DOCTOR VISIT ANALYSIS FOR HOUSE PRICE PREDICTION

Import Libraries

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

Importing Data and Checking out.

HouseDF = pd.read_csv('/content/USA_Housing.csv')
HouseDF.head()

	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

.

HouseDF.info()

```
<class 'pandas.core.frame.DataFrame'> RangeIndex:
5000 entries, 0 to 4999
Data columns (total 7 columns):
Avg. Area Income                5000 non-null float64
Avg. Area House Age             5000 non-null float64
Avg. Area Number of Rooms       5000 non-null float64
Avg. Area Number of Bedrooms    5000 non-null float64
Area Population                 5000 non-null float64
Price                           5000 non-null float64
Address                         5000 non-null object dtypes:
float64(6), object(1)
memory usage: 273.6+ KB
```

HouseDF.describe()

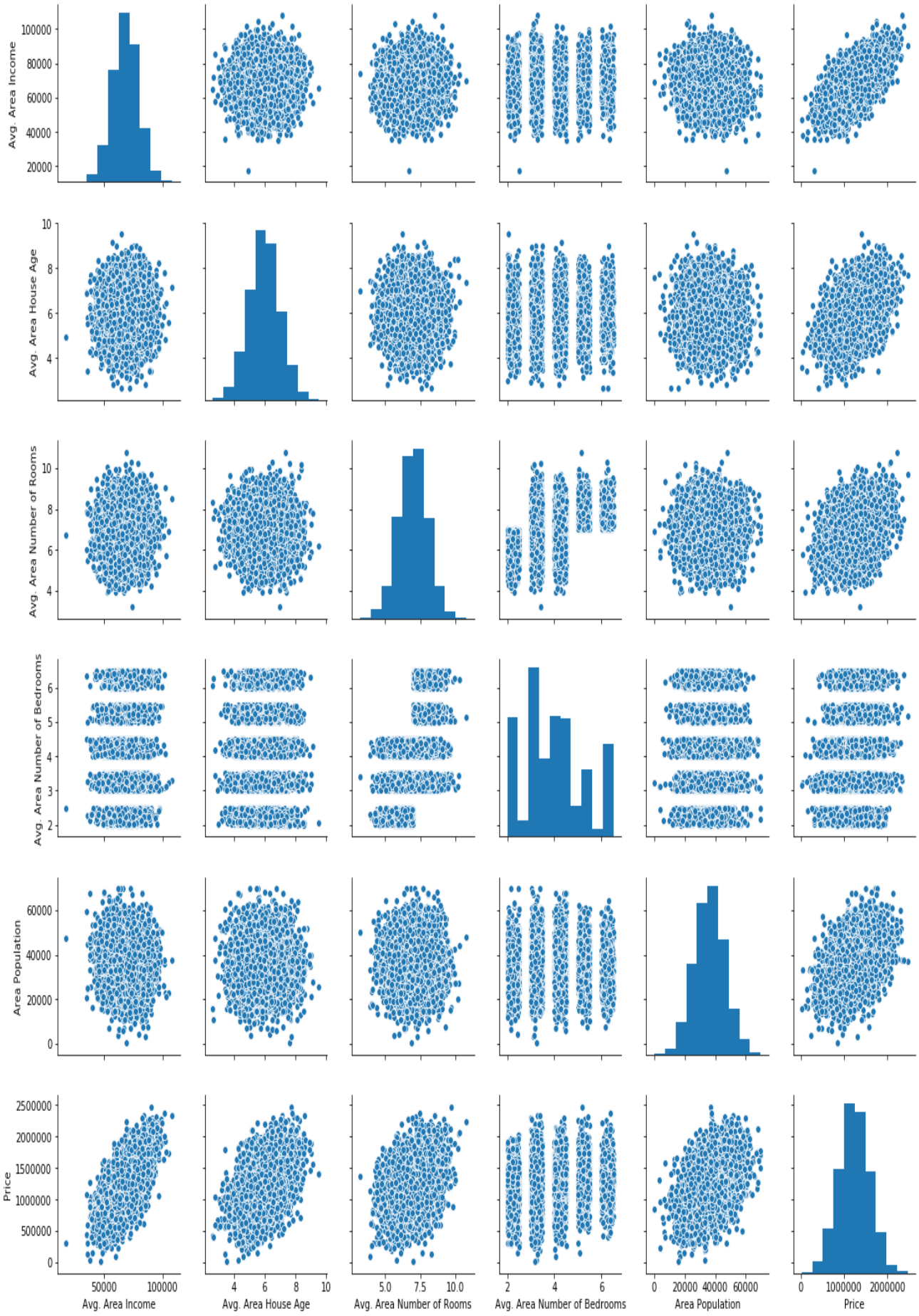
	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5.000000e+03
mean	68583.108984	5.977222	6.987792	3.981330	36163.516039	1.232073e+06
std	10657.991214	0.991456	1.005833	1.234137	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

HouseDF.columns

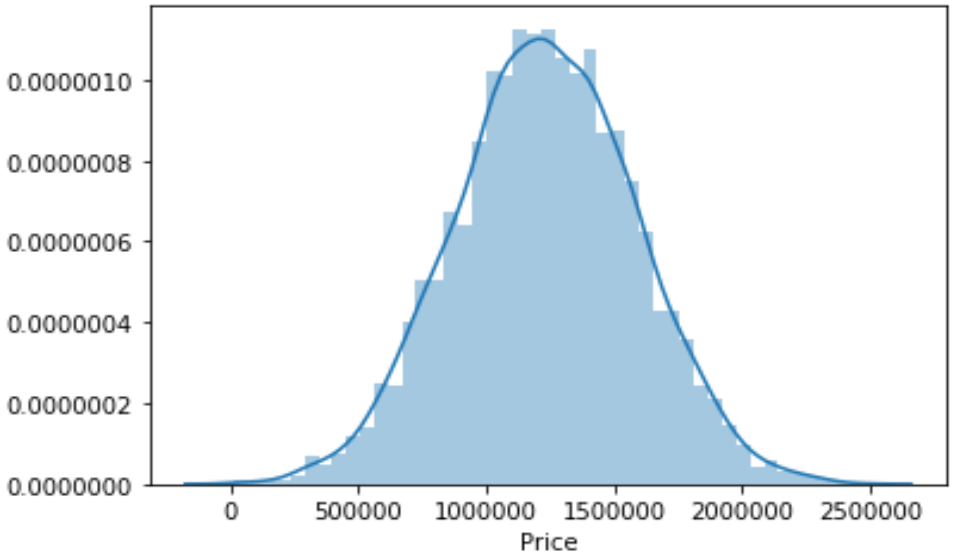
```
Index(['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number of Rooms',
'Avg. Area Number of Bedrooms', 'Area Population', 'Price', 'Address'],
dtype='object')
```

 # Exploratory Data Analysis for House Price Prediction

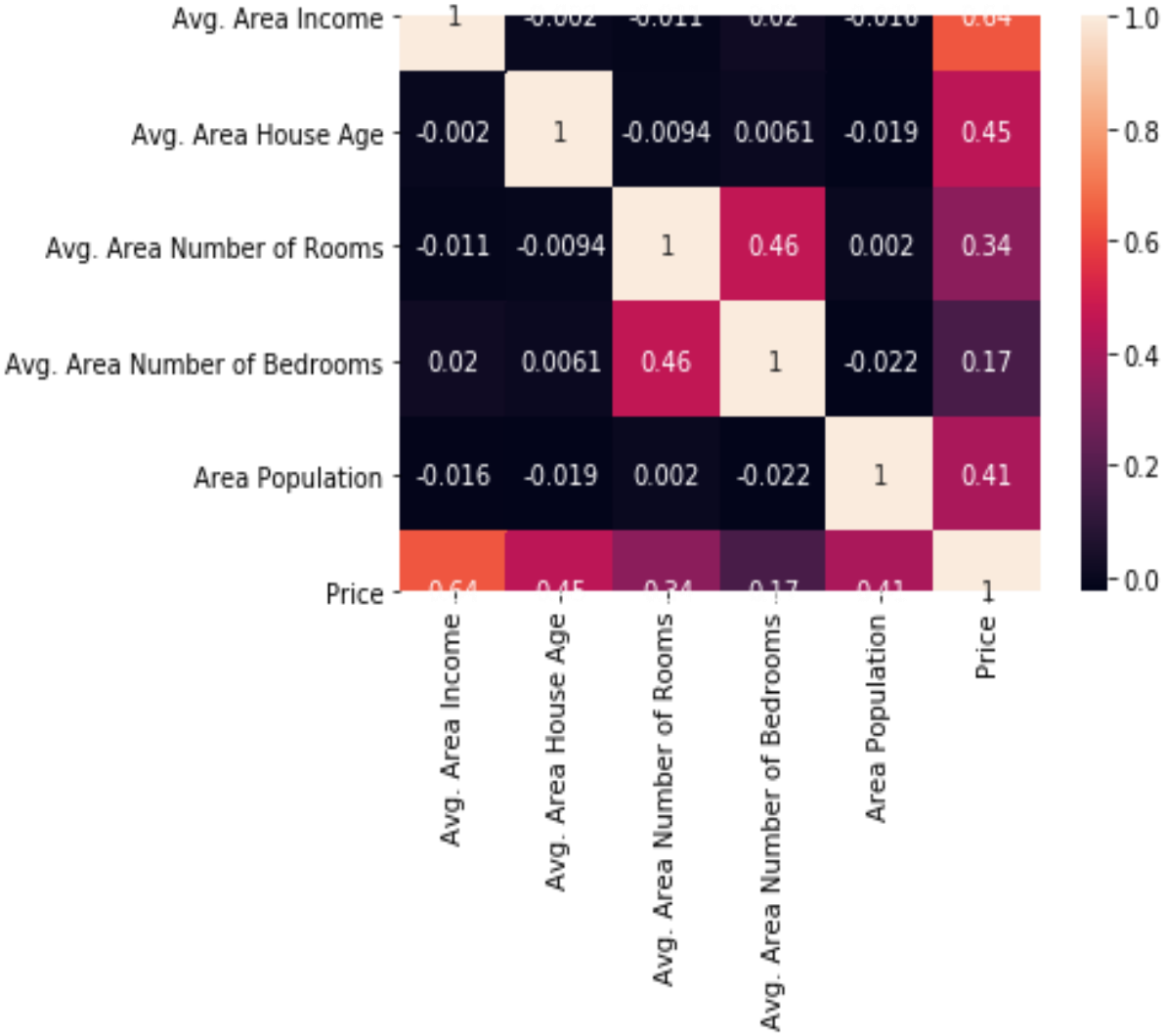
sns.pairplot(HouseDF)




```
sns.distplot(HouseDF['Price'])
```



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



 # Training a Linear Regression Model

 # X and y List

X = HouseDF[['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number of Rooms', 'Avg. Area Number of Bedrooms', 'Area Population']]

y = HouseDF['Price']

 # Split Data into Train, Test

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4, random_state=101)

 # Creating and Training the LinearRegression Model

from sklearn.linear_model import LinearRegression

lm = LinearRegression()

lm.fit(X_train,y_train)

```
LinearRegression()
```

 # LinearRegression Model Evaluation

print(lm.intercept_)

```
-2640159.7968526958
```

coeff_df = pd.DataFrame(lm.coef_,X.columns,columns=['Coefficient']) coeff_df

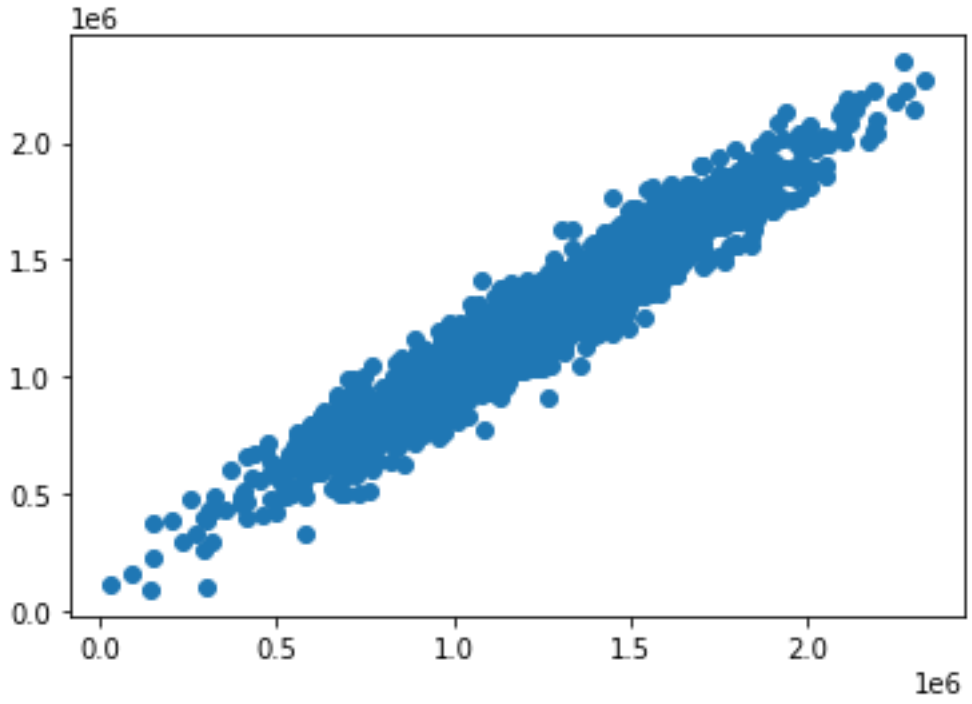
	Coefficient
Avg. Area Income	21.528276
Avg. Area House Age	164883.282027
Avg. Area Number of Rooms	122368.678027

Avg. Area Number of Bedrooms	2233.801864
Area Population	15.150420

 # Predictions from our Linear Regression Model

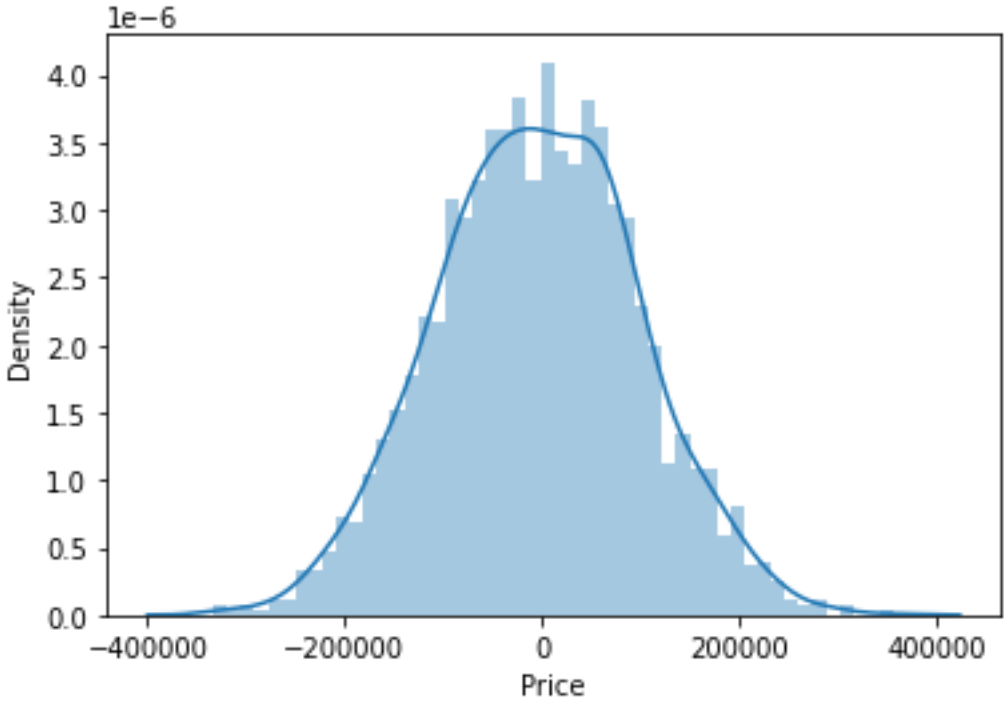
predictions = lm.predict(X_test)

plt.scatter(y_test,predictions)



 # In the above scatter plot, we see data is in line shape, which means our model has done good predictions.

sns.distplot((y_test-predictions),bins=50);



 # In the above histogram plot, we see data is in bell shape (Normally Distributed), which means our model has done good predictions.

 # Regression Evaluation *Metrics*

from sklearn import 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
```

 # Conclusion

The outcomes of this analysis have practical applications for various stakeholders in the real estate industry. Homebuyers can benefit from accurate price estimations to guide their purchasing decisions and negotiate prices effectively. Sellers can use the predictions to set competitive listing prices and understand the market demand. Additionally, real estate agents and financial institutions can leverage these models to provide valuable insights and assistance to their clients.