.240046	7.18	8236		5.586729			
4	59982.197226	5.04	0555		7.839388			
4995	60567.944140	7.83	9362		6.137356			
4996	78491.275435	6.99	9135		6.576763			
4997	63390.686886	7.25	0591		4.805081			
4998	68001.331235	5.53	4388		7.130144			
4999	65510.581804	5.99	2305		6.792336			
0 1 2 3 4  4995 4996 4997	Avg. Area Number of Be	4.09 3.09 5.13 3.26 4.23  3.46 4.02 2.13	a Population 23086.800503 40173.072174 36882.159400 34310.242831 26354.109472  22837.361035 25616.115489 33266.145490	1.059034e 1.505891e 1.058988e 1.260617e 6.309435e 1.060194e 1.482618e 1.030730e	+06 +06 +05  +06 +06 +06			
4998 4999			42625.620156 46501.283803	1.198657e 1.298950e				
0 1 2 3 4	Address 208 Michael Ferry Apt. 674\nLaurabury, NE 3701 188 Johnson Views Suite 079\nLake Kathleen, CA 9127 Elizabeth Stravenue\nDanieltown, WI 06482 USS Barnett\nFPO AP 44820 USNS Raymond\nFPO AE 09386							

```
USNS Williams\nFPO AP 30153-7653
4995
4996
                  PSC 9258, Box 8489\nAPO AA 42991-3352
     4215 Tracy Garden Suite 076\nJoshualand, VA 01...
4997
4998
                              USS Wallace\nFPO AE 73316
     37778 George Ridges Apt. 509\nEast Holly, NV 2...
4999
[5000 \text{ rows } \times 7 \text{ columns}] >
data.describe
House Age Avg. Area Number of Rooms \
          79545.458574
                                   5.682861
                                                               7.009188
          79248.642455
                                   6.002900
                                                               6.730821
1
          61287.067179
                                                               8.512727
2
                                   5.865890
          63345.240046
                                                               5.586729
                                   7.188236
          59982.197226
                                   5.040555
                                                               7.839388
4995
          60567.944140
                                   7.830362
                                                               6.137356
4996
          78491.275435
                                   6.999135
                                                               6.576763
4997
          63390.686886
                                   7.250591
                                                               4.805081
4998
          68001.331235
                                   5.534388
                                                              7.130144
4999
          65510.581804
                                   5.992305
                                                               6.792336
     Avg. Area Number of Bedrooms
                                    Area Population
                                                            Price \
0
                              4.09
                                       23086.800503
                                                     1.059034e+06
1
                              3.09
                                       40173.072174
                                                     1.505891e+06
2
                              5.13
                                       36882.159400
                                                     1.058988e+06
3
                              3.26
                                       34310.242831
                                                     1.260617e+06
4
                              4.23
                                       26354.109472
                                                     6.309435e+05
. . .
                               . . .
                                       22837.361035
                                                     1.060194e+06
4995
                              3.46
4996
                              4.02
                                       25616.115489
                                                     1.482618e+06
                                       33266.145490
                              2.13
4997
                                                     1.030730e+06
4998
                              5.44
                                       42625.620156
                                                     1.198657e+06
4999
                              4.07
                                       46501.283803
                                                     1.298950e+06
                                                Address
      208 Michael Ferry Apt. 674\nLaurabury, NE 3701...
0
```

```
1
      188 Johnson Views Suite 079\nLake Kathleen, CA...
2
      9127 Elizabeth Stravenue\nDanieltown, WI 06482...
3
                               USS Barnett\nFP0 AP 44820
4
                              USNS Raymond\nFPO AE 09386
4995
                        USNS Williams\nFPO AP 30153-7653
                  PSC 9258, Box 8489\nAP0 AA 42991-3352
4996
4997
      4215 Tracy Garden Suite 076\nJoshualand, VA 01...
                               USS Wallace\nFPO AE 73316
4998
4999 37778 George Ridges Apt. 509\nEast Holly, NV 2...
[5000 \text{ rows x 7 columns}] >
```

# #Model Training

```
x=data.iloc[:, :-1]
      Avg. Area Income Avg. Area House Age Avg. Area Number of Rooms
0
          79545.458574
                                    5.682861
                                                                 7.009188
          79248.642455
                                    6.002900
                                                                 6.730821
2
          61287.067179
                                    5.865890
                                                                 8.512727
                                                                 5.586729
          63345.240046
                                    7.188236
          59982.197226
                                    5.040555
                                                                 7.839388
          60567.944140
                                    7.830362
                                                                 6.137356
4995
4996
          78491.275435
                                    6.999135
                                                                 6.576763
4997
          63390.686886
                                    7.250591
                                                                 4.805081
4998
          68001.331235
                                    5.534388
                                                                 7.130144
4999
                                                                 6.792336
          65510.581804
                                    5.992305
                                     Area Population
      Avg. Area Number of Bedrooms
                                                               Price
                               4.09
                                         23086.800503
0
                                                       1.059034e+06
                               3.09
1
                                         40173.072174
                                                       1.505891e+06
2
                               5.13
                                         36882.159400
                                                       1.058988e+06
3
                               3.26
                                         34310.242831
                                                       1.260617e+06
                               4.23
4
                                         26354.109472
                                                       6.309435e+05
```

```
4995
                               3.46
                                        22837.361035
                                                      1.060194e+06
4996
                              4.02
                                        25616.115489
                                                      1.482618e+06
4997
                              2.13
                                        33266.145490
                                                      1.030730e+06
4998
                               5.44
                                        42625.620156
                                                      1.198657e+06
4999
                              4.07
                                        46501.283803
                                                      1.298950e+06
[5000 rows x 6 columns]
y=data.iloc[:, -1]
У
        208 Michael Ferry Apt. 674\nLaurabury, NE 3701...
1
        188 Johnson Views Suite 079\nLake Kathleen, CA...
2
        9127 Elizabeth Stravenue\nDanieltown, WI 06482...
3
                                USS Barnett\nFP0 AP 44820
4
                                USNS Raymond\nFPO AE 09386
4995
                         USNS Williams\nFP0 AP 30153-7653
4996
                    PSC 9258, Box 8489\nAP0 AA 42991-3352
4997
        4215 Tracy Garden Suite 076\nJoshualand, VA 01...
                                USS Wallace\nFPO AE 73316
4998
4999
        37778 George Ridges Apt. 509\nEast Holly, NV 2...
Name: Address, Length: 5000, dtype: object
x train,x test,y train,y test=train test split(x,y,test size=0.2,rando
m state=4)
x train
      Avg. Area Income Avg. Area House Age Avg. Area Number of Rooms
476
          84439.855749
                                    4.313978
                                                               7.698765
2298
          70689.364339
                                    5.865246
                                                                6.462900
3813
          71068.996114
                                    4.746896
                                                               9.387913
          74497.673077
                                    6.166026
                                                               8.142658
4538
1068
          79575.641539
                                    4.970709
                                                               5.850243
3671
          67097.092120
                                                                7.211963
                                    6.086754
709
          62357.030953
                                                                7.126592
                                    6.725271
2487
          79687.761870
                                    6.010368
                                                                7.337394
174
          83347.669697
                                    5.468158
                                                               5.475253
```

1146	65846.171039	6.385374	6.804131				
476 2298 3813 4538 1068	Avg. Area Number o	of Bedrooms Area Population 4.48 19835.247317 3.29 21350.099746 6.20 35724.018492 4.01 28160.457535 4.04 31050.102814	1.242422e+06 9.730686e+05 1.355557e+06 1.204753e+06				
3671 709 2487 174 1146		3.05 27191.506877 5.00 23382.539386 6.09 20867.669885 3.14 48226.718928 3.18 28214.363551	9.724178e+05 1.360101e+06 1.453382e+06				
[4000 rows x 6 columns]							
x_tes	t						
\	Avg. Area Income	Avg. Area House Age Avg. A	rea Number of Rooms				
2175	66083.165901	4.213323	8.908381				
3156	56180.591431	6.201921	7.180671				
337	77733.731186	5.624500	5.967832				
444	47065.053303	5.767575	7.266028				
2334	71028.175896	3.895831	6.623776				
		• • •					
1862	60288.475915	6.170239	7.014315				
1028	61839.767863	7.740113	5.937847				
4430	78529.527679	7.060888	7.634762				
3025	56505.827795	5.300534	7.795375				
1807	61264.201530	4.944536	7.322068				
2175 3156 337 444	Avg. Area Number o	4.1739185.9950344.2741036.2841523.2332074.5759865.4924125.875810	1.051173e+06 1.139073e+06 1.236932e+06 5.668962e+05				
2334		2.50 43922.630172	9.346104e+05				

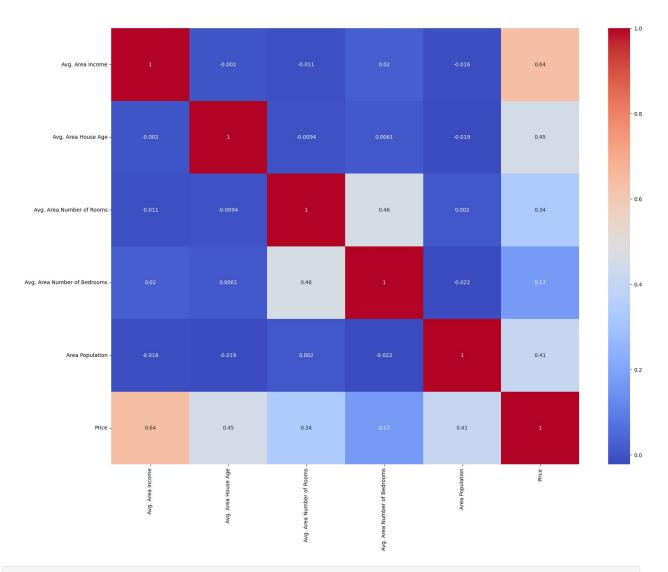
```
1862
                               3.28
                                        34651.072317
                                                       1.144938e+06
1028
                               3.24
                                        26064.820316
                                                       9.615391e+05
                                                       1.578087e+06
                               5.20
                                        23897.116272
4430
3025
                               3.43
                                        30995.488167
                                                       9.764817e+05
                               3.32
                                        43208.356563 7.647561e+05
1807
[1000 \text{ rows } \times 6 \text{ columns}]
y train
476
             125 Jesse Spring\nNew Benjaminberg, NY 16741
2298
                          PSC 7179, Box 6714\nAPO AA 57159
3813
                            USNV Wright\nFP0 AA 70734-4928
        03161 Lori Meadows Suite 563\nAndersonfurt, MT...
4538
1068
        4827 Kelsey Glen Suite 220\nMichaeltown, MD 34529
        052 Thomas Square Apt. 034\nWrightmouth, OR 04272
3671
709
                          PSC 9682, Box 5865\nAPO AA 11465
2487
        932 Schwartz Park Suite 892\nSouth Brian, CT 5...
             0647 Ramirez Hill\nNew Crystalport, AZ 33060
174
1146
        12315 Johnson Corners Suite 788\nWest Tyler, W...
Name: Address, Length: 4000, dtype: object
y_test
2175
        54042 Proctor Corner Apt. 796\nNew Staceyville...
3156
         121 Morris Rue Apt. 772\nWillisborough, NM 03840
337
                    672 Larson Ramp\nRobertside, NC 16903
444
        006 Miller Orchard Suite 211\nPort Louis, WY 0...
                3757 Price Rue\nEast Colin, MD 62622-8672
2334
1862
        0163 Samantha Coves Apt. 848\nPort Heidiville,...
1028
                          PSC 9596, Box 0250\nAP0 AE 81289
4430
             2631 Ellis Walk\nSamanthatown, VT 51809-6834
3025
                   770 Cole Rest\nLunafurt, FL 70678-5139
1807
            0995 Olivia Land Apt. 728\nAlexport, CA 92200
Name: Address, Length: 1000, dtype: object
x train = x train.iloc[:, 1:]
x test = x test.iloc[:, 1:]
x train["Avg. Area Number of Rooms"].value counts()
7.698765
7,253766
            1
            1
8.787825
            1
7.768934
9.098980
            1
4.242191
            1
```

```
6.478152  1
8.025554  1
6.769326  1
6.804131  1
Name: Avg. Area Number of Rooms, Length: 4000, dtype: int64

make_train = x_train["Avg. Area Number of Rooms"].str.split(" ", expand=True)
make_test = x_test["Avg. Area Number of Rooms"].str.split(" ", expand=True)
```

#### #Visualize

```
plt.figure(figsize=(20, 15))
correlations = data.corr()
sns.heatmap(correlations, cmap="coolwarm", annot=True)
plt.show()
<ipython-input-23-555d4168b84a>:2: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it
will default to False. Select only valid columns or specify the value
of numeric_only to silence this warning.
    correlations = data.corr()
```



```
sns.set_style("darkgrid")
plt.figure(figsize=(15, 10))
sns.distplot(data.Price)
plt.show()
```

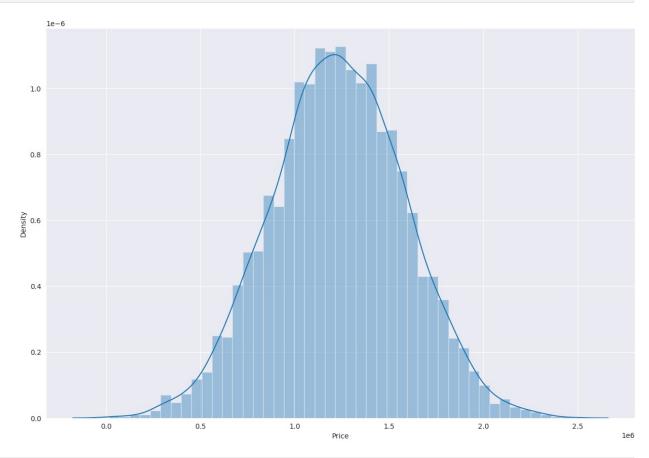
<ipython-input-30-a70e66c40847>:3: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

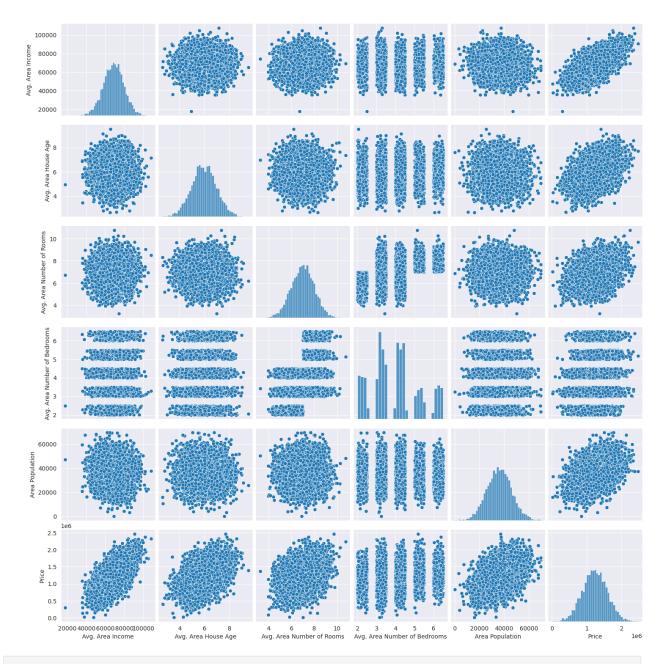
# sns.distplot(data.Price)



```
missing_cols = set(x_train.columns) - set(x_test.columns)
for col in missing_cols:
    x_test[col] = 0
x_test = x_test[x_train.columns]
```

#Exploratory Data Analysis

```
sns.pairplot(data)
<seaborn.axisgrid.PairGrid at 0x7a999352eec0>
```



sns.distplot(data['Price'])

<ipython-input-32-049e7ab17fe1>:1: UserWarning:

'distplot' is a deprecated function and will be removed in seaborn v0.14.0.

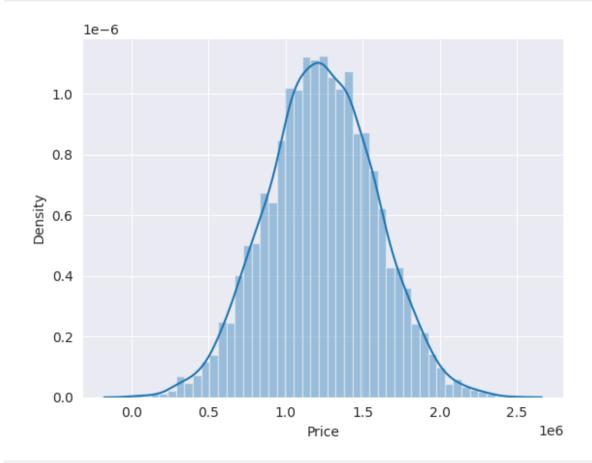
Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see

https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

sns.distplot(data['Price'])

<Axes: xlabel='Price', ylabel='Density'>



sns.heatmap(data.corr(), annot=True)

<ipython-input-34-b699050ce883>:1: FutureWarning: The default value of numeric\_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric\_only to silence this warning.

sns.heatmap(data.corr(), annot=True)

<Axes: >

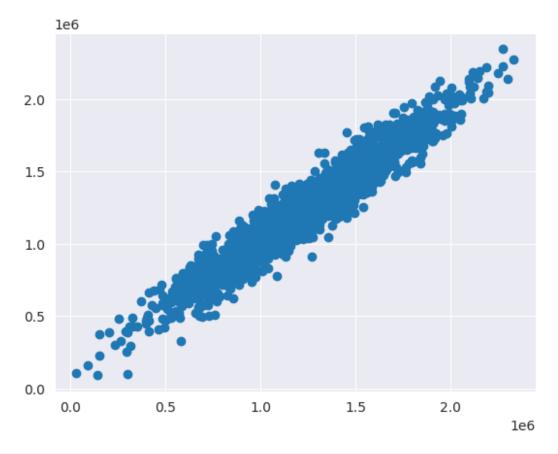


#### #Linear Regression

# -2640159.7968526953 coeff\_df = pd.DataFrame(lm.coef\_,X.columns,columns=['Coefficient']) coeff\_df Coefficient Avg. Area Income 21.528276 Avg. Area House Age 164883.282027 Avg. Area Number of Rooms 122368.678027 Avg. Area Number of Bedrooms 2233.801864 Area Population 15.150420

# #Prediction from Linear Regression

```
predictions = lm.predict(X_test)
plt.scatter(y_test,predictions)
<matplotlib.collections.PathCollection at 0x7a9986443970>
```



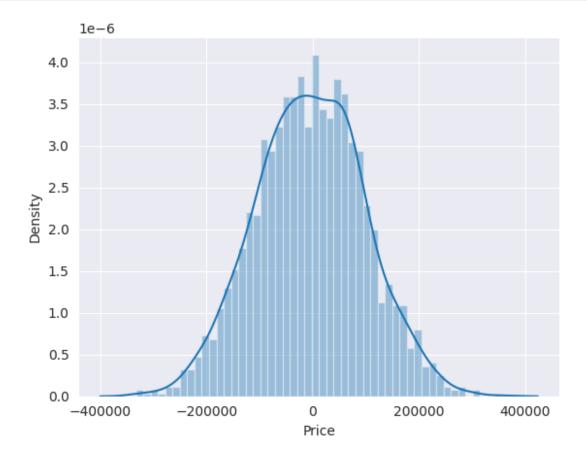
```
sns.distplot((y_test-predictions),bins=50);
<ipython-input-49-5f2bc21c0ef7>:1: UserWarning:
```

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

sns.distplot((y\_test-predictions),bins=50);



#### #Regression Evaluation Metrics

```
print('MAE:', metrics.mean_absolute_error(y_test, predictions))
print('MSE:', metrics.mean_squared_error(y_test, predictions))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, predictions)))

MAE: 82288.22251914942
MSE: 10460958907.208977
RMSE: 102278.82922290897
```

By the representation of above predicted models, the data are accurately predicted