Predicting House Prices using Machine Learning

Problem Definition:

The problem is to predict house prices using machine learning techniques. The objective is to develop a model that accurately predicts the prices of houses 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:

Data Source:

The Data set for the problem statement is collected from Kaggle.com. The dataset contains information about houses, including features like location, square footage, bedrooms, bathrooms, and price.

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

Data Preprocessing:

Data preprocessing is a critical step in the data science workflow that involves cleaning, transforming, and organizing raw data into a format suitable for analysis and modeling. Proper data preprocessing is essential because the quality of the data you feed into your models significantly impacts the accuracy and reliability of your results.

Here are the typical steps involved in data preprocessing:

- **Handling Missing Data:**

- Remove or fill missing values using techniques like mean, median, or interpolation.

- **Handling Duplicates:**
  Identify and remove duplicate records.

- **Handling Outliers:**
  Detect and either remove or transform outliers using methods like z-sore, IQR, or domain knowledge.

- **Data Formatting:**
  Standardize or normalize data to ensure consistent units and scales.

- **Data Visualization:**
  Create visualizations to explore and understand the data better.

- **Feature Selection:**
  Choose the most relevant features for modeling, considering factors like feature importance, correlation, and domain knowledge.

Model Selection:

The choice of the model depends on the characteristics of your data, the underlying assumptions, and the problem you are trying to solve.

Depending on your data and problem complexity, you may need to explore more complex models, such as:

- Linear Regression
- Lasso Regression
- Decision Tree Regressor
- Random Forest Regressor
- Support Vector Regressor
- Neural Network

Model Training:

Model training is a fundamental step in data science and machine learning where you use a dataset to teach a machine learning model to make predictions or infer patterns.

Here's a step-by-step guide on how model training works:

- **Data Splitting:**
  Divide the dataset into training, validation, and testing sets to evaluate model performance.

- **Hyperparameter Tuning:**
  Machine learning models often have hyperparameters (e.g., learning rate, number of trees in a random forest) that need to be tuned for optimal performance.
  Use techniques like grid search, random search, or Bayesian optimization to find the best hyperparameters.

- **Model Training:**
  Train the selected model on the training dataset using the chosen hyperparameters.
  The model learns from the training data by adjusting its internal parameters to minimize a loss or error function.

Evaluation:

After training, evaluate the model's performance on the validation dataset.

Use appropriate evaluation metrics (e.g., accuracy, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared.) depending on your problem type.

Final Model Selection:

Once you're satisfied with the model's performance on the validation set, select the best model configuration.

Assess the final model's performance on the test dataset, which it has never seen before.

This provides an unbiased estimate of how well your model will perform on new, unseen data.

Design to solve the problem

Data Collection:

The Data set for the problem statement is collected from Kaggle.com. The dataset contains information about houses, including features like location, square footage, bedrooms, bathrooms, and price.

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

Data Preprocessing:

Feature selection: Choose the most relevant features for your model. Features may include numerical values, categorical variables (like neighborhood names), and text data (like property descriptions)

Data transformation: Scale or normalize numerical features and encode categorical features (e.g., one-hot encoding or label encoding).

Data splitting: Divide the dataset into training, validation, and test sets (e.g., 70-15-15 or 80-10-10 splits)

Exploratory Data Analysis (EDA):

Analyze the dataset to gain insights. Visualize data distributions, correlations, and trends.

Identify patterns or relationships that may influence house prices.

Feature Engineering:

Create new features or transform existing ones to extract more valuable information from the data.

Feature engineering might involve creating derived features like price per square foot, age of the property, or distance to key locations.

Model Selection:

Choose a machine learning algorithm(s) suitable for regression problems. Common choices include Linear Regression, Decision Trees, Random Forest, Gradient Boosting, and Neural Networks.

Consider the trade-offs between model complexity and interpretability, and explore different algorithms to determine which performs best.

Model Training:

Train the selected model on the training dataset.

Optimize hyperparameters using techniques like cross-validation or grid search.

Evaluate the model's performance using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared.

Model Evaluation:

Assess the model's performance on the validation dataset. Tune

the model and repeat training as necessary.

Compare different models and select the one with the best performance.

Model Testing:

Validate the model's performance on the test dataset, which the model has never seen before.

Ensure that the model generalizes well and doesn't overfit the training data.

Model Interpretation:

Understand which features have the most impact on predictions.

Visualize feature importances to explain why the model predicts specific prices.

Deployment:

Once satisfied with the model's performance, deploy it to make predictions on new data.

This could be done through a web application, an API, or batch processing, depending on your use case.

HOUSE PRICE PREDICTION

USING MACHINE LEARNING TECHNIQUES

Importing All the necessary Libraries

In [1]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
%matplotlib inline

import seaborn as sns
sns.set_style('darkgrid')

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler

import warnings
warnings.filterwarnings("ignore")
```

Loading the Dataset

In [2]:
```
dataset = pd.read_csv('USA_Housing.csv')
dataset.head()
```

Out[2]:

	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

Data Exploration

In [3]:
```
# Shape:
dataset.shape
```

Out[3]:
```
(5000, 7)
```

In [4]:
```
# Columns:
dataset.columns
```

Out[4]:
```
Index(['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number of Rooms',
       'Avg. Area Number of Bedrooms', 'Area Population', 'Price', 'Address'],
      dtype='object')
```

In [5]:
```
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
```

In [6]:
```
dataset.describe()
```

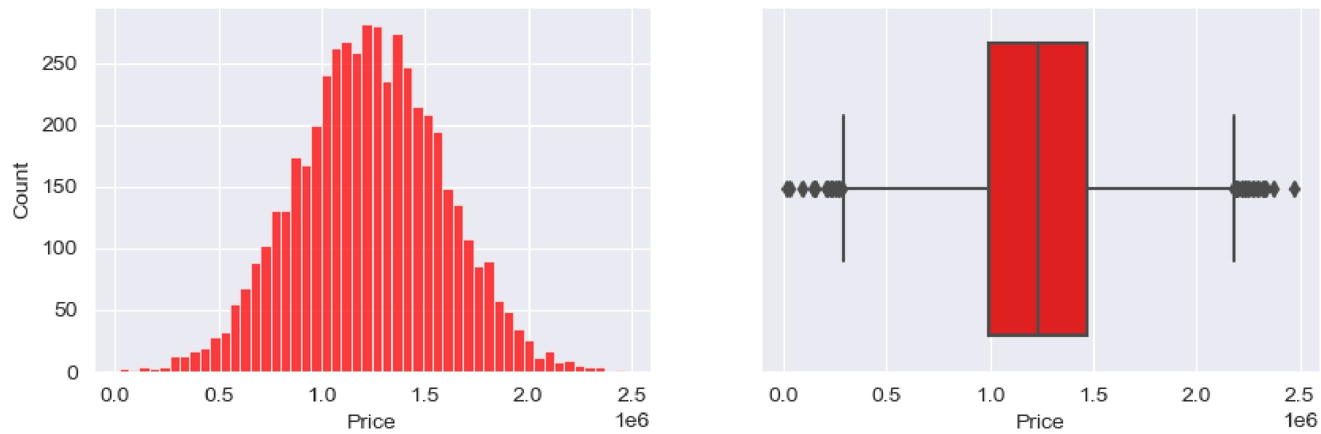
Out[6]:

	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

EDA and Pre-Processing of Data

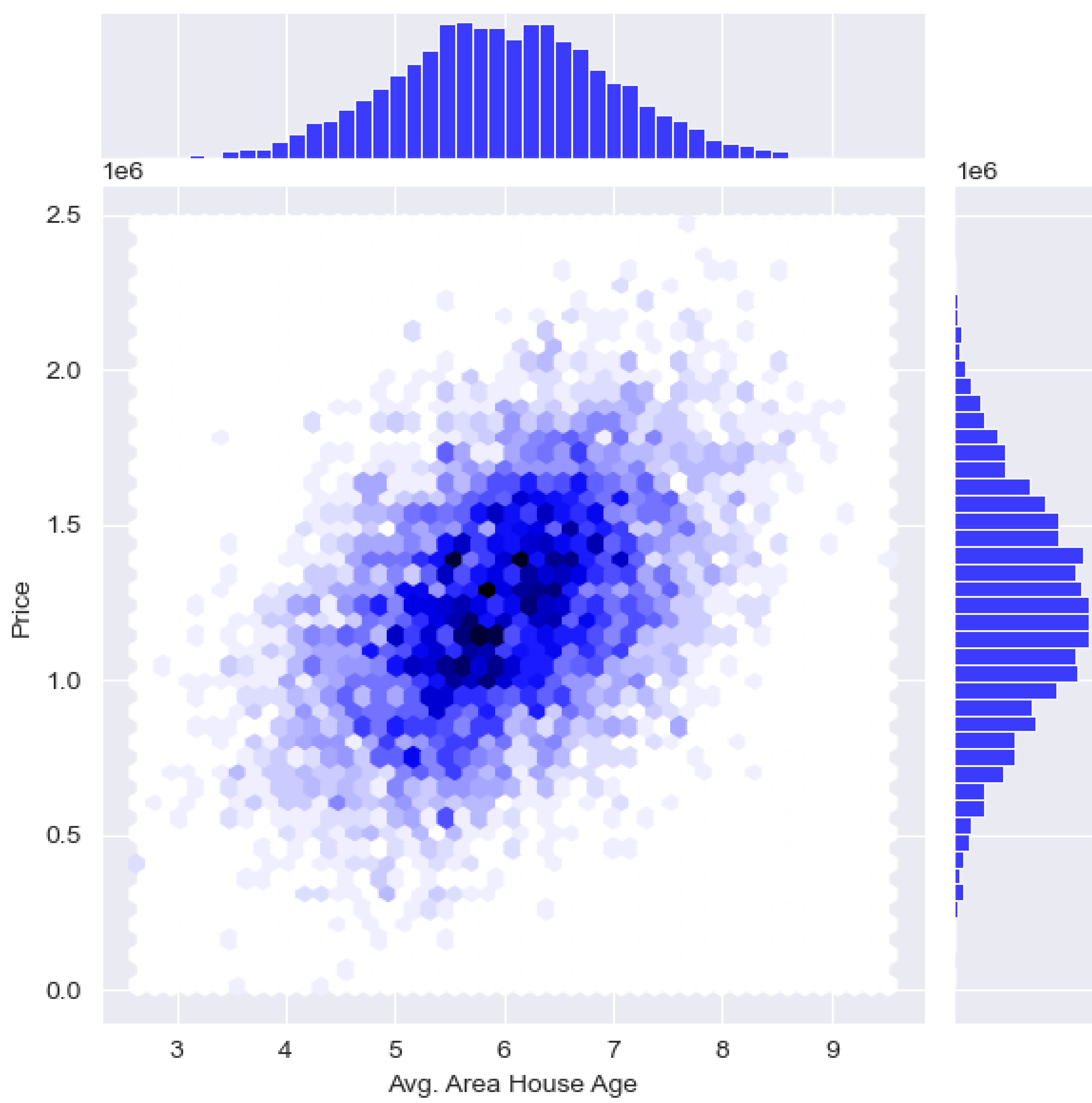
Distribution of Price column

In [7]:
```
plt.figure(figsize=(10,3))

plt.subplot(121)
sns.histplot(dataset, x='Price', bins=50, color='r')

plt.subplot(122)
sns.boxplot(dataset, x='Price',  color='r');
```



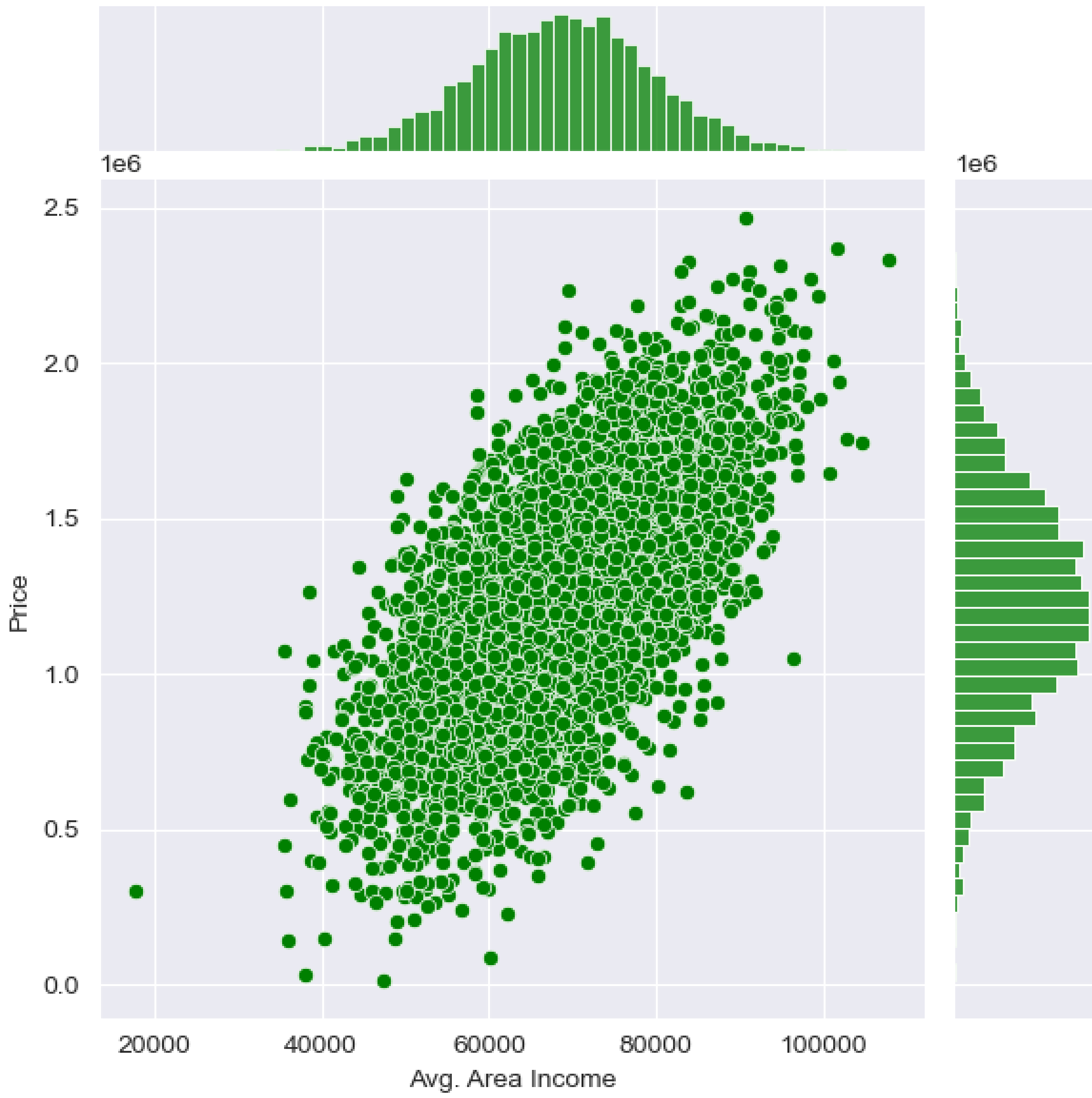
Avg. Area House Age Vs Price

In [8]:
```
sns.jointplot(dataset, x='Avg. Area House Age', y='Price', kind='hex', color='b');
```



Avg. Area Income Vs Price

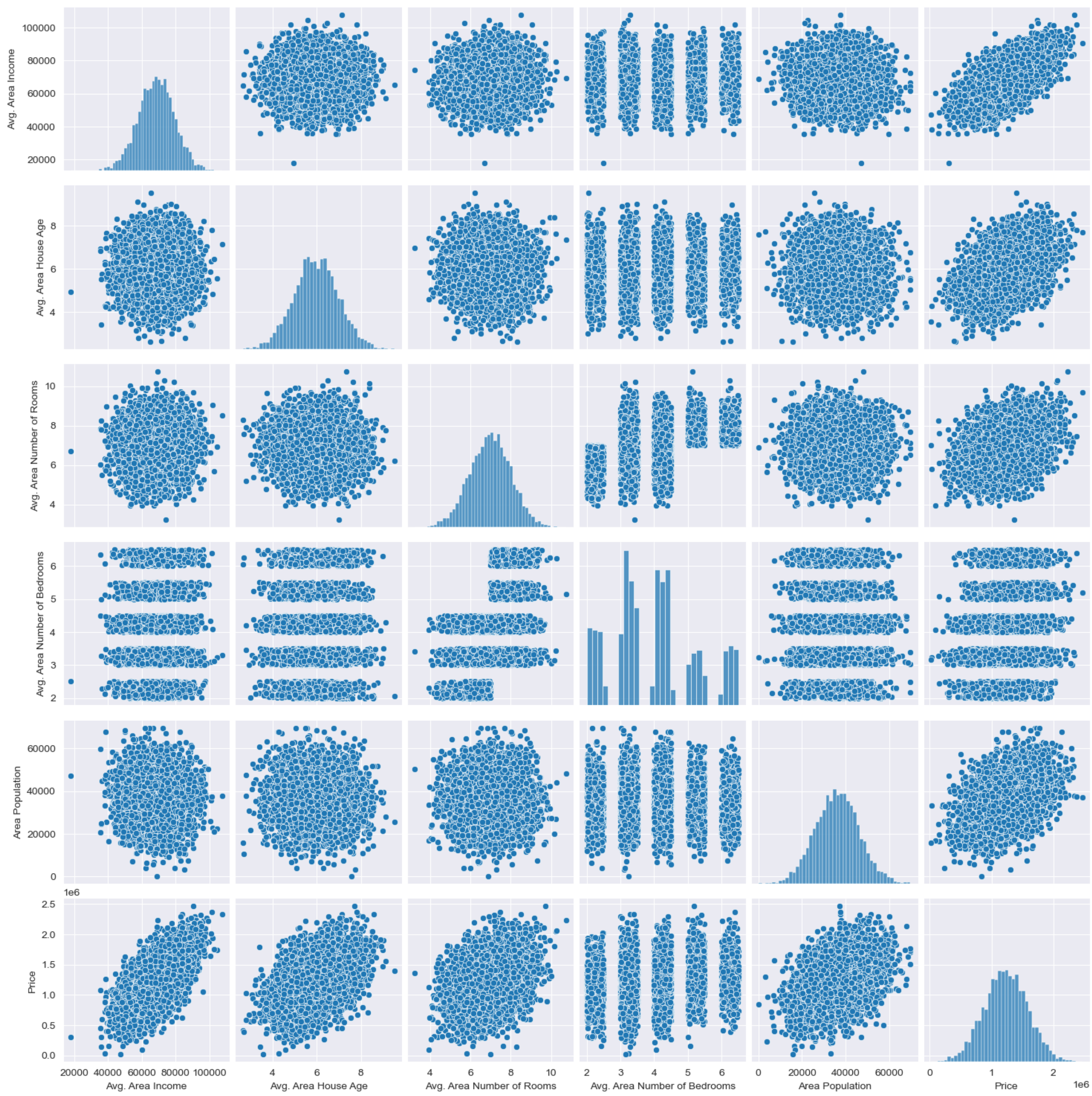
In [9]:
```
sns.jointplot(dataset, x='Avg. Area Income', y='Price', color='g');
```



Correlation among all the columns

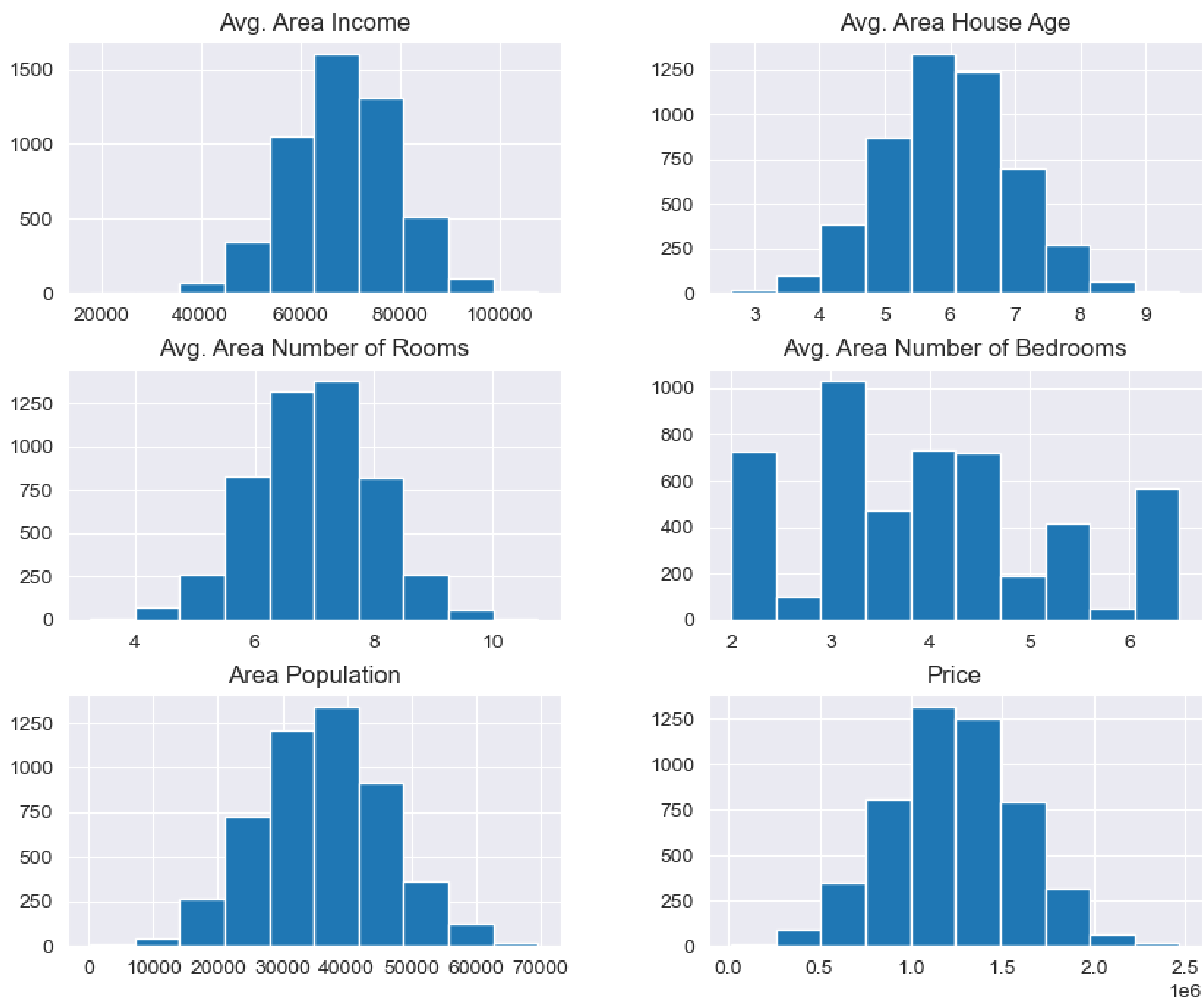
```
In [10]: plt.figure(figsize=(12,8))
         sns.pairplot(dataset);
```

<Figure size 1200x800 with 0 Axes>



Distribution of all the columns

In [11]:
```
dataset.hist(figsize=(10,8));
```



Visualising Correlation

In [12]:
```
dataset.corr(numeric_only=True)
```

Out[12]:

	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

In [13]:
```
plt.figure(figsize=(10,5))
sns.heatmap(dataset.corr(numeric_only = True), annot=True);
```

Dividing Dataset in to features and target variable

In [14]:
```
X = dataset[['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number of Rooms',
       'Avg. Area Number of Bedrooms', 'Area Population']]
Y = dataset['Price']
```

Split the dataset into train and test

In [15]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=10
```

In [16]:
```
Y_train.head()
```

Out[16]:
```
3413    1.305210e+06
1610    1.400961e+06
3459    1.048640e+06
4293    1.231157e+06
1039    1.391233e+06
Name: Price, dtype: float64
```

In [17]:
```
Y_train.shape
```

Out[17]:
```
(4000,)
```

In [18]:
```
Y_test.head()
```

Out[18]:
```
1718    1.251689e+06
2511    8.730483e+05
345     1.696978e+06
2521    1.063964e+06
54      9.487883e+05
Name: Price, dtype: float64
```

In [19]:
```
Y_test.shape
```

Out[19]:
```
(1000,)
```

Standardizing the data

In [20]:
```
sc = StandardScaler()
X_train_scal = sc.fit_transform(X_train)
X_test_scal = sc.fit_transform(X_test)
```

In [21]:
```
X_train_scal
```

Out[21]:
```
array([[ 0.05569623,  0.65886183, -0.86300913,  0.29911519,  0.06391981],
       [-0.05545523, -0.58559522,  2.37598858,  1.2000951 ,  0.69883088],
       [-1.11165023, -0.48032202,  0.13621855,  1.73581289,  1.14379364],
       ...,
       [-1.20704442, -2.26895761, -0.11765963, -1.34862286,  2.71900465],
       [-0.50898477, -0.03604344, -1.07361484,  0.11242565, -0.34813857],
       [ 0.62279188,  1.69958661,  1.456617  ,  0.29911519,  2.01048875]])
```

In [22]:
```
X_test_scal
```

Out[22]:
```
array([[-0.21555096, -0.281372  ,  0.77408385,  0.20931536,  0.07088885],
       [-0.64310056, -1.06017806,  0.41824478,  1.74293863, -1.01812409],
       [ 0.42413203,  0.75165241,  1.2987239 , -0.58171138,  0.71366541],
       ...,
       [ 0.25042527, -0.08048033,  0.40212954, -0.04897908,  0.15625295],
       [ 1.69352407, -0.96166121,  0.18304551,  1.07298741, -2.88549085],
       [ 0.11007237, -0.14440016, -0.20680012, -1.2920211 , -0.80666516]])
```

Till now we have completed all the Data Pre-Processing steps. Now the data is ready for model building

Model Building and Evaluation

In [23]:
```
from sklearn.model_selection import KFold, cross_val_score
import sklearn.metrics as mt

def cross_val(model):
    k=10
    kfold=KFold(n_splits=k, shuffle=True, random_state=45)
    vali=cross_val_score(model, X_train_scal,Y_train, cv=kfold)
    return vali.mean()

def success(true_,pred):
    rmse=mt.mean_absolute_error(true_,pred)
    r2=mt.r2_score(true_,pred)
    return[rmse,r2]
```

Trying different types of model

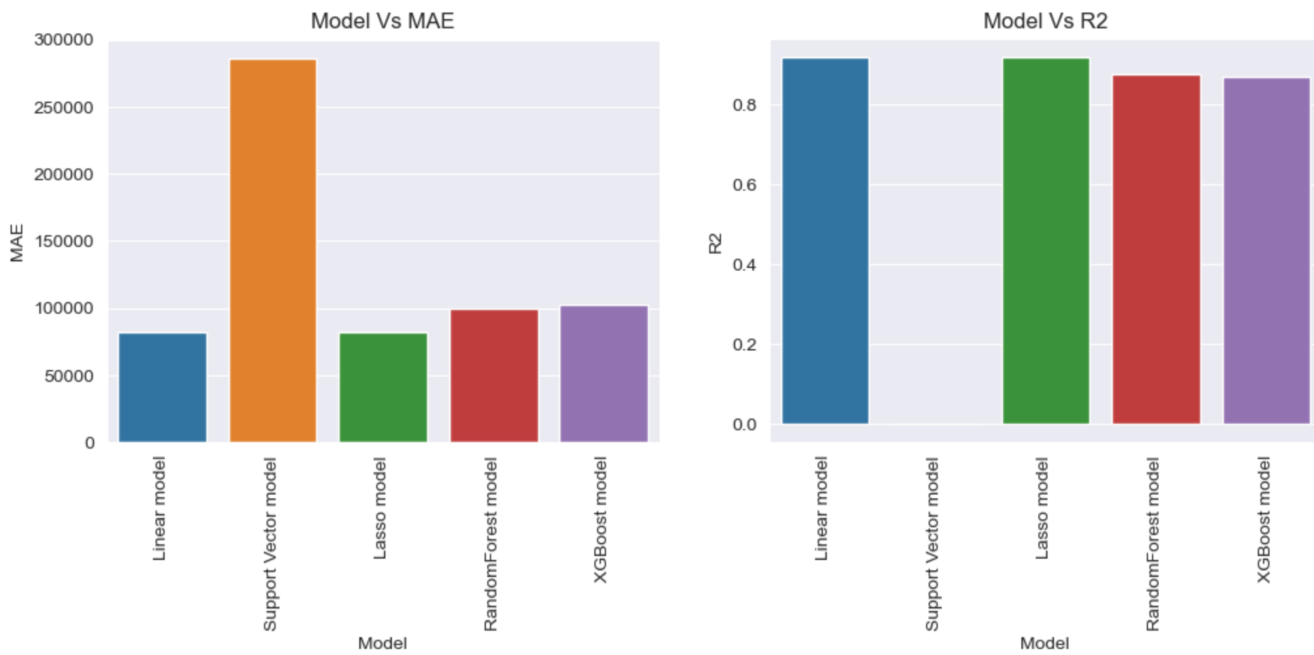
In [24]:
```
from sklearn.linear_model import LinearRegression,Lasso
from sklearn.svm import SVR
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor



li_model=LinearRegression()
li_model.fit(X_train_scal,Y_train)
li_pred = li_model.predict(X_test_scal)

svm_model= SVR()
svm_model.fit(X_train_scal,Y_train)
svm_pred = svm_model.predict(X_test_scal)

lasso_model=Lasso(alpha=1)
lasso_model.fit(X_train_scal,Y_train)
lasso_pred = lasso_model.predict(X_test_scal)

rf_model=RandomForestRegressor(n_estimators=50)
rf_model.fit(X_train_scal,Y_train)
rf_pred = rf_model.predict(X_test_scal)

xg_model=XGBRegressor()
xg_model.fit(X_train_scal,Y_train)
xg_pred = xg_model.predict(X_test_scal)
```

In [25]:
```
result=[["Linear model", success(Y_test,li_pred)[0], success(Y_test,li_pred)[1], cross_v
        ["Support Vector model", success(Y_test,svm_pred)[0], success(Y_test,svm_pred)[1
        ["Lasso model", success(Y_test,lasso_pred)[0], success(Y_test,lasso_pred)[1], cr
        ["RandomForest model", success(Y_test,rf_pred)[0], success(Y_test,rf_pred)[1], c
        ["XGBoost model", success(Y_test,xg_pred)[0], success(Y_test,xg_pred)[1], cross_


pd.options.display.float_format="{:.4f}".format

result=pd.DataFrame(result,columns=["Model","MAE","R2","Verification"])
result
```

Out[25]:

	Model	MAE	R2	Verification
0	Linear model	82295.4978	0.9183	0.9165
1	Support Vector model	286137.8109	-0.0006	-0.0016
2	Lasso model	82295.5068	0.9183	0.9165
3	RandomForest model	99280.7353	0.8773	0.8812
4	XGBoost model	102525.1997	0.8707	0.8759

In [26]:
```
plt.figure(figsize=(12,4))

plt.subplot(121)
plt.xticks(rotation=90)
plt.title('Model Vs MAE')
sns.barplot(x=result['Model'], y=result['MAE'])

plt.subplot(122)
plt.xticks(rotation=90)
plt.title('Model Vs R2')
sns.barplot(x=result['Model'], y=result['R2']);
```



Linear Regression is giving us best Accuracy with low MAE. So, we can built our final model using Linear Regression.

In [27]:
```
model = LinearRegression()
model.fit(X_train_scal, Y_train)
```

Out[27]:
```
▾ LinearRegression
LinearRegression()
```

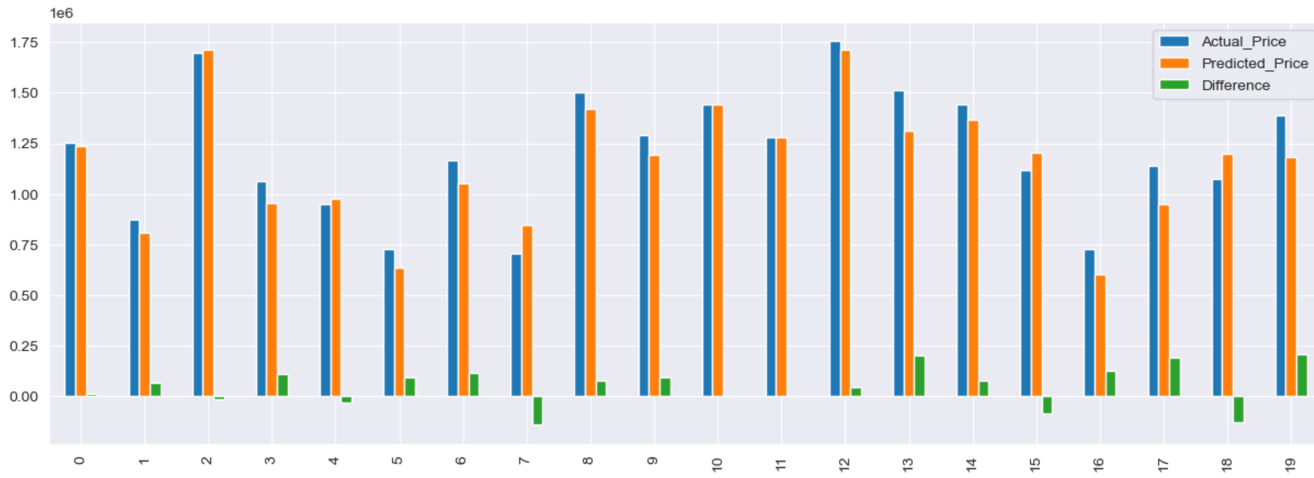
In [28]:
```
Y_pred = model.predict(X_test_scal)
```

In [29]:
```
df = pd.DataFrame()

df['Actual_Price'] = Y_test
df['Predicted_Price'] = Y_pred
df['Difference'] = (df['Actual_Price']-df['Predicted_Price'])

df.head()
```

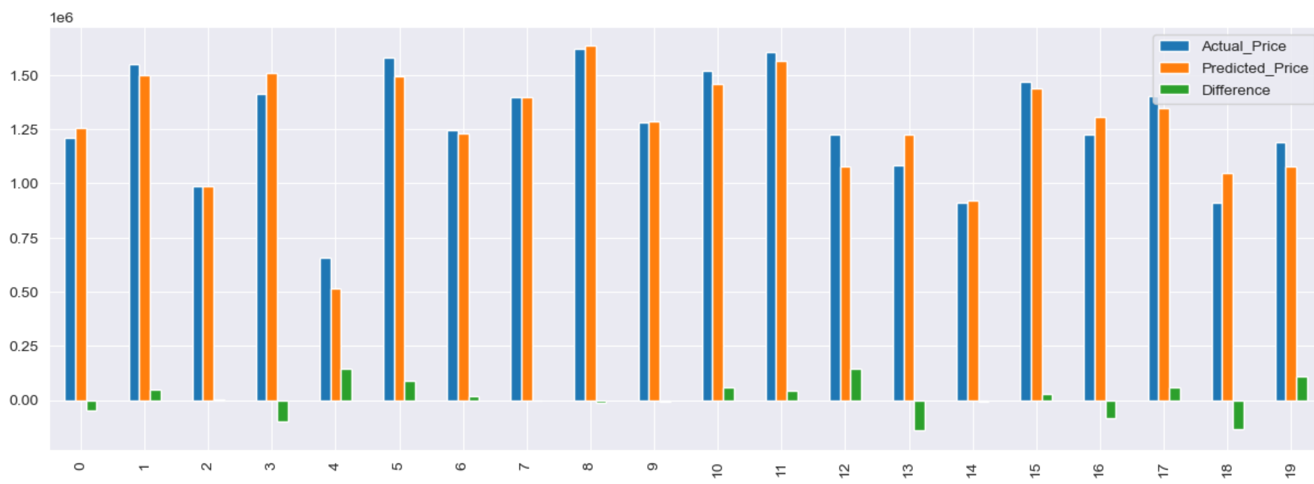
Out[29]:

	Actual_Price	Predicted_Price	Difference
1718	1251688.6157	1237794.7616	13893.8541
2511	873048.3196	807875.3706	65172.9490
345	1696977.6628	1711953.5693	-14975.9065
2521	1063964.2879	955131.9614	108832.3265
54	948788.2757	978003.1335	-29214.8578

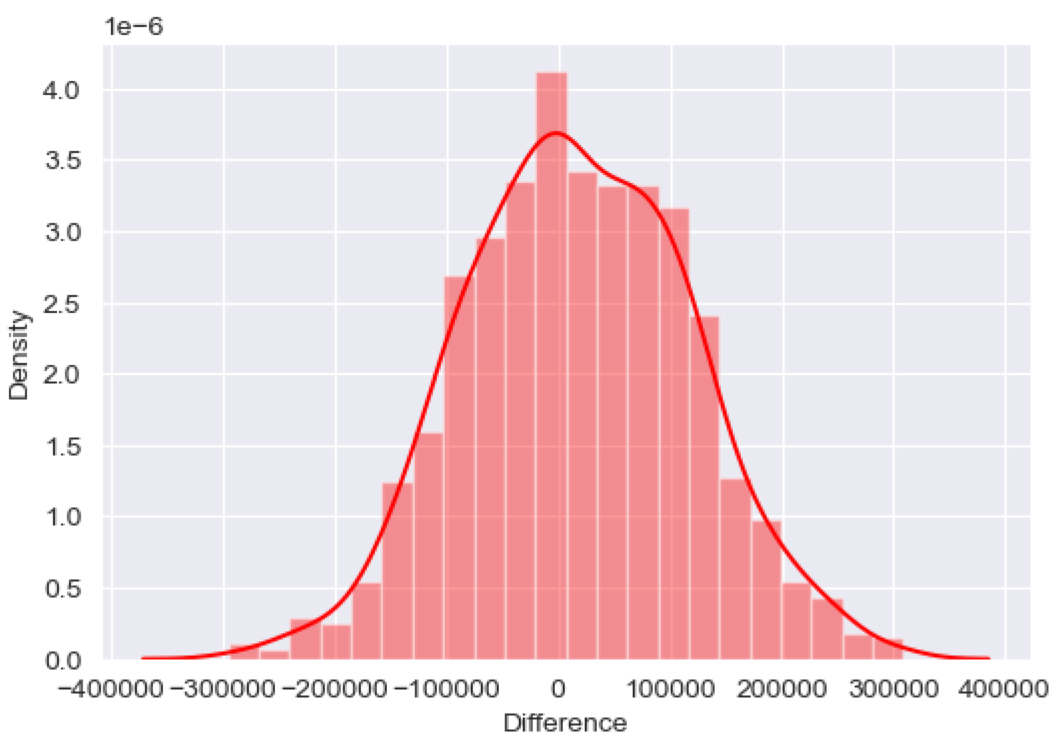
In [30]:
```
df.head(20).reset_index().plot(x=None,y=['Actual_Price','Predicted_Price','Difference'],
plt.show()
```



In [31]:
```
df.tail(20).reset_index().plot(x=None,y=['Actual_Price','Predicted_Price','Difference'],
plt.show()
```



In [32]:
```
plt.figure(figsize=(6,4))
sns.distplot(df['Difference'], color='r');
```



The error distribution is normal

In [33]:
```
# Accuracy and Mean Absolute Error:

from sklearn.metrics import r2_score, mean_absolute_error

print("Accuracy: ", r2_score(Y_test, Y_pred)*100)
print("Mean Absolute Error: ", mean_absolute_error(Y_test, Y_pred))
```

```
Accuracy:  91.8292817939292
Mean Absolute Error:  82295.49779231752
```

The model is giving the accuracy of 91.83%.

Saving the model

In [34]:
```
# Saving model as a pickle file:

import pickle
with open("House_Price.pickle",'wb') as file:
    pickle.dump(model, file)
```

In [35]:
```
file.close()
```

Here our model is ready for the deployment purpose

In [ ]:
```
```