Predicting House Prices using Machine Learning

Problem Definition and Design Thinking :

In this part you will need to understand the problem statement and create a document on what have you understood and how will you proceed ahead with solving the problem .Please think on a design and present in form of a document.

Problem Definition : The problem is to predict house prices using machine learning techniquies .The objectives is to develop a model that accurately predicts the prices of house based on a set of features such as location ,square footage ,number of bedrooms and bathrooms,and other relevant factors.This project involves data preprocessing ,feature engineering , model selection ,training ,and evaluation .

Design Thinking:

1. **Data Source:** Choose a dataset containing information about houses ,including features like location ,square footage ,bedrooms ,and price.
2. **Data Preprocessing:** Clean and preprocess the data ,handle missing values , and convert categorical features into numerical representations.
3. **Feature Selection:** Select the most revelant features of predicting house prices.
4. **Model Selection:** Choose a suitable regression algorithim (e.g linear Regression ,random Forest Regressor) for predicting house prices.
5. **Model Training:** Train the selected model using the preproccsed data .
6. **Evaluation:**Evaluate the model’s performance using metrics like Mean Absolute error(MAE),Root Mean Squared Error(RMSE),and R-Squared.

METHODOLOGY:

1. **Data collection :** Gather a dataset with information on houses .including features like square footage ,number of bedrooms ,location ,etc,.along with their corresponding sales prices.
2. **Data processing:** Clean and prepare the data by handling missing values ,encoding cateogorial variables ,and scalling features if necessary.
3. **Feature selection /engineering:** Identify revelant features that can influence house prices .you may need to create new features or select the most important ones.
4. **Split the data:** divide the dataset into a trainig set and a testing /validation set to evaluate the model's performance.
5. **Choose a model:** Select a machine learning model suitable for regression tasks.common choice include linear regression ,decision trees,random forests or more advanced model lilke gradient boosting or neural networks.
6. **Model training:** Train the selected model using the training data.
7. **Model evaluation:** Assess the model's performance on the validation /testing set using appropriate metrices like mean absolute error (MAE)mean squared error(MSE)or root mean squared error(RMSE).
8. **Hyperparameter tuning:** Optimize the model's hyperparameters to improve its performance.
9. **Final model selection :** Choose the best performing model based on evaluation results.
10. **Deployment:** Deploy the trained model in a production environment if you intend to use it for real-time predictions.
11. **Continuous monitoring :** Continously monitor the model's performance and retrain it periodically with new data to keep it up-to-date.
12. **Interpretability:** Depending on the model used, consider techniques for interpreting the model's predictions especially if transparency is important.

Data loading and preprocessing:

Import the required Libraries:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot
as plt import seaborn as
sns

%matplotlib inline
```
add Codeadd Markdown

```
import warnings
warnings.filterwarnings('ignore')
```
add Codeadd Markdown

Loading the dataset:

add Codeadd Markdown

```
data = pd.read_csv('/kaggle/input/usa-
housing/USA_Housing.csv') data.head()
```

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price	Address
0	79545.4586	5.682861	7.009188	4.09	23086.8005	1.06E+06	208 Michael Ferry Apt. 674\nLaurabury, NE 3701...
1	79248.6425	6.0029	6.730821	3.09	40173.0722	1.51E+06	188 Johnson Views Suite 079\nLake Kathleen, CA...

add Codeadd
Markdown
We can interpret that this is a regression problem since the house prise can't be labelled, it is a continuous variable.

The dataset contains the following features:-

- Avg. Area Income: Average Income of residents of the area the house is located in.
- Avg. Area House Age: Average Age of Houses in same area
- Avg. Area Number of Rooms: Average Number of Rooms for Houses in same area • Avg. Area Number of Bedrooms: Average Number of Bedrooms for Houses in same area
- Area Population: Population of the area the house is located in.
- Price: Price of the house.

Address: Address for a particular house.

add Codeadd Markdown

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'> RangeIndex: 5000 entries, 0 to 4999 Data columns (total 7 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   Avg. Area Income              5000 non-null   float64
 1   Avg. Area House Age           5000 non-null   float64
 2   Avg. Area Number of Rooms     5000 non-null   float64
 3   Avg. Area Number of Bedrooms  5000 non-null   float64
 4   Area Population               5000 non-null   float64
```

5 Price 5000 non-null float64 6 Address 5000 non-null object
dtypes: float64(6), object(1) memory usage: 273.6+ KB
add Codeadd Markdown

data.isnull().sum() *#The data does not have any null values*

Avg. Area Income 0
Avg. Area House Age 0
Avg. Area Number of Rooms 0
Avg. Area Number of Bedrooms 0
Area Population 0
Price 0
Address 0 dtype: int64
data.describe()

add Codeadd Markdown

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')

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price
count	5000	5000	5000	5000	5000	5.00E+03
mean	68583.109	5.977222	6.987792	3.98133	36163.516	1.23E+06

std	10657.9912	0.991456	1.005833	1.234137	9925.65011	3.53E+05
min	17796.6312	2.644304	3.236194	2	172.610686	1.59E+04
25%	61480.5624	5.322283	6.29925	3.14	29403.9287	9.98E+05
50%	68804.2864	5.970429	7.002902	4.05	36199.4067	1.23E+06
75%	75783.3387	6.650808	7.665871	4.49	42861.2908	1.47E+06
max	107701.748	9.519088	10.759588	6.5	69621.7134	2.47E+06

add Codeadd Markdown

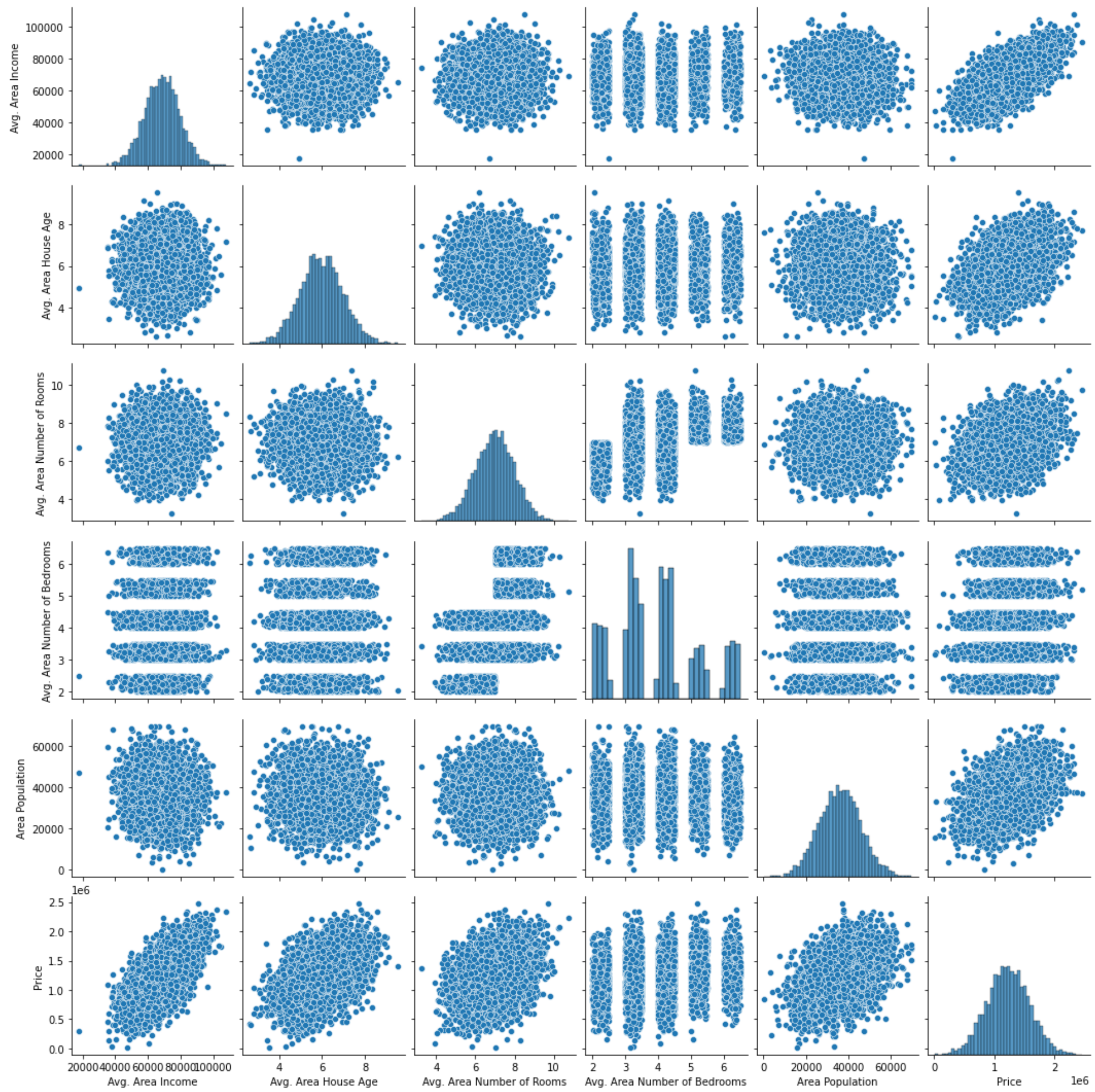
EDA(Exploratory Data Analysis):

Creating plots to analyze our data using different visualization techniques.

add Codeadd Markdown

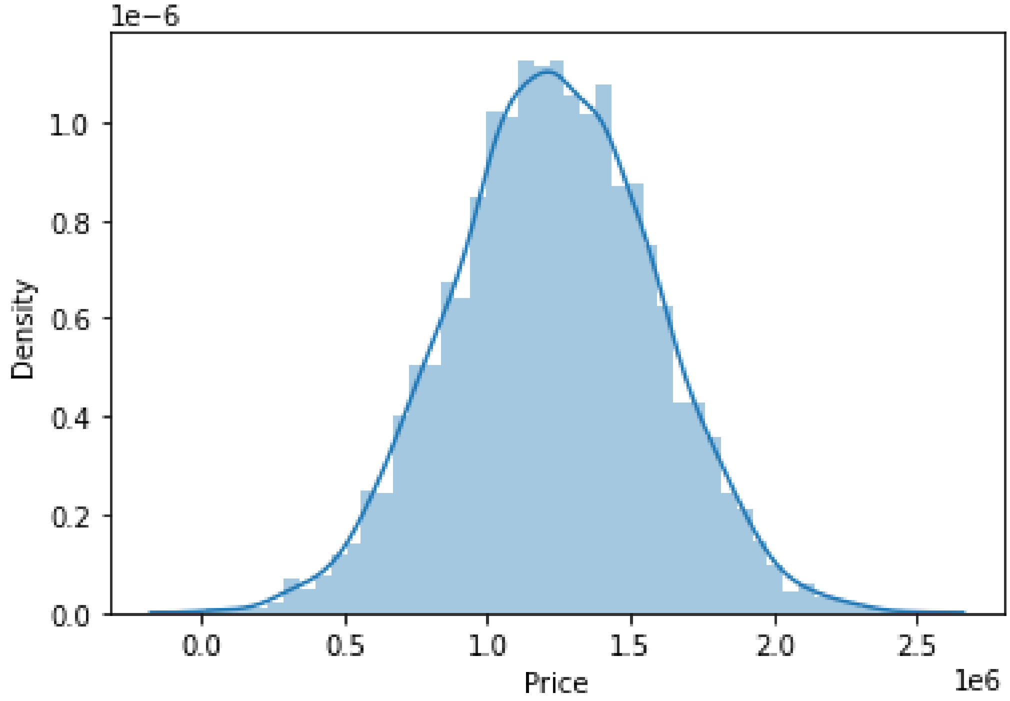
```
sns.pairplot(data)
```

<seaborn.axisgrid.PairGrid at 0x7f95ba648190>



add Codeadd Markdown

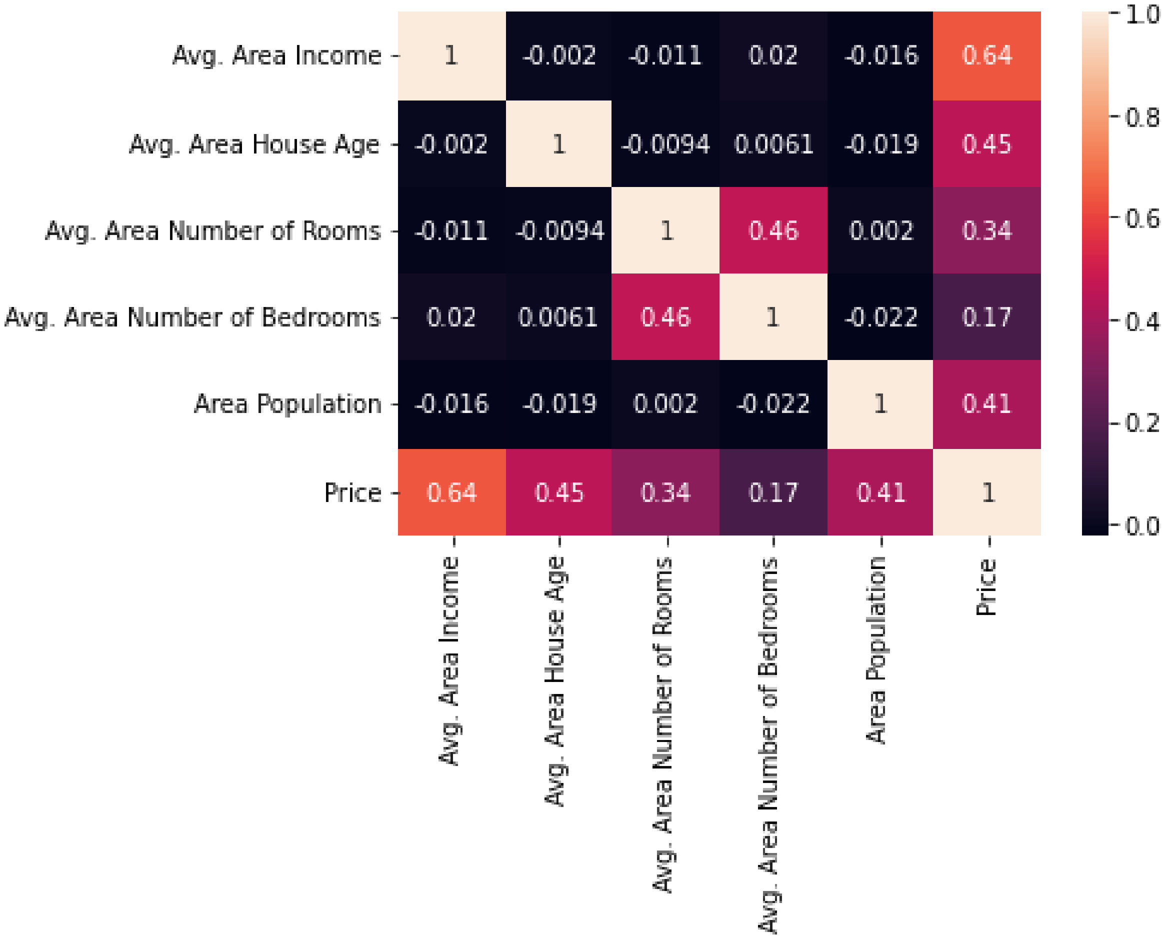
```
sns.distplot(data['Price'])
plt.plot()
```



add Codeadd Markdown

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

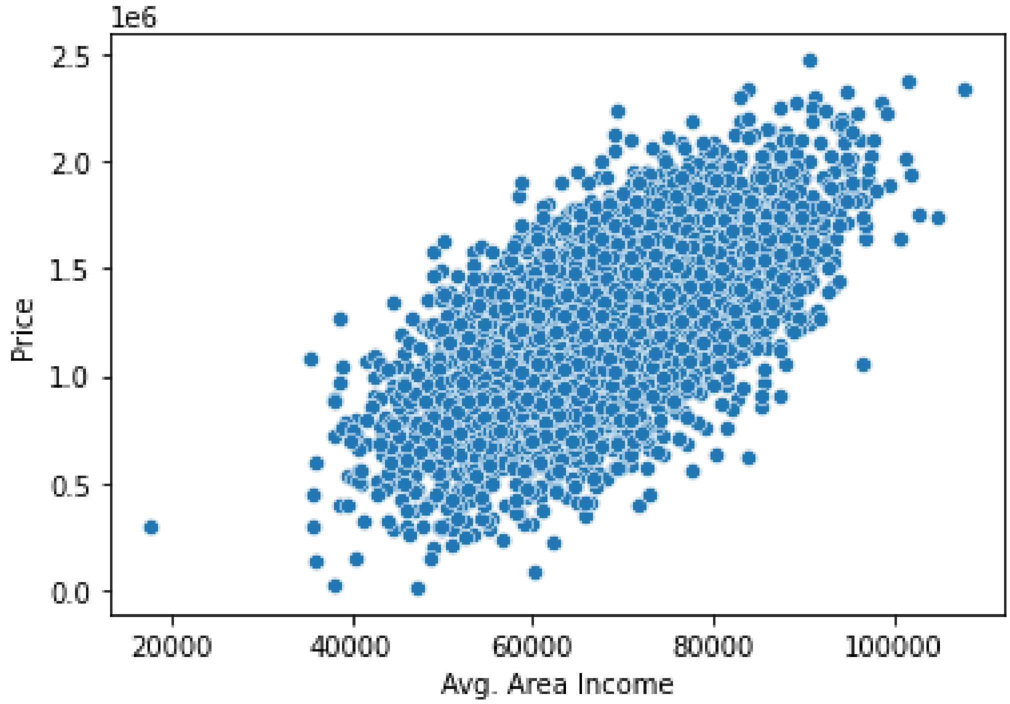
<AxesSubplot:>



add Codeadd Markdown

```
sns.scatterplot(x=data['Avg. Area Income'], y=data['Price'])
```

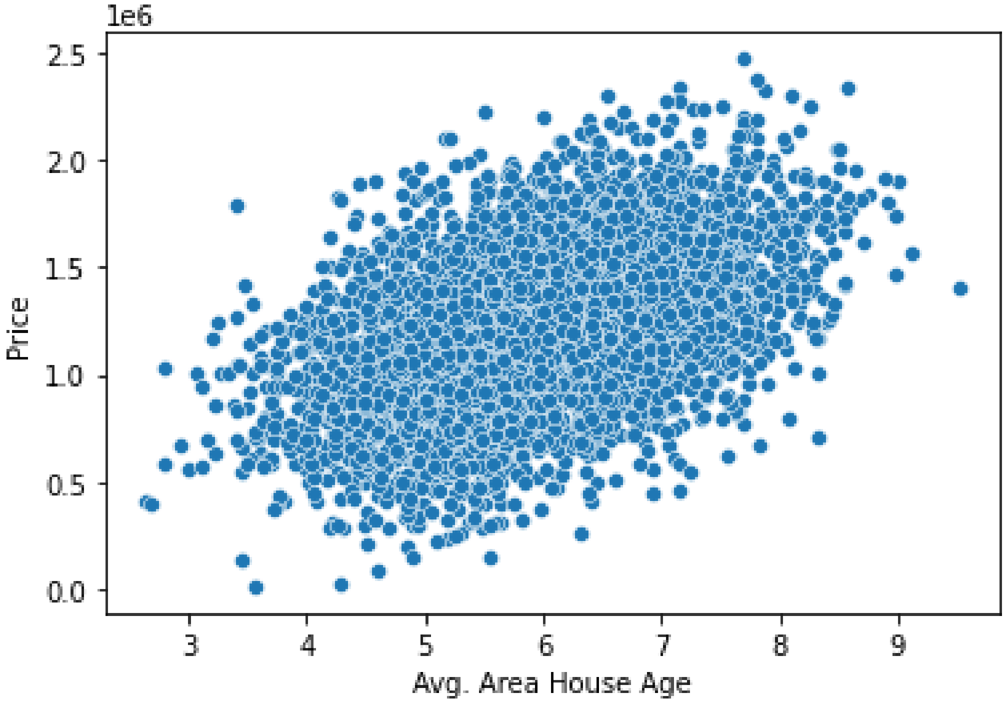
```
<AxesSubplot:xlabel='Avg. Area Income', ylabel='Price'>
```



add Codeadd Markdown

sns.scatterplot(x=data['Avg. Area House Age'], y=data['Price'])

<AxesSubplot:xlabel='Avg. Area House Age', ylabel='Price'>



add

Codeadd Markdown

Training Our Linear Regression Model:

add Codeadd Markdown

```
#dividing the data into dependent and independent features
X = data.drop(labels = ['Price', 'Address'], axis=1)
Y = data['Price']
```

add Codeadd Markdown

X

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population
0	79545.4586	5.682861	7.009188	4.09	23086.8005

1	6.0029	6.730821	3.09	40173.0722	79248.6425
2	5.86589	8.512727	5.13	36882.1594	61287.0672
3	7.188236	5.586729	3.26	34310.2428	63345.24
4	5.040555	7.839388	4.23	26354.1095	59982.1972
...	...	...	...	...	...
4995	7.830362	6.137356	3.46	22837.361	60567.9441
4996	6.999135	6.576763	4.02	25616.1155	78491.2754
4997	7.250591	4.805081	2.13	33266.1455	63390.6869

5000 rows × 5
column
add Codeadd Markdown

Y

0 1.059034e+06
1 1.505891e+06
2 1.058988e+06
3 1.260617e+06
4 6.309435e+05
...
4995 1.060194e+06
4996 1.482618e+06
4997 1.030730e+06
4998 1.198657e+06
4999 1.298950e+06
Name: Price, Length: 5000, dtype:
float64 add Codeadd Markdown

#Shape of X and Y

```
print(f"X Shape:
{X.shape}") print(X)
print(f"y Shape:
{Y.shape}")
print(Y)
```

X Shape: (5000, 5)

```
    Avg. Area Income  Avg. Area House Age  Avg. Area Number of Rooms  \
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
...             ...                  ...                        ...
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
0                           4.09     23086.800503
1                           3.09     40173.072174
2                           5.13     36882.159400
3                           3.26     34310.242831
4                           4.23     26354.109472
...                          ...              ...
4995                        3.46     22837.361035
4996                        4.02     25616.115489
4997                        2.13     33266.145490
4998                        5.44     42625.620156
4999                        4.07     46501.283803
```

[5000 rows x 5 columns] y
Shape: (5000,) 0
1.059034e+06
1 1.505891e+06
2 1.058988e+06
3 1.260617e+06
4 6.309435e+05
...
4995 1.060194e+06
4996 1.482618e+06
4997 1.030730e+06
4998 1.198657e+06
4999 1.298950e+06
Name: Price, Length: 5000, dtype: float64 add Codeadd Markdown

Spliting data for our model:

add Codeadd Markdown

from sklearn.model_selection **import** train_test_split

#Train-Test Split to train our model on the training set and then use the test set to evaluate the model

X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3, random_state=10)

Scale/Normalize the Training data:

add Codeadd Markdown

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_norm = scaler.fit_transform(X_train)
X_test =
    scaler.transform(X_test)
```
add Codeadd Markdown

```
X_norm array([[ 0.24082188, -1.0185292 , -0.77505327, -
    1.34738436, -1.03787896],       [ 0.98865562,
    1.66179379,  3.18432256, -0.45796685, -0.92397092],
     [ 0.14525596, -0.18436613,  1.45749594,  1.78174815,  0.71971398],
     ...,
     [ 0.20142052,  0.59892004, -0.52979241, -
    0.66819281, -1.2877454 ],       [ 0.49559505,
    0.75068063,  0.60135685,  0.20505347,  0.48354548],
     [-0.4372132 ,  0.40979201,  1.9322583 ,  0.01908436, -
    2.21714608]])
```

Creating and fitting our Linear Regression Model:

add Codeadd Markdown

```
from sklearn.linear_model import LinearRegression

lin_model = LinearRegression(normalize=True)
lin_model.fit(X_norm,y_train)
LinearRegression(normalize=Tr
    ue)
```

add Codeadd Markdown

View Parameters:

add Codeadd Markdown

print(f"Model parameters:- w: {lin_model.coef_}, b:{lin_model.intercept_}")

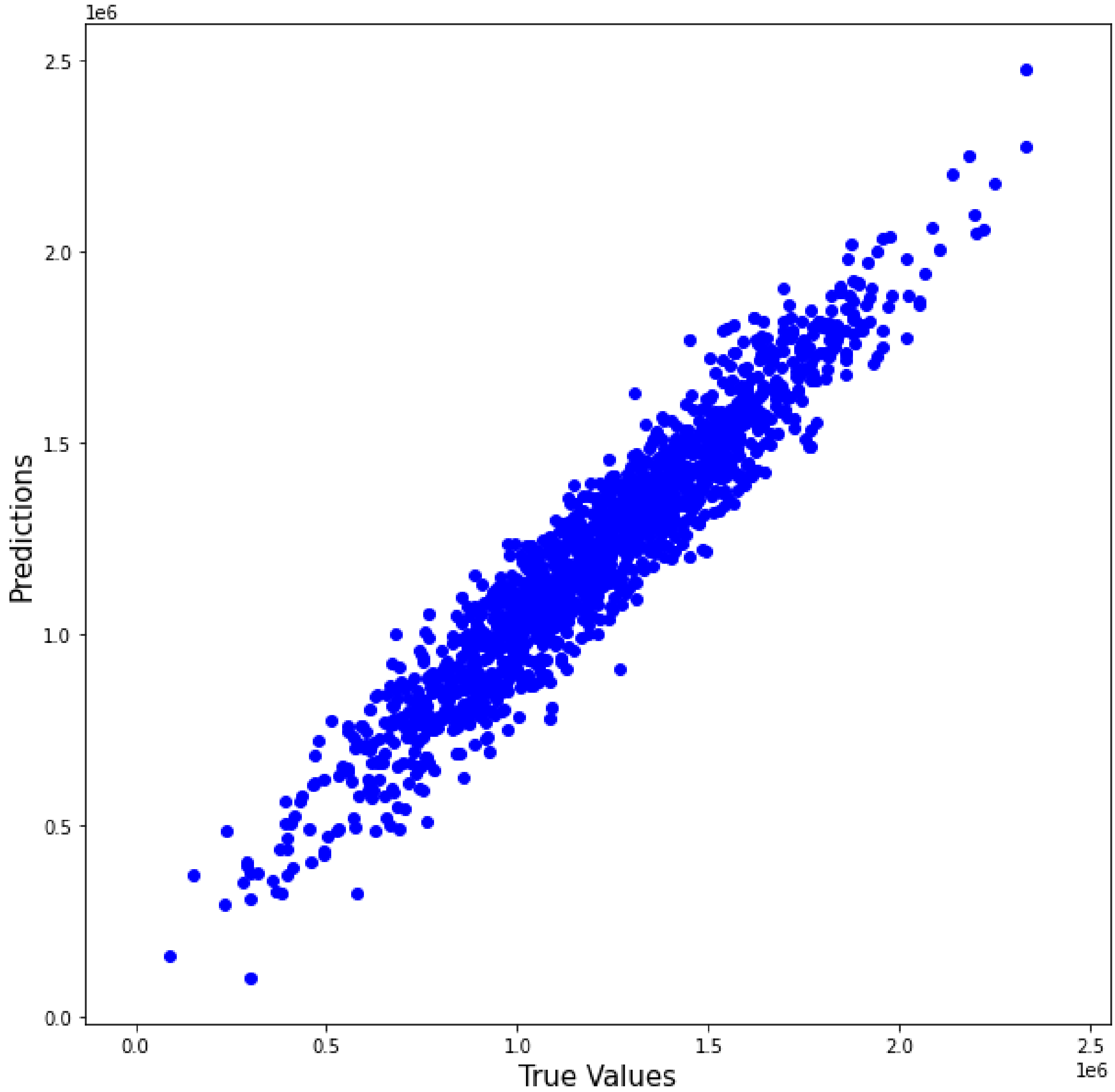
Model parameters:- w: [230102.81587921 164125.74656351 121432.99857953
591.86181588
149933.87898543],
b:1236207.893936157 add
Codeadd Markdown

Making predictions:

add Codeadd Markdown

 # make a prediction using lin_model.predict()
y_pred_linear_model = lin_model.predict(X_test) add
Codeadd Markdown

```
plt.figure(figsize=(10,10))
plt.scatter(y_test,
y_pred_linear_model, c='blue')
plt.xlabel('True Values',
fontsize=15)
plt.ylabel('Predictions',
fontsize=15) plt.axis('equal')
plt.show()
```



add Codeadd Markdown

Regression Evaluation Metrics:

add Codeadd Markdown

The common evaluation metrics for regression problems are:

- Mean Absolute Error(MAE)
- Mean Squared Error(MSE)
- Root Mean Squared Error (RMSE)

add Codeadd Markdown

from sklearn **import** metrics

def evaluated_results(true, predicted):
print('____')
print('MAE:', metrics.mean_absolute_error(true,
predicted))   print('MSE:',
metrics.mean_squared_error(true, predicted))
print('RMSE:',
np.sqrt(metrics.mean_squared_error(true, predicted)))
print('____')

add Codeadd Markdown
y_train_pred = lin_model.predict(X_norm)

print('Test set evaluation:')
evaluated_results(y_test,
y_pred_linear_model)
print('Train set evaluation:')
evaluated_results(y_train,
y_train_pred) Test set evaluation:

____

MAE: 81349.24091897604

MSE: 10408992254.1173

RMSE:
102024.46889897197
____
_________________ Train
set evaluation:

____

MAE: 81383.52050897086

MSE: 10146811289.400652

RMSE: 100731.38184995107

Feature Selection:

Feature selection is essential to choose the most relevant features for your model. Here's an example using Python's `scikit-learn` library with a hypothetical dataset:

```python
From sklearn.feature_selection import SelectKBest
From sklearn.feature_selection import f_regression

# Assuming X contains your feature data and y contains target prices
X_new = SelectKBest(score_func=f_regression, k=5).fit_transform(X, y)
```

This code uses the F-regression method to select the top 5 features based on their relevance to predicting house prices.

Model Training:

You can choose from various regression algorithms, such as Linear Regression, Random Forest, or Gradient Boosting. Here's an example of training a simple Linear Regression model:

```python
From sklearn.linear_model import LinearRegression
```

Model = LinearRegression()

Model.fit(X_new, y)

```

**Phase 4: Evaluation**

You should evaluate the model’s performance using metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), or R-squared. Here's an example:

```python
From sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
Import numpy as np

Predictions = model.predict(X_new)
Mae = mean_absolute_error(y, predictions)
Mse = mean_squared_error(y, predictions)
R2 = r2_score(y, predictions)

Print(f”Mean Absolute Error: {mae}”)
Print(f”Mean Squared Error: {mse}”)
Print(f”R-squared: {r2}”)
``