

In [1]:

```
1 import pandas as pd
2 import numpy as np
3 import seaborn as sns
4 import matplotlib.pyplot as plt
5 from sklearn import preprocessing, svm
6 from sklearn.model_selection import train_test_split
7 from sklearn.linear_model import LinearRegression
```

In [2]:

```
1 df=pd.read_csv(r"C:\Users\HP\Downloads\USA_Housing.csv")
2 df
```

Out[2]:

| | Avg. Area Income | Avg. Area House Age | Avg. Area Number of Rooms | Avg. Area Number of Bedrooms | Area Population | Price | |
|------|---------------------|------------------------------|---------------------------------------|---------------------------------------|--------------------|--------------|-------------------------------|
| 0 | 79545.458574 | 5.682861 | 7.009188 | 4.09 | 23086.800503 | 1.059034e+06 | 208 Michael 674\nLaur |
| 1 | 79248.642455 | 6.002900 | 6.730821 | 3.09 | 40173.072174 | 1.505891e+06 | 188 Johns Suite C Kathl |
| 2 | 61287.067179 | 5.865890 | 8.512727 | 5.13 | 36882.159400 | 1.058988e+06 | 9127 Stravenue\nD: W |
| 3 | 63345.240046 | 7.188236 | 5.586729 | 3.26 | 34310.242831 | 1.260617e+06 | USS Barnett\ |
| 4 | 59982.197226 | 5.040555 | 7.839388 | 4.23 | 26354.109472 | 6.309435e+05 | USNS Raymc , |
| ... | ... | ... | ... | ... | ... | ... | |
| 4995 | 60567.944140 | 7.830362 | 6.137356 | 3.46 | 22837.361035 | 1.060194e+06 | USNS Willia AP 30 |
| 4996 | 78491.275435 | 6.999135 | 6.576763 | 4.02 | 25616.115489 | 1.482618e+06 | PSC 9 8489\nAPO F |
| 4997 | 63390.686886 | 7.250591 | 4.805081 | 2.13 | 33266.145490 | 1.030730e+06 | 4215 Trac Suite 076\nJo |
| 4998 | 68001.331235 | 5.534388 | 7.130144 | 5.44 | 42625.620156 | 1.198657e+06 | USS Wallace\ |
| 4999 | 65510.581804 | 5.992305 | 6.792336 | 4.07 | 46501.283803 | 1.298950e+06 | 37778 Georg Apt. 509\nE |

5000 rows × 7 columns



In [3]:

```
1 df.head()
```

Out[3]:

| | Avg. Area Income | Avg. Area House Age | Avg. Area Number of Rooms | Avg. Area Number of Bedrooms | Area Population | Price | Ad |
|---|---------------------|------------------------------|---------------------------------------|---------------------------------------|--------------------|--------------|--|
| 0 | 79545.458574 | 5.682861 | 7.009188 | 4.09 | 23086.800503 | 1.059034e+06 | 208 Michael Ferr 674\nLaurabu 3 |
| 1 | 79248.642455 | 6.002900 | 6.730821 | 3.09 | 40173.072174 | 1.505891e+06 | 188 Johnson Suite 079\nKathleen, |
| 2 | 61287.067179 | 5.865890 | 8.512727 | 5.13 | 36882.159400 | 1.058988e+06 | 9127 Eliz Stravenue\nDanie WI 06 |
| 3 | 63345.240046 | 7.188236 | 5.586729 | 3.26 | 34310.242831 | 1.260617e+06 | USS Barnett\nFF |
| 4 | 59982.197226 | 5.040555 | 7.839388 | 4.23 | 26354.109472 | 6.309435e+05 | USNS Raymond\nAE (|

In [4]:

```
1 df.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 [5]:

```
1 df.describe()
```

Out[5]:

| | 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 |

In [6]:

```
1 df.columns
```

Out[6]:

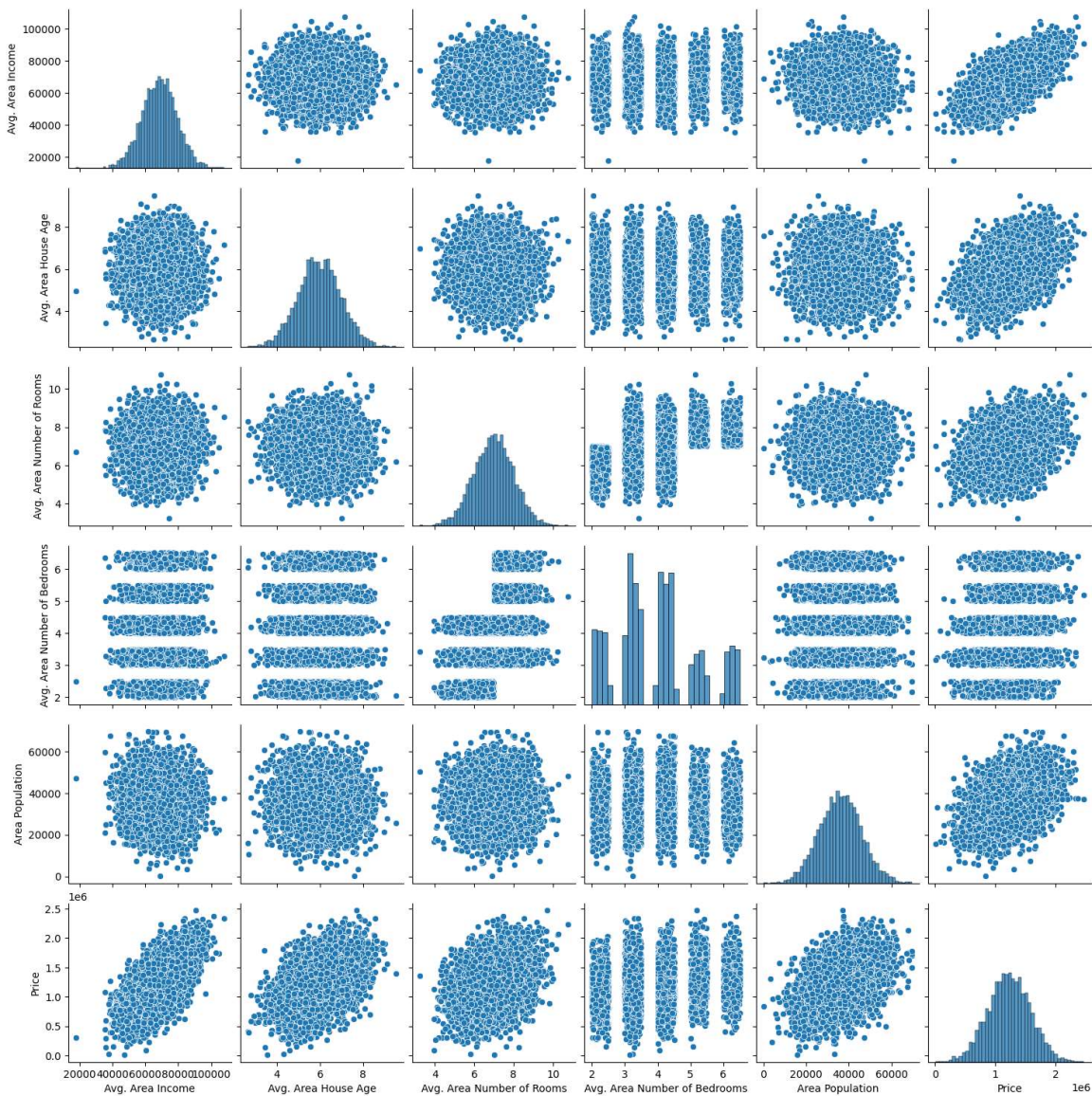
```
Index(['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number of Rooms',  
      'Avg. Area Number of Bedrooms', 'Area Population', 'Price', 'Address'],  
      dtype='object')
```

In [7]:

```
1 sns.pairplot(df)
```

Out[7]:

<seaborn.axisgrid.PairGrid at 0x27622b66e50>

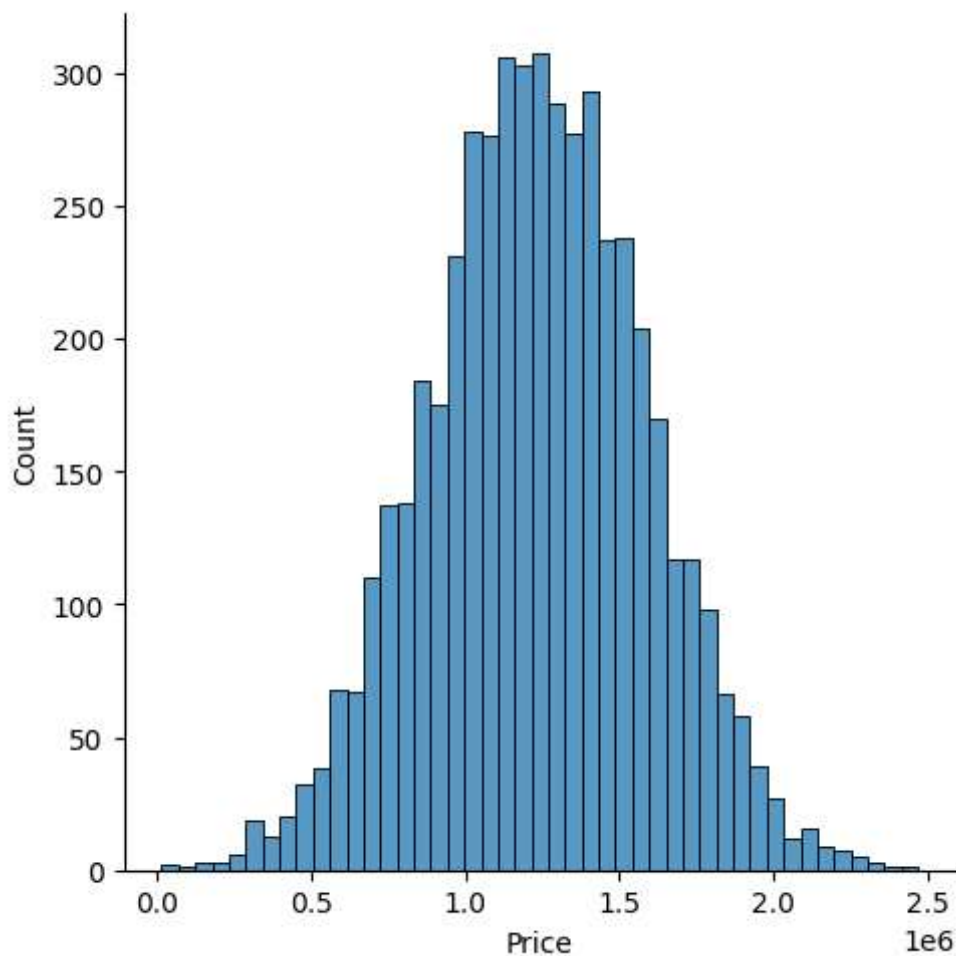


In [8]:

```
1 sns.displot(df['Price'])
```

Out[8]:

<seaborn.axisgrid.FacetGrid at 0x27626aea1d0>

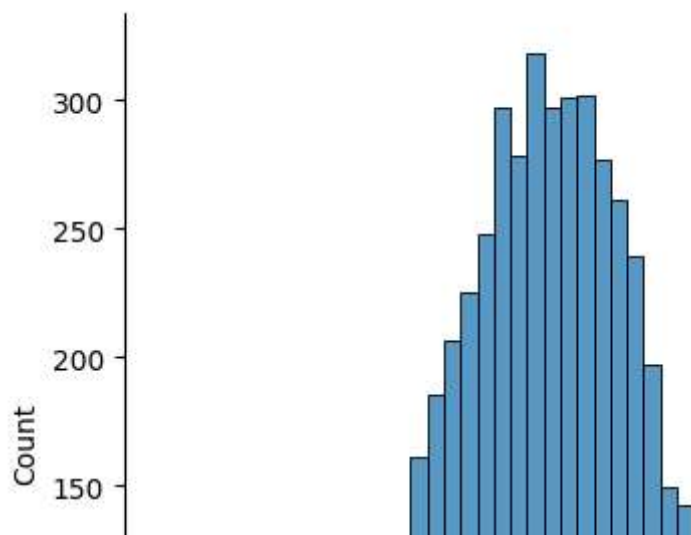


In [9]:

```
1 sns.displot(df['Area Population'])
```

Out[9]:

<seaborn.axisgrid.FacetGrid at 0x27627f2d8d0>



In [10]:

```
1 Housedf=df[['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number of Rooms',
2             'Avg. Area Number of Bedrooms', 'Area Population', 'Price']]
```

In [11]:

```
1 sns.heatmap(Housedf.corr())
```

Out[11]:

<Axes: >



In [12]:

```
1 X=Housedf[['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number of Rooms',
2             'Avg. Area Number of Bedrooms', 'Area Population']]
3 y=df['Price']
```

In [13]:

```
1 from sklearn.model_selection import train_test_split
2 X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.3,random_state=101)
```

In [14]:

```
1 from sklearn.linear_model import LinearRegression
2 lm=LinearRegression()
3 lm.fit(X_train,y_train)
```

Out[14]:

```
LinearRegression
LinearRegression()
```

In [15]:

```
1 print(lm.intercept_)
```

-2641372.6673014304

In [16]:

```
1 coeff_df=pd.DataFrame(lm.coef_,X.columns,columns=['coefficient'])
2 coeff_df
```

Out[16]:

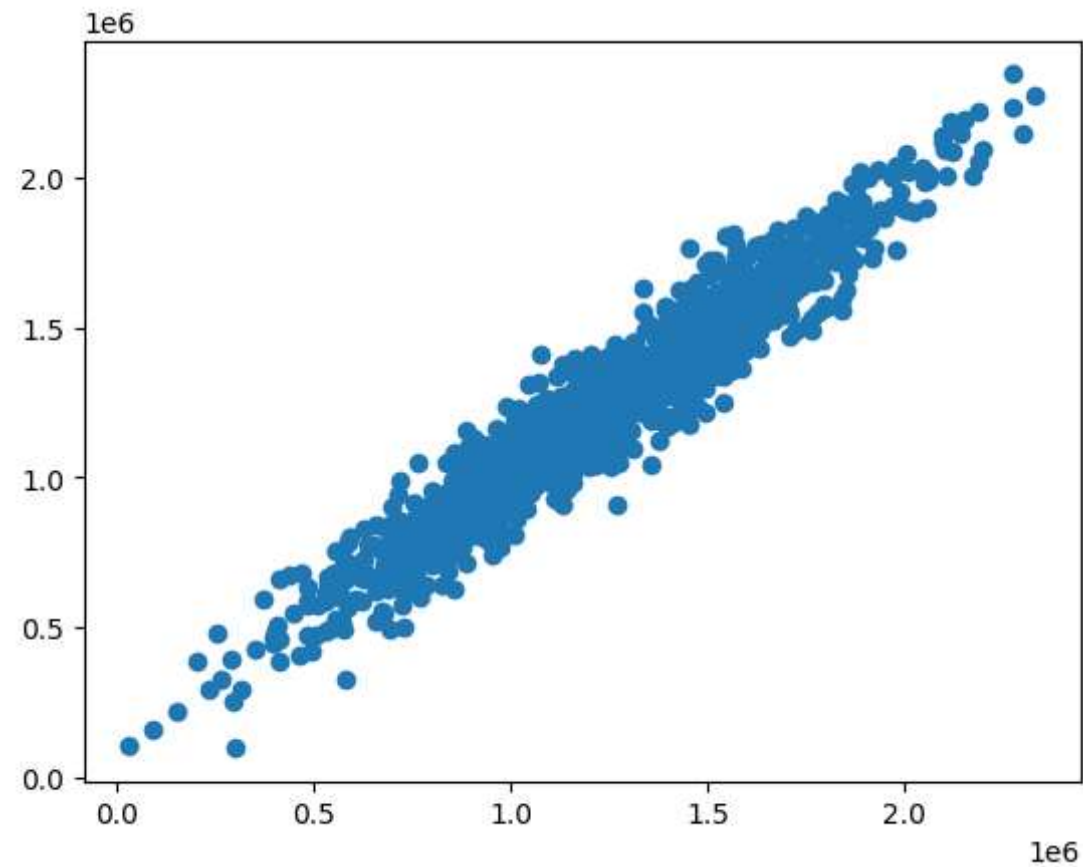
| | coefficient |
|------------------------------|---------------|
| Avg. Area Income | 21.617635 |
| Avg. Area House Age | 165221.119872 |
| Avg. Area Number of Rooms | 121405.376596 |
| Avg. Area Number of Bedrooms | 1318.718783 |
| Area Population | 15.225196 |

In [17]:

```
1 predictions=lm.predict(X_test)
2 plt.scatter(y_test,predictions)
```

Out[17]:

<matplotlib.collections.PathCollection at 0x27628a15310>

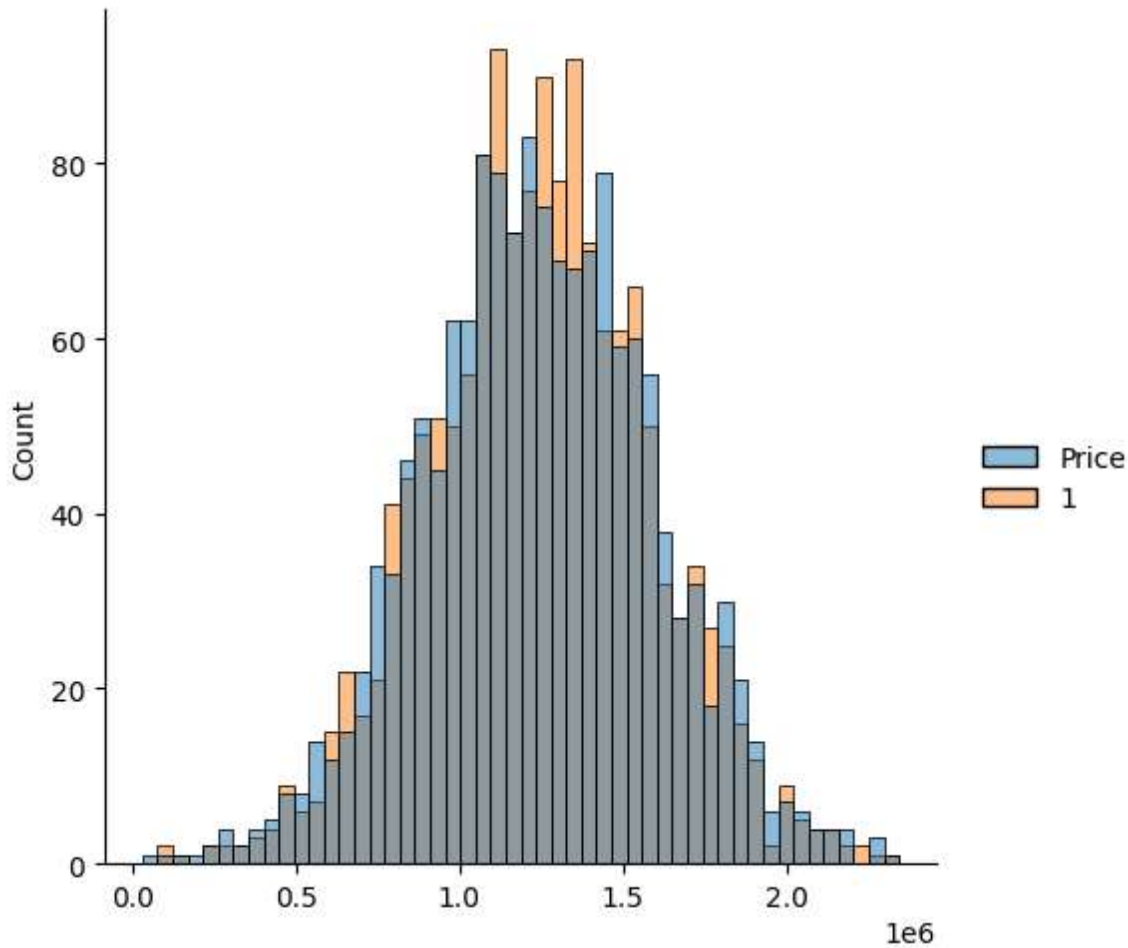


In [18]:

```
1 sns.displot((y_test,predictions),bins=50)
```

Out[18]:

```
<seaborn.axisgrid.FacetGrid at 0x27628a2f490>
```



In [19]:

```
1 from sklearn import metrics
2 print('MAE:',metrics.mean_absolute_error(y_test,predictions))
3 print('MSE:',metrics.mean_squared_error(y_test,predictions))
4 print('RMSE:',np.sqrt(metrics.mean_squared_error(y_test,predictions)))
```

MAE: 81257.55795855941

MSE: 10169125565.897606

RMSE: 100842.08231635048

In [20]:

```
1 from sklearn.linear_model import Ridge, RidgeCV, Lasso
2 from sklearn.preprocessing import StandardScaler
```

In [21]:

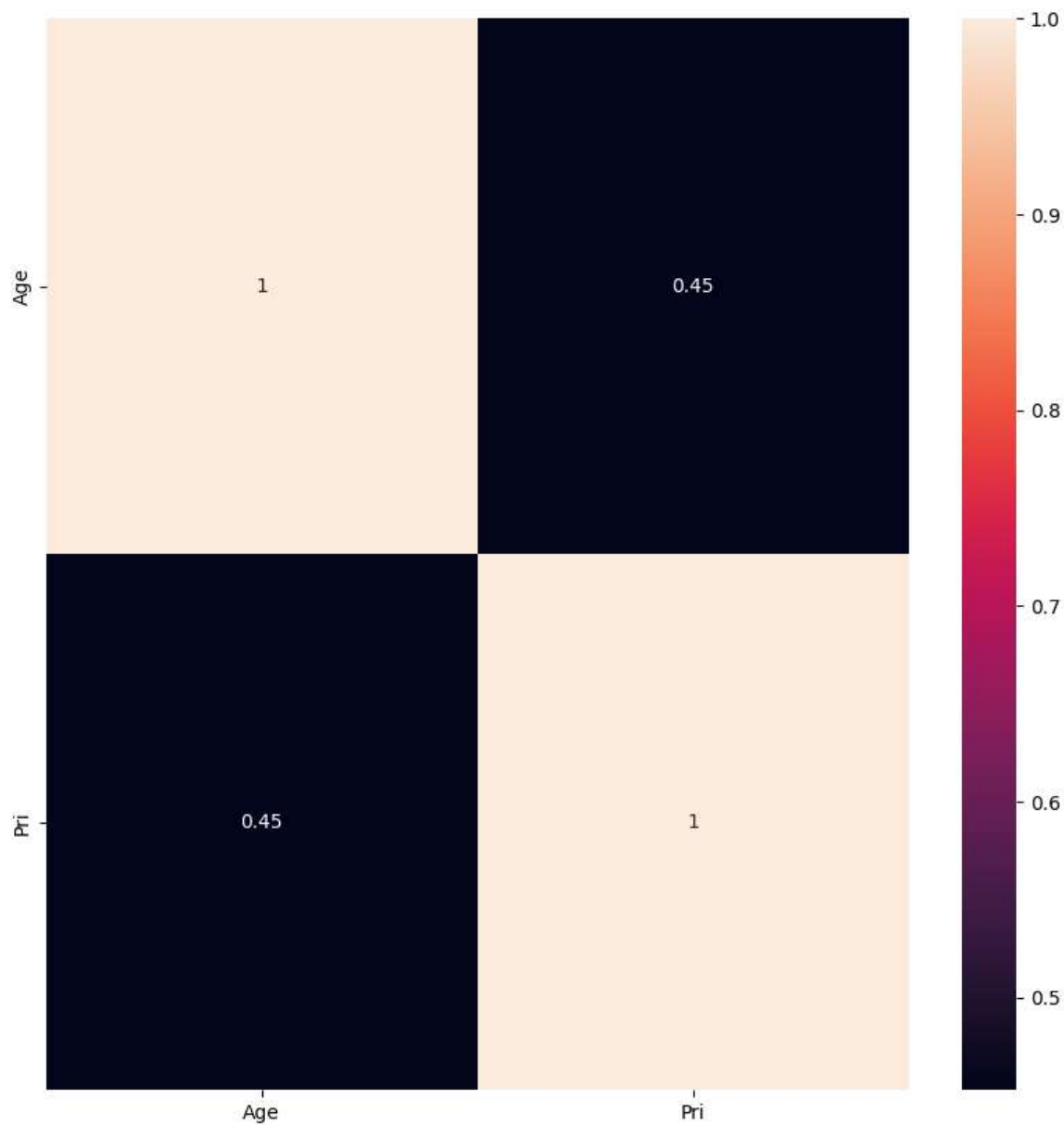
```
1 df=df[['Avg. Area House Age','Price']]
2 df.columns=['Age','Pri']
```


In [22]:

```
1 plt.figure(figsize = (10, 10))  
2 sns.heatmap(df.corr(), annot = True)  
3
```

Out[22]:

<Axes: >



In [23]:

```
1 features = df.columns[0:2]
2 target = df.columns[-1]
3 #X and y values
4 X = df[features].values
5 y = df[target].values
6 #splot
7 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
8 print("The dimension of X_train is {}".format(X_train.shape))
9 print("The dimension of X_test is {}".format(X_test.shape))
10 #Scale features
11 scaler = StandardScaler()
12 X_train = scaler.fit_transform(X_train)
13 X_test = scaler.transform(X_test)
14
```

The dimension of X_train is (3500, 2)

The dimension of X_test is (1500, 2)

In [24]:

```
1 #Model
2 lr = LinearRegression()
3 #Fit model
4 lr.fit(X_train, y_train)
5 #predict
6 #prediction = lr.predict(X_test)
7 #actual
8 actual = y_test
9 train_score_lr = lr.score(X_train, y_train)
10 test_score_lr = lr.score(X_test, y_test)
11 print("\nLinear Regression Model:\n")
12 print("The train score for lr model is {}".format(train_score_lr))
13 print("The test score for lr model is {}".format(test_score_lr))
```

Linear Regression Model:

The train score for lr model is 1.0

The test score for lr model is 1.0

In [25]:

```
1 #Ridge Regression Model
2 ridgeReg = Ridge(alpha=10)
3 ridgeReg.fit(X_train,y_train)
4 #train and test scorefor ridge regression
5 train_score_ridge = ridgeReg.score(X_train, y_train)
6 test_score_ridge = ridgeReg.score(X_test, y_test)
7 print("\nRidge Model:\n")
8 print("The train score for ridge model is {}".format(train_score_ridge))
9 print("The test score for ridge model is {}".format(test_score_ridge))
10
```

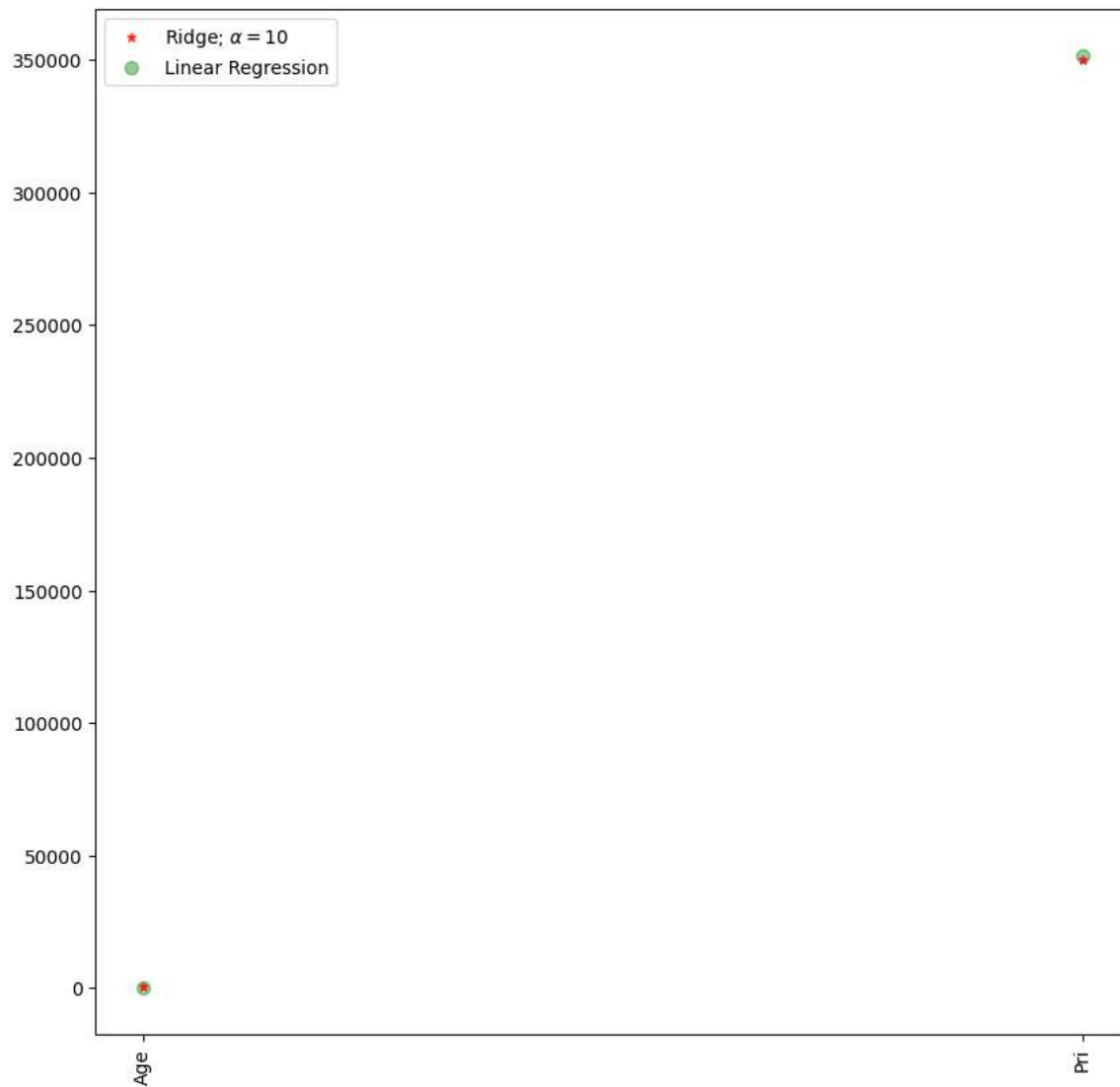
Ridge Model:

The train score for ridge model is 0.9999898738321127

The test score for ridge model is 0.9999900217008085

In [26]:

```
1 plt.figure(figsize = (10, 10))
2 plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker='*',markersize=5,color='red')
3 #plt.plot(rr100.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,color='blue')
4 plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker='o',markersize=7,color='green')
5 plt.xticks(rotation = 90)
6 plt.legend()
7 plt.show()
```



In [27]:

```
1 #Lasso regression model
2 print("\nLasso Model: \n")
3 lasso = Lasso(alpha = 10)
4 lasso.fit(X_train,y_train)
5 train_score_ls =lasso.score(X_train,y_train)
6 test_score_ls =lasso.score(X_test,y_test)
7 print("The train score for ls model is {}".format(train_score_ls))
8 print("The test score for ls model is {}".format(test_score_ls))
9
```

Lasso Model:

The train score for ls model is 0.9999999991901091

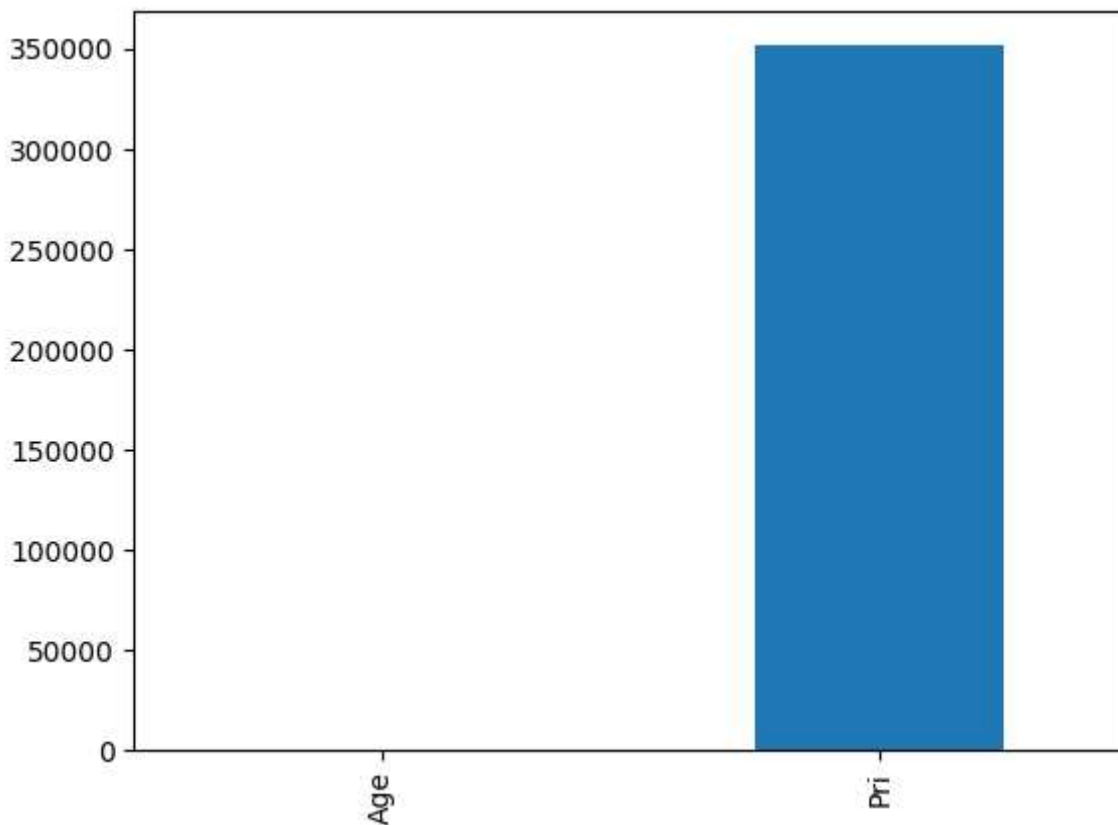
The test score for ls model is 0.9999999991882496

In [28]:

```
1 pd.Series(lasso.coef_, features).sort_values(ascending = True).plot(kind = "bar")
```

Out[28]:

<Axes: >



In [29]:

```
1 #Using the linear CV model
2 from sklearn.linear_model import LassoCV
3 #Lasso Cross validation
4 lasso_cv = LassoCV(alphas = [0.0001, 0.001,0.01, 0.1, 1, 10], random_state=0).fit(X_train, y_train)
5 #score
6 print(lasso_cv.score(X_train, y_train))
7 print(lasso_cv.score(X_test, y_test))
8
```

0.999999999723694

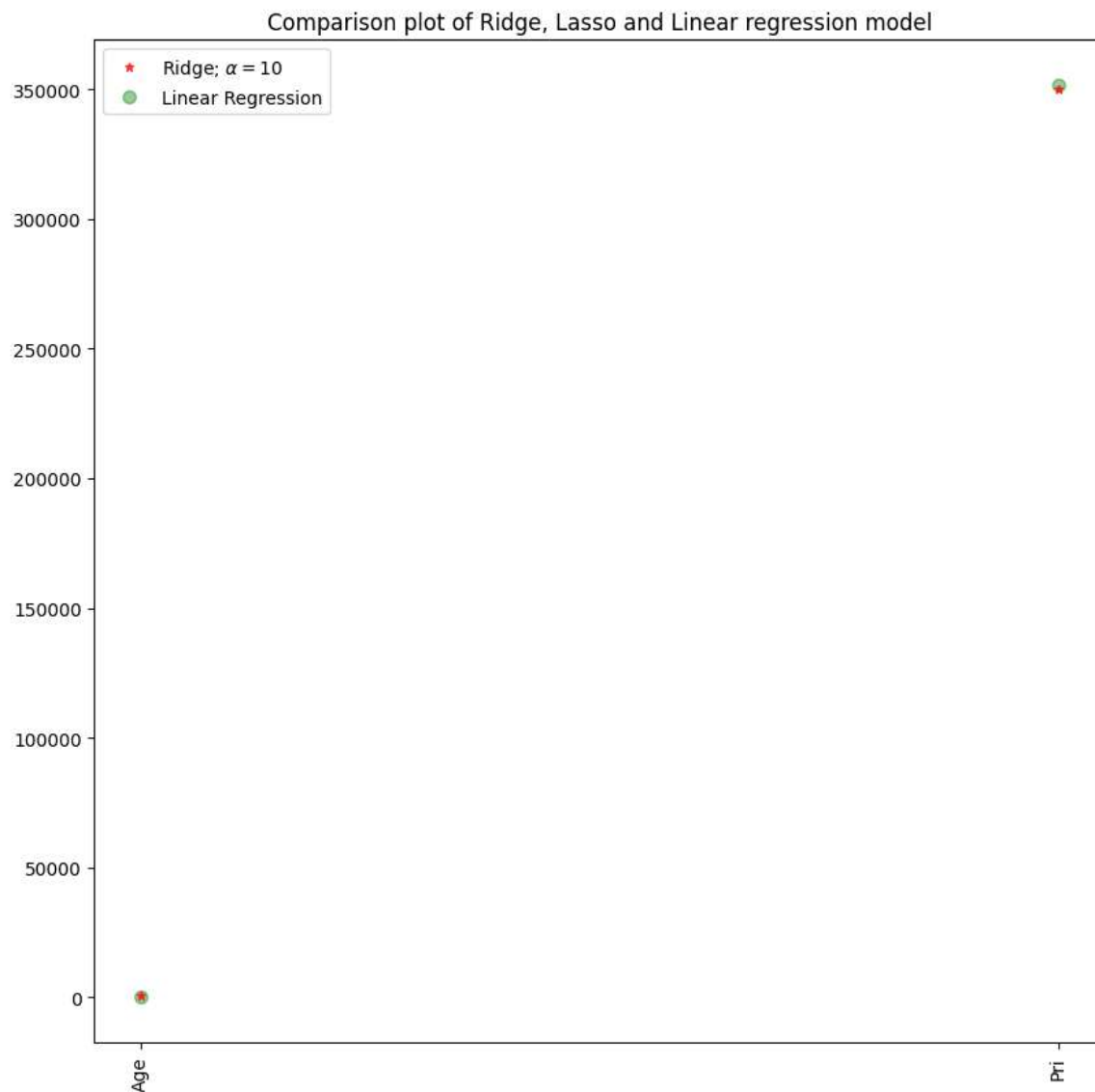
0.99999999973398

In [30]:

```

1  #plot size
2  plt.figure(figsize = (10, 10))
3  #add plot for ridge regression
4  plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker='*',markersize=5,color='blue')
5  #add plot for lasso regression
6  #plt.plot(lasso_cv.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,color='blue')
7  #add plot for linear model
8  plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker='o',markersize=7,color='red')
9  #rotate axis
10 plt.xticks(rotation = 90)
11 plt.legend()
12 plt.title("Comparison plot of Ridge, Lasso and Linear regression model")
13 plt.show()
14

```



In [31]:

```
1 #Using the linear CV model
2 from sklearn.linear_model import RidgeCV
3 #Ridge Cross validation
4 ridge_cv = RidgeCV(alphas = [0.0001, 0.001,0.01, 0.1, 1, 10]).fit(X_train, y_train)
5 #score
6 print("The train score for ridge model is {}".format(ridge_cv.score(X_train, y_train))
7 print("The train score for ridge model is {}".format(ridge_cv.score(X_test, y_test)))
```

The train score for ridge model is 0.9999999999999982

The train score for ridge model is 0.9999999999999983

In [32]:

```
1 from sklearn.linear_model import ElasticNet
2 regr=ElasticNet()
3 regr.fit(X,y)
4 print(regr.coef_)
5 print(regr.intercept_)
```

[0. 1.]

9.88272950053215e-06

In [33]:

```
1 y_pred_elastic=regr.predict(X_train)
2
```

In [34]:

```
1 mean_squared_error=np.mean((y_pred_elastic-y_train)**2)
2 print("Mean Squared Error on test set",mean_squared_error)
```

Mean Squared Error on test set 1628866435688.2292

In []:

```
1
```