In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Check out the Data

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

In [3]:
```
USAhousing.head()
```

Out[3]:

	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 F 674\nLaura
1	79248.642455	6.002900	6.730821	3.09	40173.072174	1.505891e+06	188 Johns Suite 07 Kathle
2	61287.067179	5.865890	8.512727	5.13	36882.159400	1.058988e+06	9127 E Stravenue\nDar WI
3	63345.240046	7.188236	5.586729	3.26	34310.242831	1.260617e+06	USS Barnett\r
4	59982.197226	5.040555	7.839388	4.23	26354.109472	6.309435e+05	USNS Raymo A

In [4]:
```
USAhousing.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]:
```
USAhousing.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

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price
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]:
```
USAhousing.columns
```

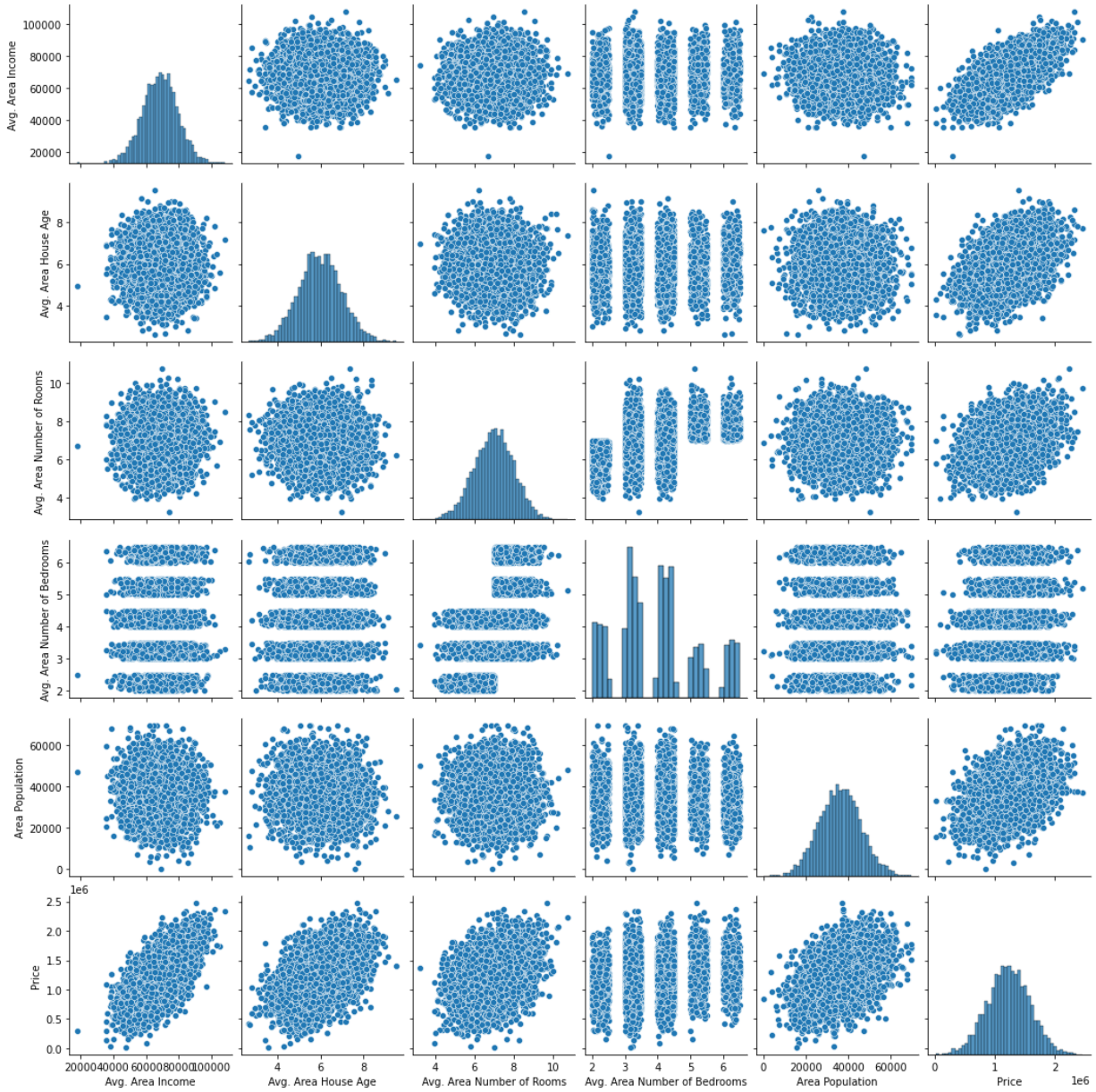
Out[6]:
```
Index(['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number of Room
s',
       'Avg. Area Number of Bedrooms', 'Area Population', 'Price', 'Addres
s'],
      dtype='object')
```

EDA

Let's create some simple plots to check out the data!

In [7]:
```
sns.pairplot(USAhousing)
```

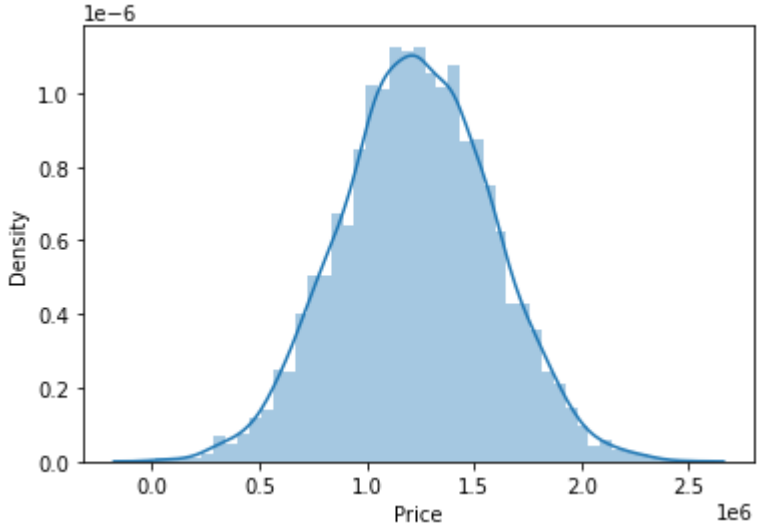
Out[7]:
```
<seaborn.axisgrid.PairGrid at 0x7fe410025dc0>
```



In [8]:
```
sns.distplot(USAhousing['Price'])
```

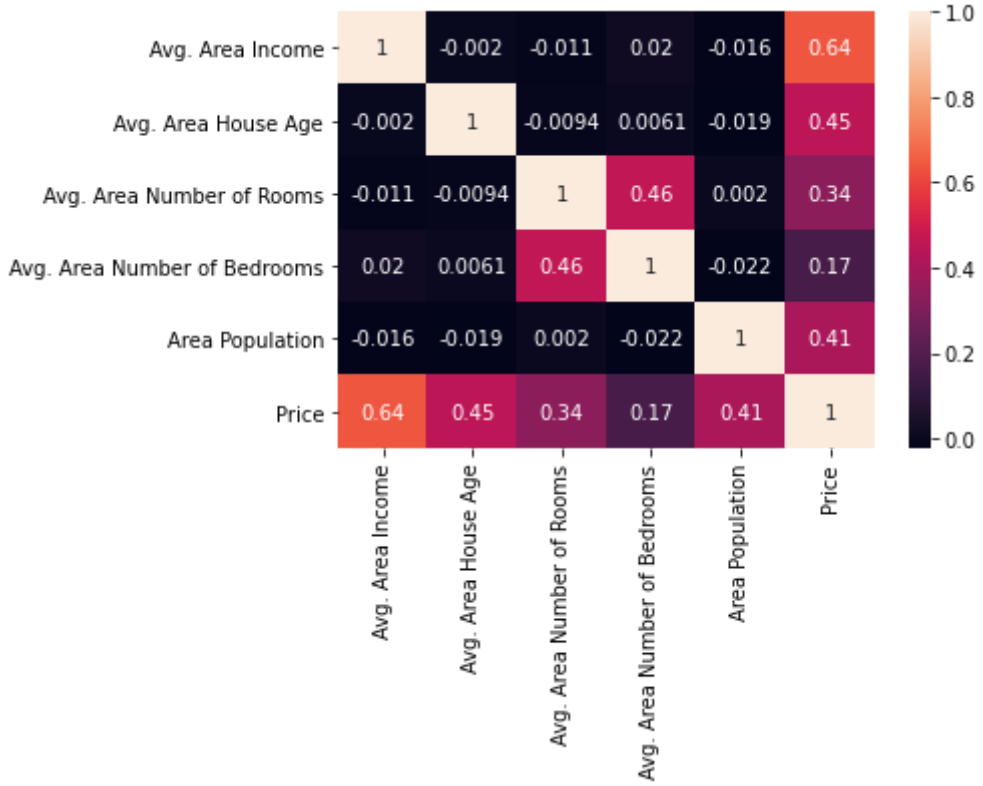
```
/Users/himanshubairwa/opt/anaconda3/lib/python3.8/site-packages/seaborn/distr
ibutions.py:2557: FutureWarning: `distplot` is a deprecated function and will
be removed in a future version. Please adapt your code to use either `displot
` (a figure-level function with similar flexibility) or `histplot` (an axes-l
evel function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[8]: <AxesSubplot:xlabel='Price', ylabel='Density'>



In [23]:
```
sns.heatmap(USAhousing.corr(), annot= True)
```

Out[23]: <AxesSubplot:>



Training a Linear Regression Model

Let's now begin to train out regression model! We will need to first split up our data into an X array that contains the features to train on, and a y array with the target variable, in this case the Price column. We will toss out the Address column because it only has text info that the linear regression model can't use.

X and y arrays

In [10]:
```
X = USAhousing[['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number
                'Avg. Area Number of Bedrooms', 'Area Population']]
y = USAhousing['Price']
```

Train Test Split

Now let's split the data into a training set and a testing set. We will train out model on the training set and then use the test set to evaluate the model.

In [11]:
```
from sklearn.model_selection import train_test_split
```

In [12]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4, rand
```

Creating and Training the Model

In [13]:
```
from sklearn.linear_model import LinearRegression
```

In [14]:
```
lm = LinearRegression()
```

In [15]:
```
lm.fit(X_train,y_train)
```

Out[15]:
```
LinearRegression()
```

Model Evaluation

Let's evaluate the model by checking out it's coefficients and how we can interpret them.

In [16]:
```
# print the intercept
print(lm.intercept_)
```

```
-2640159.7968537207
```

In [17]:
```
coeff_df = pd.DataFrame(lm.coef_,X.columns,columns=['Coefficient'])
coeff_df
```

Out[17]:

	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

Interpreting the coefficients:

- Holding all other features fixed, a 1 unit increase in **Avg. Area Income** is associated with an **increase of $21.52** .
- Holding all other features fixed, a 1 unit increase in **Avg. Area House Age** is associated with an **increase of $164883.28** .

- Holding all other features fixed, a 1 unit increase in **Avg. Area Number of Rooms** is associated with an **increase of $122368.67** .
- Holding all other features fixed, a 1 unit increase in **Avg. Area Number of Bedrooms** is associated with an **increase of $2233.80** .
- Holding all other features fixed, a 1 unit increase in **Area Population** is associated with an **increase of $15.15** .

Does this make sense? Probably not because I made up this data. If you want real data to repeat this sort of analysis, check out the boston dataset:

```
from sklearn.datasets import load_boston
boston = load_boston()
print(boston.DESCR)
boston_df = boston.data
```

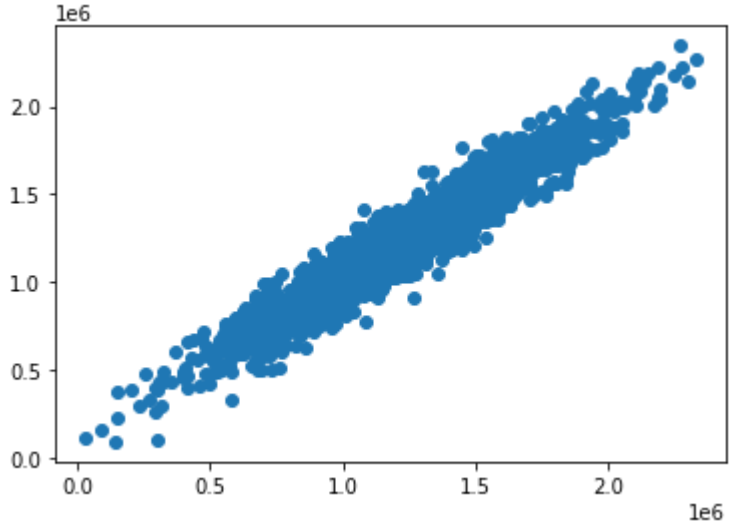
Predictions from our Model

Let's grab predictions off our test set and see how well it did!

In [18]:
```
predictions = lm.predict(X_test)
```

In [19]:
```
plt.scatter(y_test,predictions)
```

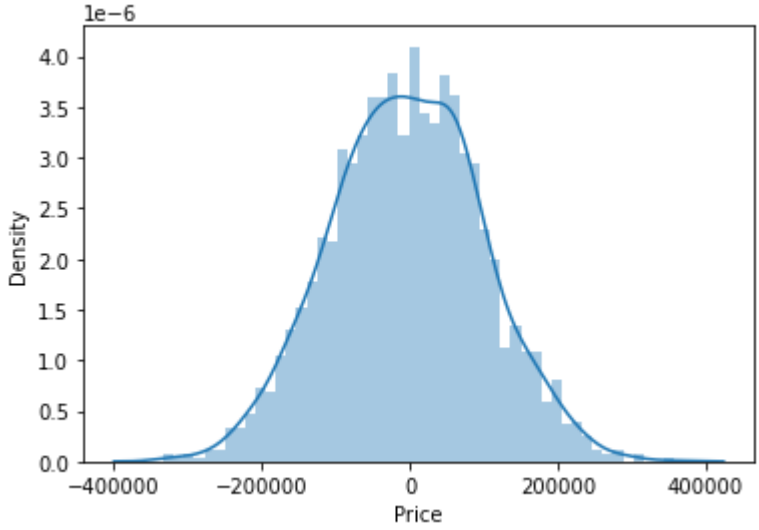
Out[19]:
```
<matplotlib.collections.PathCollection at 0x7fe47285ed90>
```



Residual Histogram

In [20]:
```
sns.distplot((y_test-predictions),bins=50);
```

```
/Users/himanshubairwa/opt/anaconda3/lib/python3.8/site-packages/seaborn/distr
ibutions.py:2557: FutureWarning: `distplot` is a deprecated function and will
be removed in a future version. Please adapt your code to use either `displot
` (a figure-level function with similar flexibility) or `histplot` (an axes-l
evel function for histograms).
  warnings.warn(msg, FutureWarning)
```



Regression Evaluation Metrics

Here are three common evaluation metrics for regression problems:

Mean Absolute Error (MAE) is the mean of the absolute value of the errors:

$$\frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Mean Squared Error (MSE) is the mean of the squared errors:

$$\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Root Mean Squared Error (RMSE) is the square root of the mean of the squared errors:

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Comparing these metrics:

- **MAE** is the easiest to understand, because it's the average error.
- **MSE** is more popular than MAE, because MSE "punishes" larger errors, which tends to be useful in the real world.
- **RMSE** is even more popular than MSE, because RMSE is interpretable in the "y" units.

All of these are **loss functions**, because we want to minimize them.

In [21]:
```
from sklearn import metrics
```

In [22]:
```
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: 82288.2225191493
MSE: 10460958907.20825
```

```
RMSE: 102278.8292229054
```

This was your first real Machine Learning Project! Congrats on helping your neighbor out! We'll let this end here for now, but go ahead and explore the Boston Dataset mentioned earlier if this particular data set was interesting to you!

Up next is your own Machine Learning Project!

Great Job!

In [ ]: