HOUSE PRICE PREDICTION USING MACHINE LEARNING

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PHASE III:DEVOLOUPMENT PART 1

INTRODUCTION:

- House price prediction using machine learning (ML) is the use of ML algorithms to predict the future selling price of a house based on historical data on various features of the house, such as its location, size, amenities, and condition
- ML models can be trained on large datasets of house sales data to learn the relationships between these features and house prices. Once trained, the model can be used to predict the price of a new house by providing it with the relevant feature information.
- House price prediction using ML can be a valuable tool for buyers, sellers, and investors in the real estate market. Buyers can use it to get an estimate of the fair market value of a house they are interested in purchasing. Sellers can

use it to set a competitive asking price for their home. And investors can use it to identify investment opportunities.

GIVEN DATA:

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price	Address
0	79545.458574	5.682861	7.009188	4.09	23086.800503	1.059034e+06	208 Michael Ferry Apt. 674\nLaurabury, NE 3701...
1	79248.642455	6.002900	6.730821	3.09	40173.072174	1.505891e+06	188 Johnson Views Suite 079\nLake Kathleen, CA...
2	61287.067179	5.865890	8.512727	5.13	36882.159400	1.058988e+06	9127 Elizabeth Stravenue\nDanieltown, WI 06482...
3	63345.240046	7.188236	5.586729	3.26	34310.242831	1.260617e+06	USS Barnett\nFPO AP 44820
4	59982.197226	5.040555	7.839388	4.23	26354.109472	6.309435e+05	USNS Raymond\nFPO AE 09386
...	...	...	...	...	...	...	...
4995	60567.944140	7.830362	6.137356	3.46	22837.361035	1.060194e+06	USNS Williams\nFPO AP 30153-7653
4996	78491.275435	6.999135	6.576763	4.02	25616.115489	1.482618e+06	PSC 9258, Box 8489\nAPO AA 42991-3352
4997	63390.686886	7.250591	4.805081	2.13	33266.145490	1.030730e+06	4215 Tracy Garden Suite 076\nJoshualand, VA 01...
4998	68001.331235	5.534388	7.130144	5.44	42625.620156	1.198657e+06	USS Wallace\nFPO AE 73316
4999	65510.581804	5.992305	6.792336	4.07	46501.283803	1.298950e+06	37778 George Ridges Apt. 509\nEast Holly, NV 2...

5000 rows × 7 columns

Necessory steps to follow:

Loading and preprocessing a dataset are two important steps in machine learning. Loading involves reading the data from a file or database into memory. Preprocessing involves cleaning and transforming the data so that it is ready for machine learning algorithms.

Loading a dataset:

The first step is to load the dataset into memory. This can be done using a variety of programming languages and libraries

Preprocessing a dataset

Once the dataset is loaded into memory, it is important to preprocess the data before using it for machine learning. Preprocessing involves cleaning and transforming the data so that it is ready for machine learning algorithm

Some common preprocessing tasks include:

- Handling missing values: Missing values are a common problem in datasets. There are a number of ways to handle missing values, such as dropping rows with missing values, imputing missing values with the mean or median of the column, or using a machine learning algorithm to predict the missing values.

- Encoding categorical data: Categorical data is data that can be divided into categories, such as gender, country, or product type. Categorical data must be encoded before it can be used by machine learning algorithms. One common way to encode categorical data is to use one-hot encoding.
- Scaling numerical data: Scaling numerical data involves transforming the data so that it has a mean of 0 and a standard deviation of 1. This is done to improve the performance of many machine learning algorithms.
- Feature engineering: Feature engineering is the process of creating new features from existing features. This can be done to improve the performance of machine learning algorithms.

Program:

Importing dependences:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score,
mean_absolute_error,mean_squared_error
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
import xgboost as xg
```

Loading Dataset:

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

Data Exploration:

```
dataset
```

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price	Address
0	79545.458574	5.682861	7.009188	4.09	23086.800503	1.059034e+06	208 Michael Ferry Apt. 674\nLaurabury, NE 3701...
1	79248.642455	6.002900	6.730821	3.09	40173.072174	1.505891e+06	188 Johnson Views Suite 079\nLake Kathleen, CA...
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4	59982.197226	5.040555	7.839388	4.23	26354.109472	6.309435e+05	USNS Raymond\nFPO AE 09386
...	...	...	...	...	...	...	...
4995	60567.944140	7.830362	6.137356	3.46	22837.361035	1.060194e+06	USNS Williams\nFPO AP 30153-7653
4996	78491.275435	6.999135	6.576763	4.02	25616.115489	1.482618e+06	PSC 9258, Box 8489\nAPO AA 42991-3352
4997	63390.686886	7.250591	4.805081	2.13	33266.145490	1.030730e+06	4215 Tracy Garden Suite 076\nJoshualand, VA 01...
4998	68001.331235	5.534388	7.130144	5.44	42625.620156	1.198657e+06	USS Wallace\nFPO AE 73316
4999	65510.581804	5.992305	6.792336	4.07	46501.283803	1.298950e+06	37778 George Ridges Apt. 509\nEast Holly, NV 2...

5000 rows × 7 columns

```
dataset.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
```

```
dataset.describe()
```

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5.000000e+03
mean	68583.108984	5.977222	6.987792	3.981330	36163.516039	1.232073e+06
std	10657.991214	0.991456	1.005833	1.234137	9925.650114	3.531176e+05
min	17796.631190	2.644304	3.236194	2.000000	172.610686	1.593866e+04
25%	61480.562388	5.322283	6.299250	3.140000	29403.928702	9.975771e+05
50%	68804.286404	5.970429	7.002902	4.050000	36199.406689	1.232669e+06
75%	75783.338666	6.650808	7.665871	4.490000	42861.290769	1.471210e+06
max	107701.748378	9.519088	10.759588	6.500000	69621.713378	2.469066e+06

```
dataset.columns
```

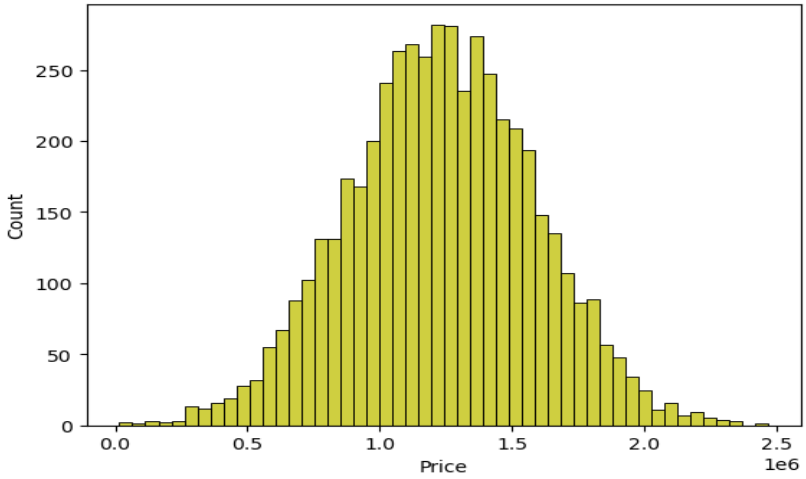
```
Index(['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number
of Rooms',
```

```
       'Avg. Area Number of Bedrooms', 'Area Population', 'Price',
'Address'],
      dtype='object')
```

Visualisation and Pre-Processing of Data

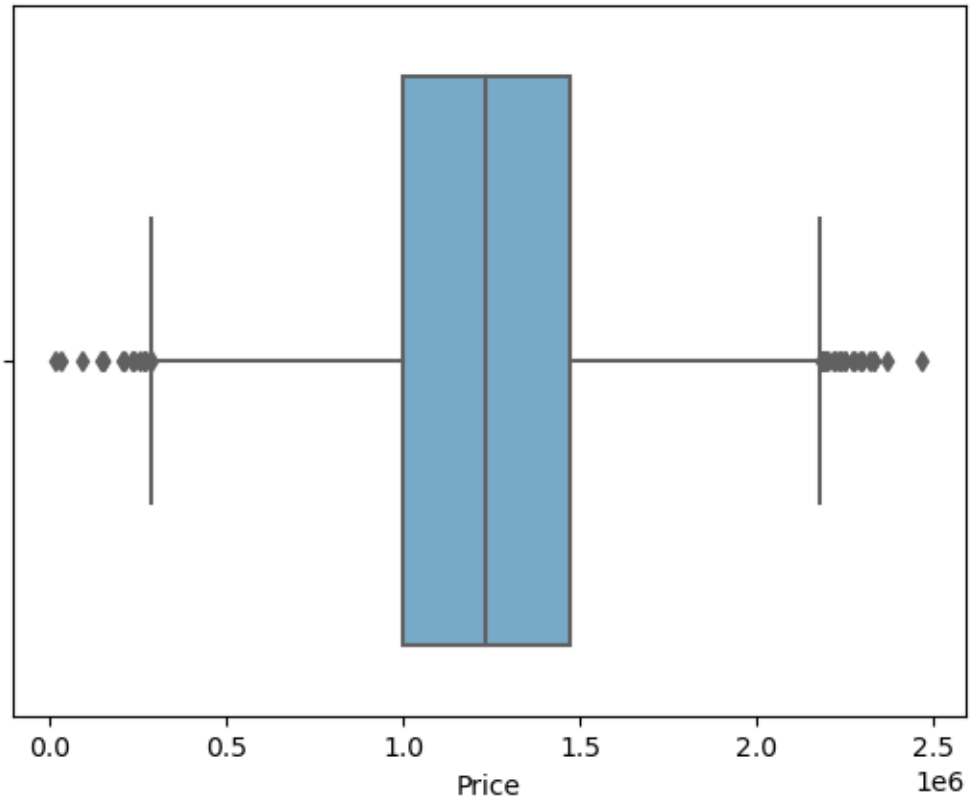
```
sns.histplot(dataset, x='Price', bins=50, color='y')
```

```
<Axes: xlabel='Price', ylabel='Count'>
```



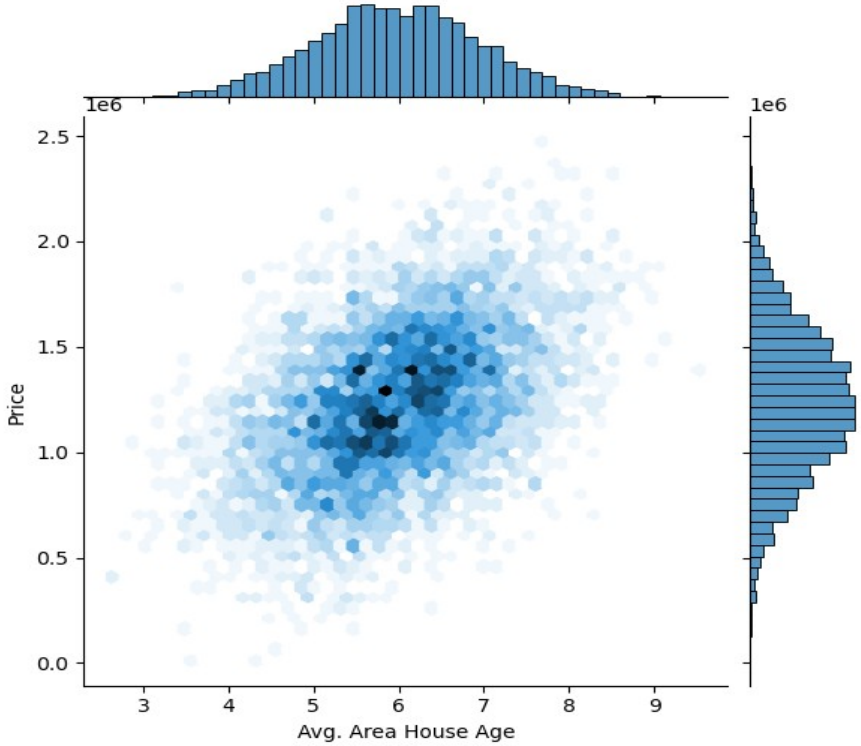

```
sns.boxplot(dataset, x='Price',  palette='Blues')
```

```
<Axes: xlabel='Price'>
```

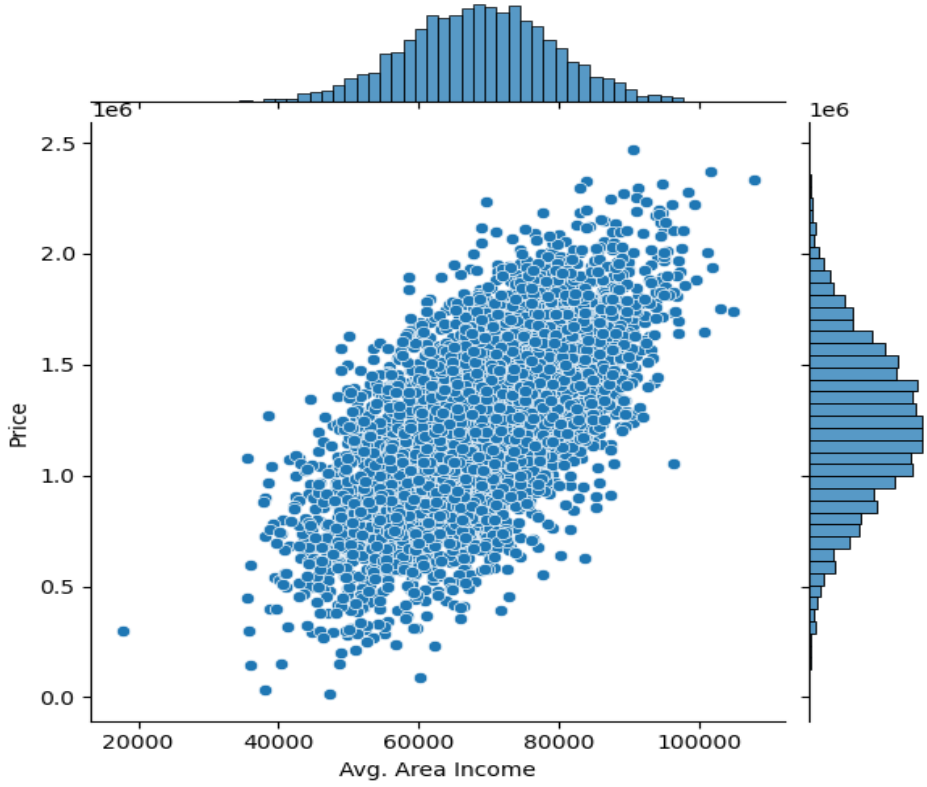



```
sns.jointplot(dataset, x='Avg. Area House Age', y='Price',
kind='hex')
```

```
<seaborn.axisgrid.JointGrid at 0x7caf1d571810>
```

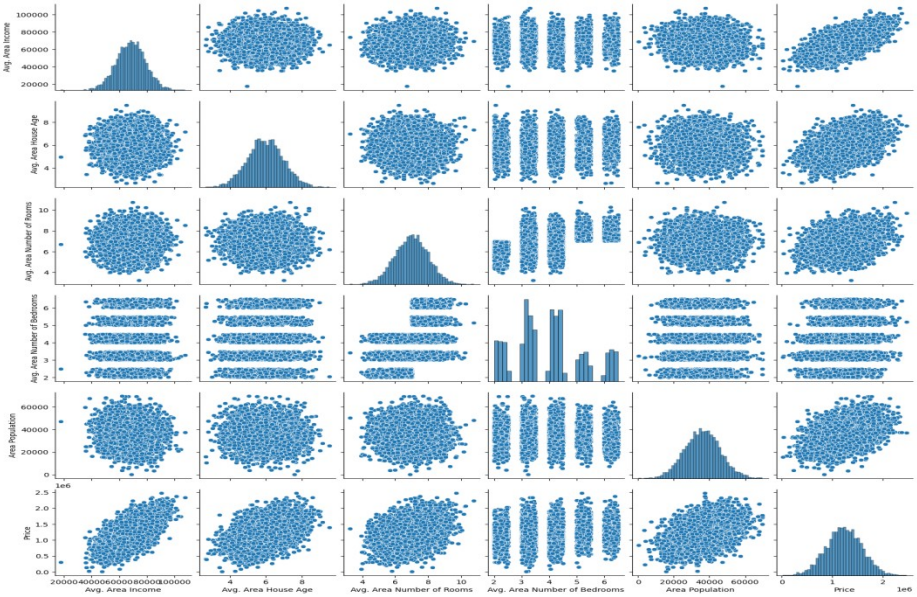



```
sns.jointplot(dataset, x='Avg. Area Income', y='Price')
<seaborn.axisgrid.JointGrid at 0x7caf1d8bf7f0>
```



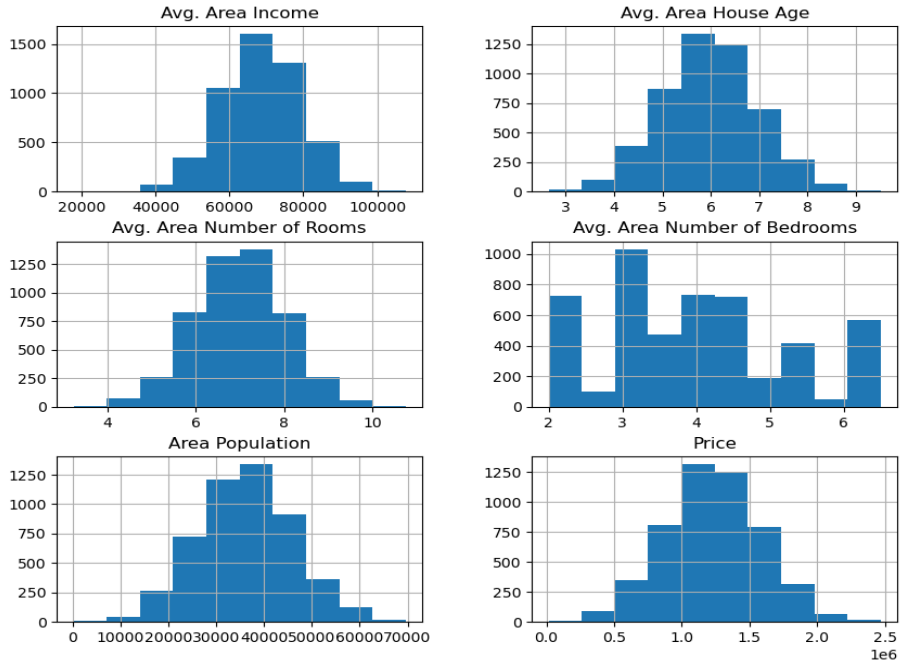
```
plt.figure(figsize=(12,8))
sns.pairplot(dataset)
```

```
<seaborn.axisgrid.PairGrid at 0x7caf0c2ac550>
<Figure size 1200x800 with 0 Axes>
```




```
dataset.hist(figsize=(10,8))
```

```
array([[<Axes: title={'center': 'Avg. Area Income'}>,
        <Axes: title={'center': 'Avg. Area House Age'}>],
       [<Axes: title={'center': 'Avg. Area Number of Rooms'}>,
        <Axes: title={'center': 'Avg. Area Number of Bedrooms'}>],
       [<Axes: title={'center': 'Area Population'}>,
        <Axes: title={'center': 'Price'}>]], dtype=object)
```



Visualising Correlation

```
dataset.corr(numeric_only=True)
```

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price
Avg. Area Income	1.000000	-0.002007	-0.011032	0.019788	-0.016234	0.639734
Avg. Area House Age	-0.002007	1.000000	-0.009428	0.006149	-0.018743	0.452543
Avg. Area Number of Rooms	-0.011032	-0.009428	1.000000	0.462695	0.002040	0.335664
Avg. Area Number of Bedrooms	0.019788	0.006149	0.462695	1.000000	-0.022168	0.171071
Area Population	-0.016234	-0.018743	0.002040	-0.022168	1.000000	0.408556
Price	0.639734	0.452543	0.335664	0.171071	0.408556	1.000000

```
plt.figure(figsize=(10,5))
sns.heatmap(dataset.corr(numeric_only = True), annot=True)
```

```
<Axes: >
```

Thank you