Linear Regression with Python

Your neighbor is a real estate agent and wants some help predicting housing prices for regions in the USA. It would be great if you could somehow create a model for her that allows her to put in a few features of a house and returns back an estimate of what the house would sell for.

She has asked you if you could help her out with your new data science skills. You say yes, and decide that Linear Regression might be a good path to solve this problem!

Your neighbor then gives you some information about a bunch of houses in regions of the United States,it is all in the data set: USA_Housing.csv.

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

Let's get started!

Check out the data

We've been able to get some data from your neighbor for housing prices as a csv set, let's get our environment ready with the libraries we'll need and then import the data!

Import Libraries

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 Mich 674\nLau 3701...
1	79248.642455	6.002900	6.730821	3.09	40173.072174	1.505891e+06	188 Johr Suite 079 Kathleen
2	61287.067179	5.865890	8.512727	5.13	36882.159400	1.058988e+06	9127 Eliz Stravenu WI 06482
3	63345.240046	7.188236	5.586729	3.26	34310.242831	1.260617e+06	USS Bar 44820
4	59982.197226	5.040555	7.839388	4.23	26354.109472	6.309435e+05	USNS Ra AE 0938

In [4]:
```
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 [5]:
```
#let us see some statistics about the data
USAhousing.describe()
```

Out[5]:

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5.00000C
mean	68583.108984	5.977222	6.987792	3.981330	36163.516039	1.232073
std	10657.991214	0.991456	1.005833	1.234137	9925.650114	3.531176
min	17796.631190	2.644304	3.236194	2.000000	172.610686	1.593866
25%	61480.562388	5.322283	6.299250	3.140000	29403.928702	9.975771
50%	68804.286404	5.970429	7.002902	4.050000	36199.406689	1.232669
75%	75783.338666	6.650808	7.665871	4.490000	42861.290769	1.47121C
max	107701.748378	9.519088	10.759588	6.500000	69621.713378	2.469066

In [6]:
```
#to See the names of all the columns
USAhousing.columns
```

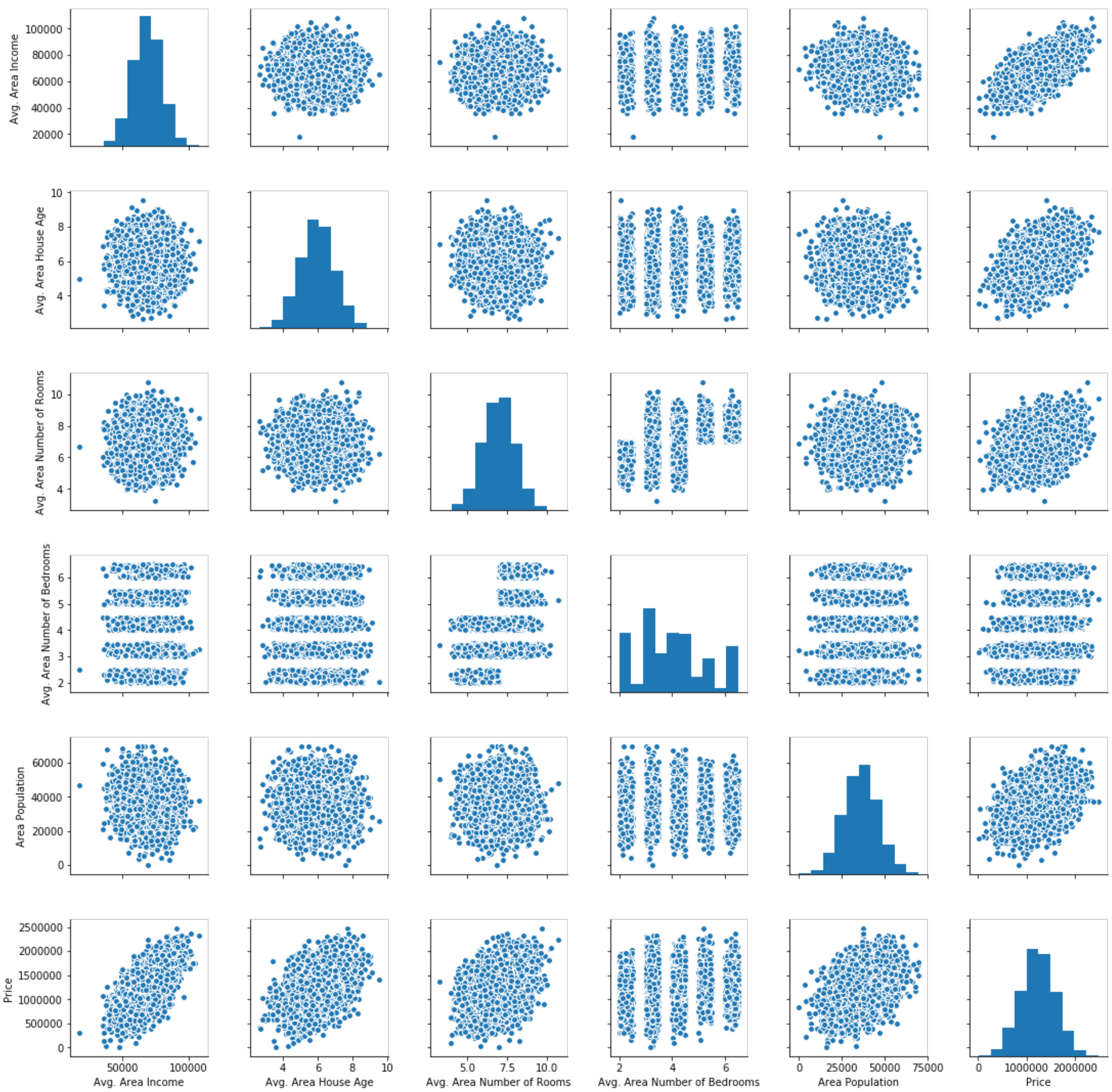
Out[6]:
```
Index(['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number
of Rooms',
       'Avg. Area Number of Bedrooms', 'Area Population', 'Price', '
Address'],
      dtype='object')
```

EDA

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

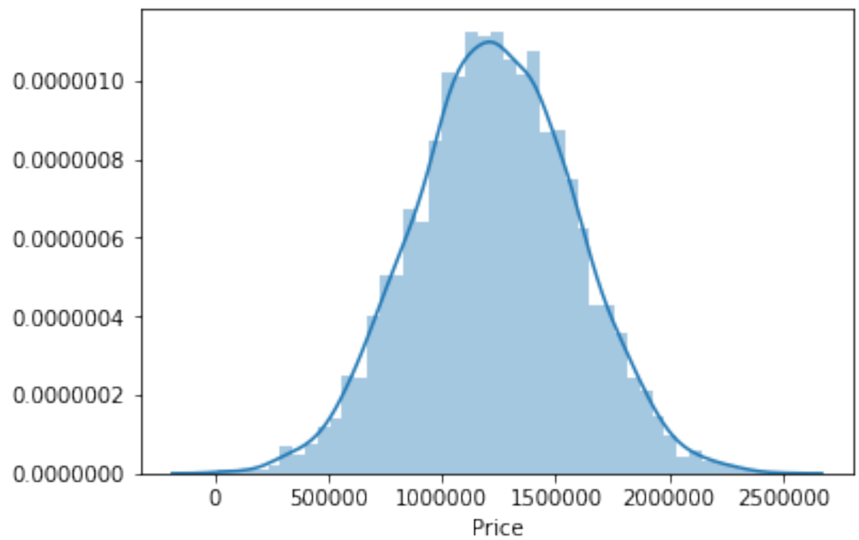
In [7]:
```
sns.pairplot(USAhousing)
```

Out[7]: <seaborn.axisgrid.PairGrid at 0x11784a2b0>



In [8]:
```
# as we are going to predict the price of the house, let us see how it
's distributed
sns.distplot(USAhousing['Price'])
```

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x1a226e39e8>



In [9]:
```
#if we want to see the correlation between each feature, we can use co
rr() method.
sns.heatmap(USAhousing.corr())
```

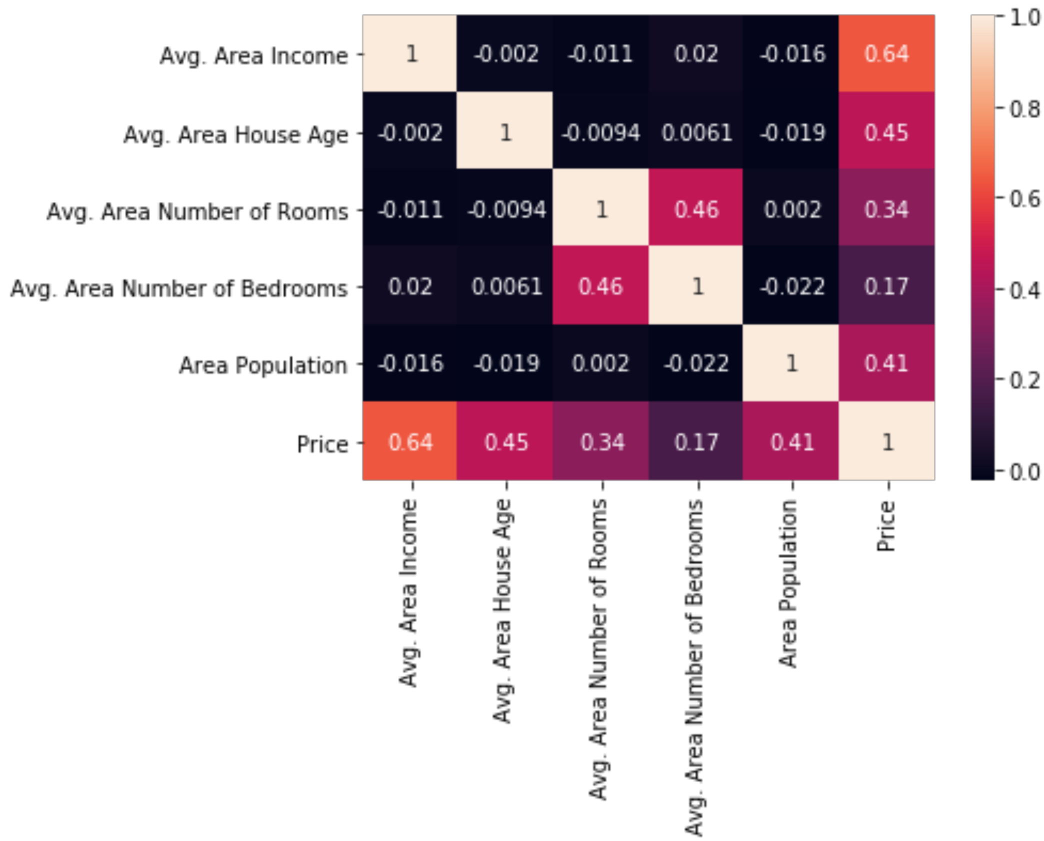
Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x1a22dd8908>

In [10]:

```
sns.heatmap(USAhousing.corr(),annot=True)
```

Out[10]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a23432358>
```



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 [264]:

```
X = USAhousing[['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number of Rooms',
               '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_state=101)
```

Creating and Training the Model

In [267]:
```
from sklearn.linear_model import LinearRegression
```

In [268]:
```
#create an instance for the model
lm = LinearRegression()
```

In [269]:
```
lm.fit(X_train,y_train)
```

Out[269]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normaliz
e=False)
```

Model Evaluation

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

In [270]:
```
# print the intercept
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** .

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 (http://scikit-learn.org/stable/modules/generated/sklearn.datasets.load_boston.html):

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

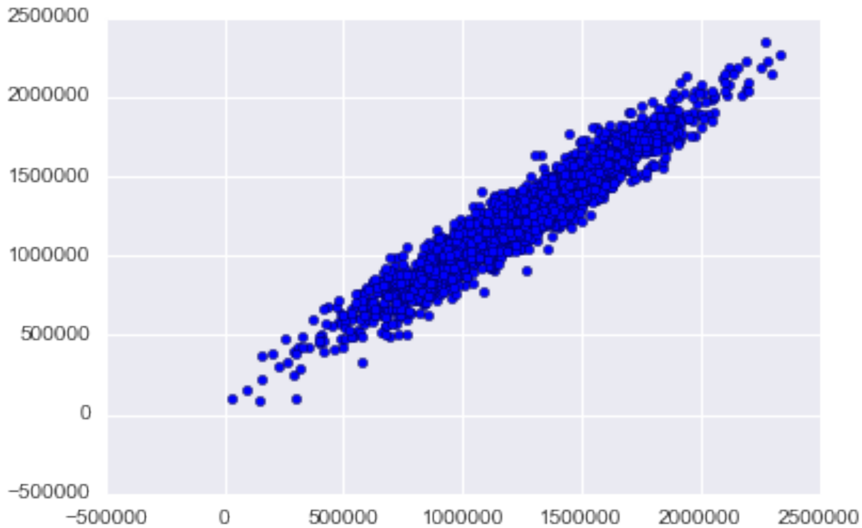
Predictions from our Model

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

In [279]:
```
#in prediction, we only pass the test features
predictions = lm.predict(X_test)
```

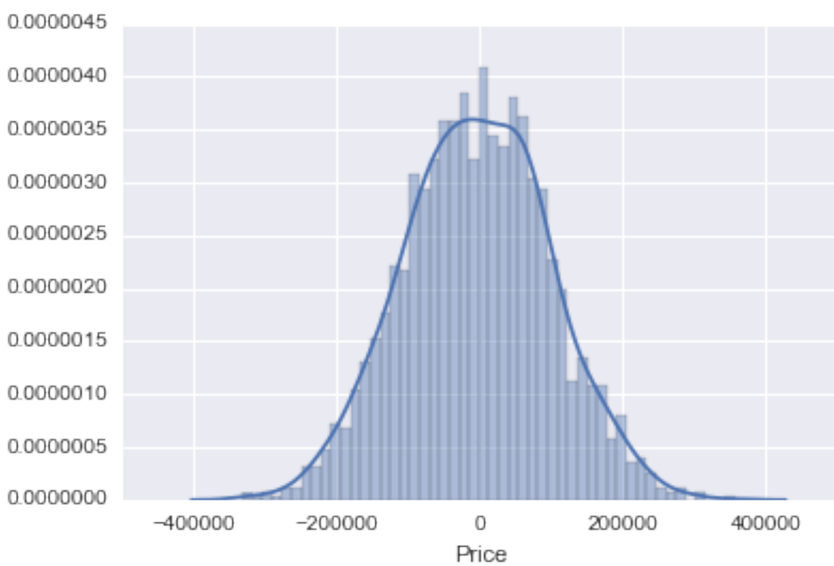
In [282]:
```
#let us compare the predictions with the actual class values using vis
ualizations

plt.scatter(y_test,predictions)
```

Out[282]: <matplotlib.collections.PathCollection at 0x142622c88>



Residual Histogram-- Residual is the difference between the actual and your predictions if the residual is normally distributed , your model is the right choice for the data.

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
```

Great Job!