Linear Regression with Python - House Price Prediction

The data contains the following columns:

- 'Avg. Area Income': Avg. Income of residents of the city house is located in.
- 'Avg. Area House Age': Avg Age of Houses in same city
- 'Avg. Area Number of Rooms': Avg Number of Rooms for Houses in same city
- 'Avg. Area Number of Bedrooms': Avg Number of Bedrooms for Houses in same city
- 'Area Population': Population of city house is located in
- 'Price': Price that the house sold at
- 'Address': Address for the house

Import Libraries

In [255]:

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

Check out the Data

In [256]:

```
USAhousing = pd.read_csv('USA_Housing.csv')
```

In [257]:

```
USAhousing.head()
```

Out[257]:

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price	Addr
0	79545.458574	5.682861	7.009188	4.09	23086.800503	1.059034e+06	208 Michael Ferry / 674\nLaurabury, 370
1	79248.642455	6.002900	6.730821	3.09	40173.072174	1.505891e+06	188 Johnson Vie Suite 079\nL Kathleen, C
2	61287.067179	5.865890	8.512727	5.13	36882.159400	1.058988e+06	9127 Elizab Stravenue\nDanielto WI 0648
3	63345.240046	7.188236	5.586729	3.26	34310.242831	1.260617e+06	USS Barnett\nFPO 44
4	59982.197226	5.040555	7.839388	4.23	26354.109472	6.309435e+05	USNS Raymond\nF AE 09

In [258]:

```
USAhousing.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: 273.5+ KB
```

In [259]:

```
USAhousing.describe()
```

Out[259]:

	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 [260]:

```
USAhousing.columns
```

Out[260]:

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

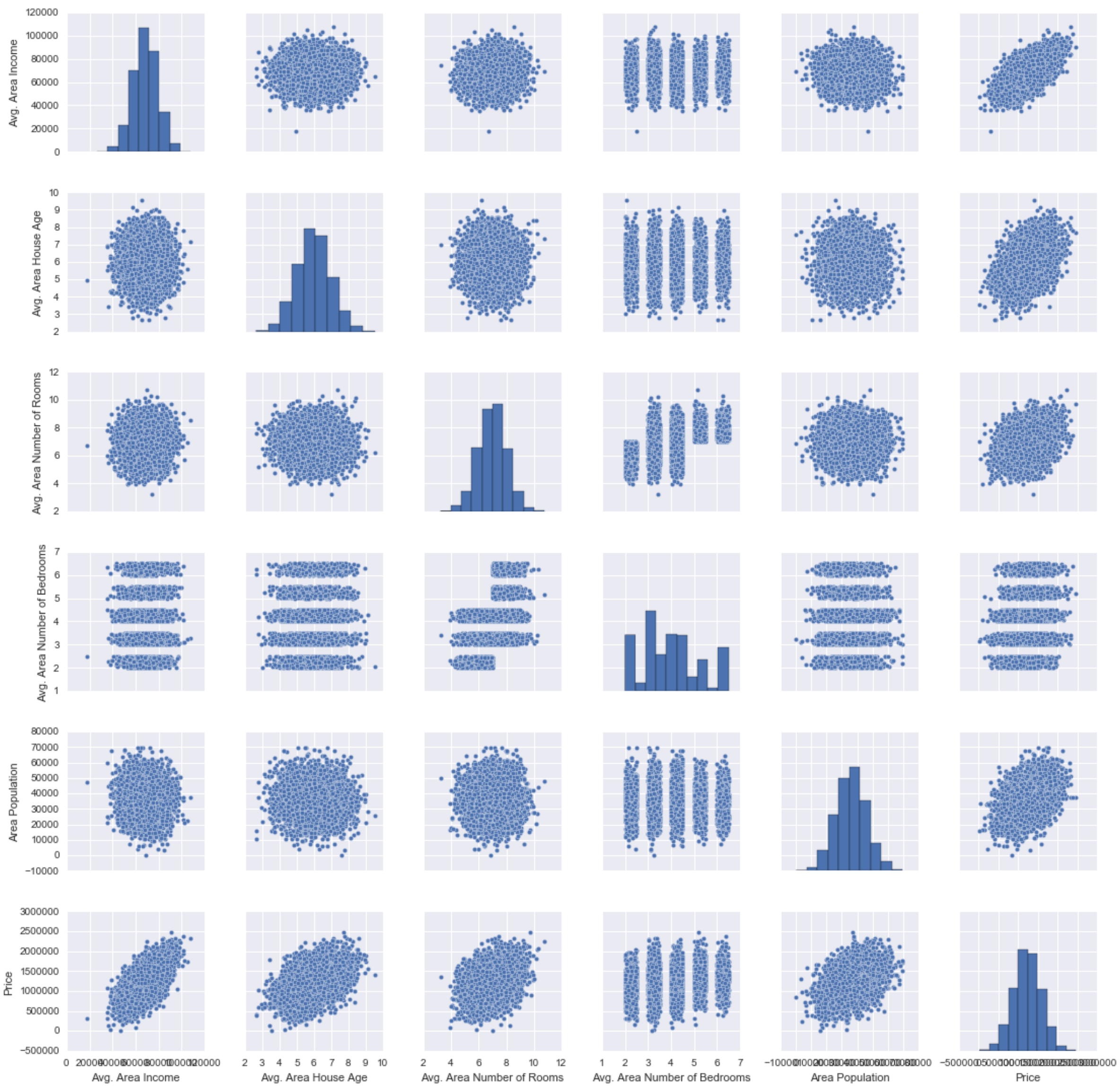
Plottings

In [261]:

```
sns.pairplot(USAhousing)
```

Out[261]:

<seaborn.axisgrid.PairGrid at 0x13e898358>

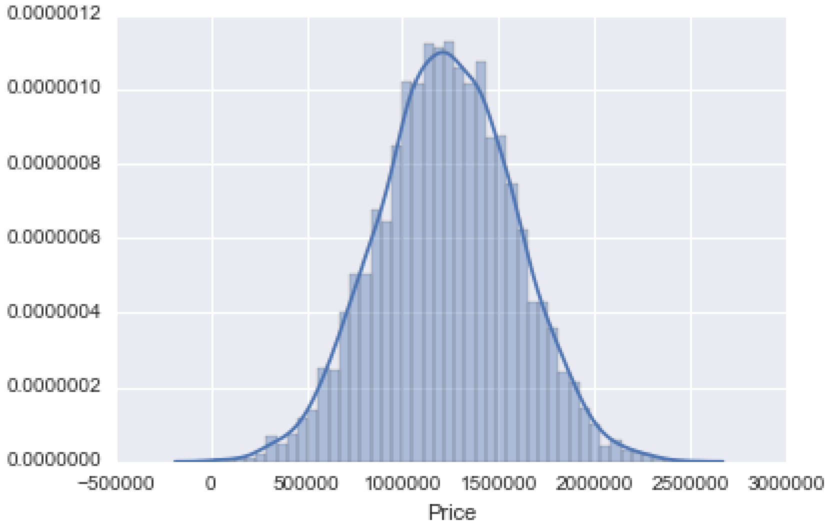


In [262]:

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

Out[262]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x13e6dad30>
```

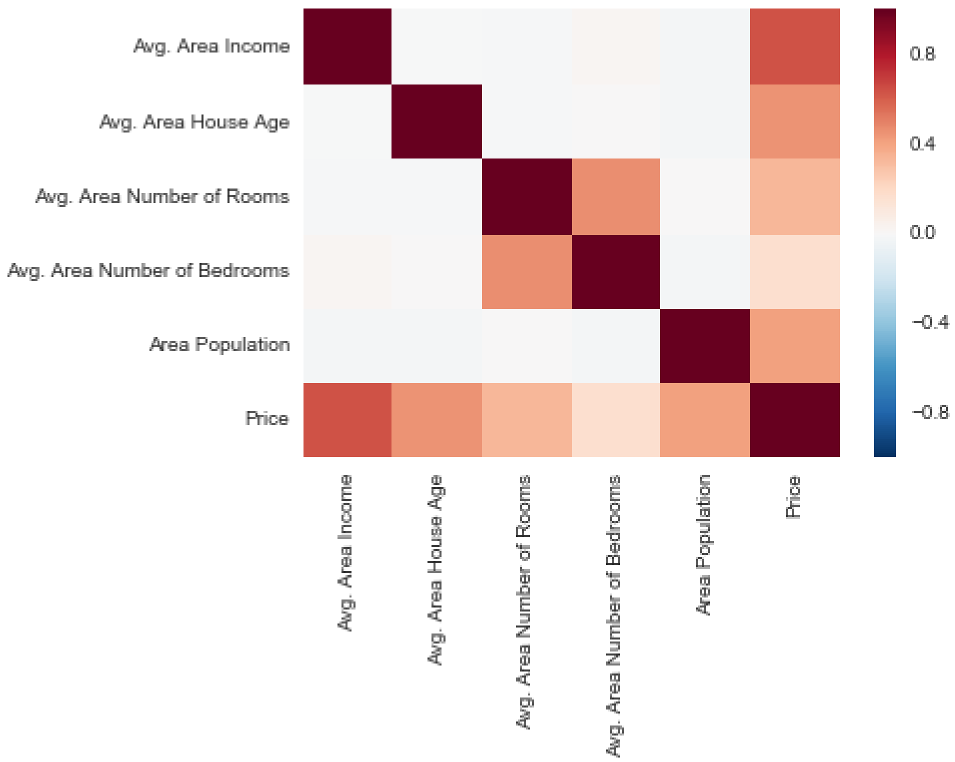


In [263]:

```
sns.heatmap(USAhousing.corr())
```

Out[263]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x141dca908>
```



Training a Linear Regression Model

X and y arrays

In [264]:

```
X = USAhousing[['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number of Room
               '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 [265]:

```
from sklearn.model_selection import train_test_split
```

In [266]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4, random_stat
```

Creating and Training the Model

In [267]:

```
from sklearn.linear_model import LinearRegression
```

In [268]:

```
lm = LinearRegression()
```

In [269]:

```
lm.fit(X_train,y_train)
```

Out[269]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=
False)
```

Model Evaluation

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

In [270]:

```

print(lm.intercept_)
```

```
-2640159.79685
```

In [277]:

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

Out[277]:

	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 *.

Predictions from our Model

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

In [279]:

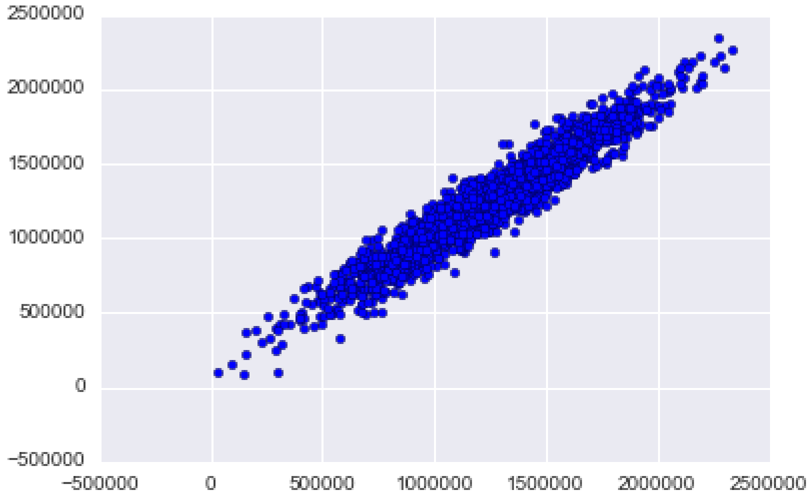
```
predictions = lm.predict(X_test)
```

In [282]:

```
plt.scatter(y_test,predictions)
```

Out[282]:

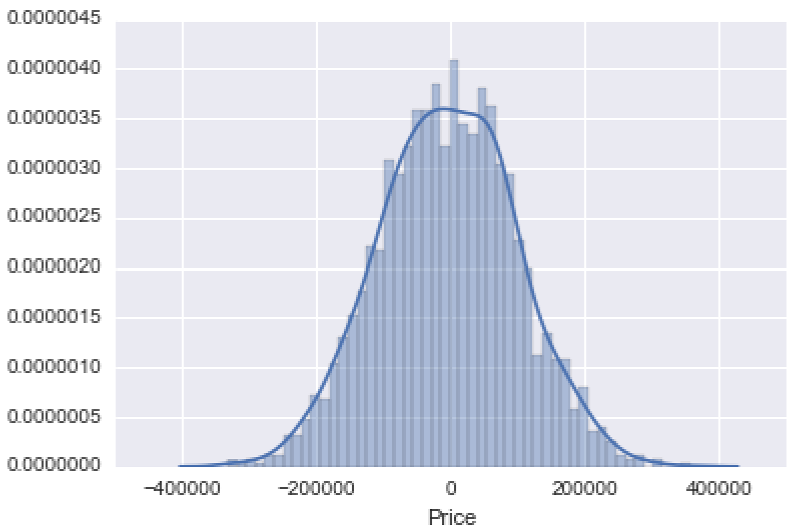
```
<matplotlib.collections.PathCollection at 0x142622c88>
```



Residual Histogram

In [281]:

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



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 [275]:

```
from sklearn import metrics
```

In [276]:

```
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: 82288.2225191
MSE: 10460958907.2
RMSE: 102278.829223
```