In [1]:

Applying linear regression model to fake housing data to predict the prices

In [2]:

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

In [3]:

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

In [4]:

Let's checkout the info() method which provides information about shape, name of columns, data type, non-null values df.info() # clearly the 'Prices' is the target column

<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]:

```
df.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	5.00000
mean	68583.108984	5.977222	6.987792	3.981330	36163.516039	1.23207
std	10657.991214	0.991456	1.005833	1.234137	9925.650114	3.53117
min	17796.631190	2.644304	3.236194	2.000000	172.610686	1.59386
25%	61480.562388	5.322283	6.299250	3.140000	29403.928702	9.97577
50%	68804.286404	5.970429	7.002902	4.050000	36199.406689	1.23266
75%	75783.338666	6.650808	7.665871	4.490000	42861.290769	1.47121
max	107701.748378	9.519088	10.759588	6.500000	69621.713378	2.46906

In [6]:

```
Out[6]:
```

In [7]:

```
# Generally speaking column_names without a underscore is not my thing and I like to co
nvert it to one with underscores
df.columns = df.columns.str.replace(' ','_')
df.columns
```

Out[7]:

In [8]:

df.head()

Out[8]:

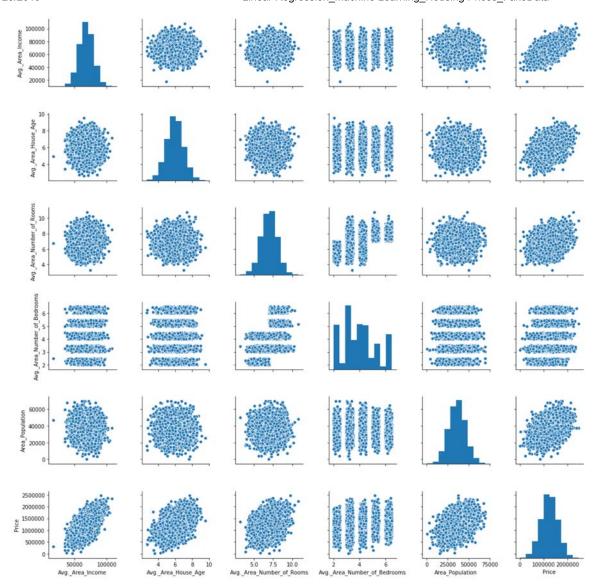
	AvgArea_Income	AvgArea_House_Age	AvgArea_Number_of_Rooms	AvgA
0	79545.458574	5.682861	7.009188	4.09
1	79248.642455	6.002900	6.730821	3.09
2	61287.067179	5.865890	8.512727	5.13
3	63345.240046	7.188236	5.586729	3.26
4	59982.197226	5.040555	7.839388	4.23

In [9]:

sns.pairplot(df)

Out[9]:

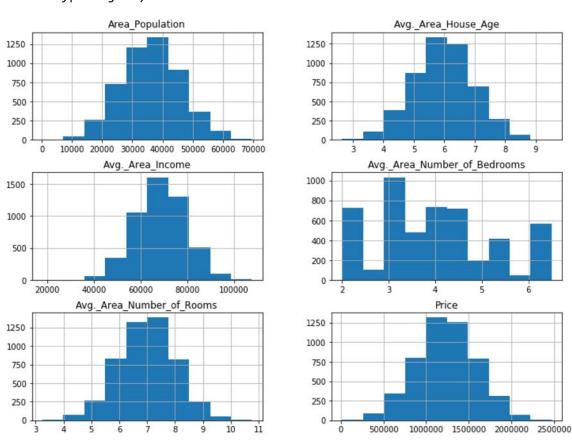
<seaborn.axisgrid.PairGrid at 0x1fe86b2b278>



In [10]:

df.hist(figsize=(12,9))

Out[10]:

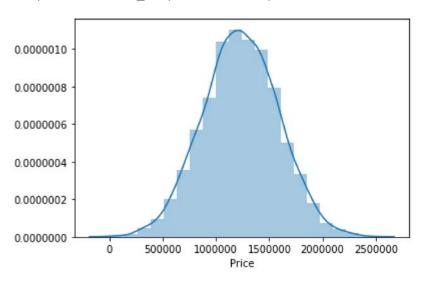


In [11]:

sns.distplot(df['Price'],bins=20)

Out[11]:

<matplotlib.axes._subplots.AxesSubplot at 0x1fe899990f0>



In [12]:

df.corr()

Out[12]:

	AvgArea_Income	AvgArea_House_Age	Avg/
AvgArea_Income	1.000000	-0.002007	-0.0110
AvgArea_House_Age	-0.002007	1.000000	-0.009
AvgArea_Number_of_Rooms	-0.011032	-0.009428	1.0000
AvgArea_Number_of_Bedrooms	0.019788	0.006149	0.4626
Area_Population	-0.016234	-0.018743	0.0020
Price	0.639734	0.452543	0.3356

In [13]:

```
# Above table is hard to read and comprehend
# The below chart solves this problem
sns.heatmap(df.corr(), annot=True)
```

Out[13]:

<matplotlib.axes._subplots.AxesSubplot at 0x1fe896ccc88>



In [14]:

In [15]:

```
# Let's check X and y (head())
print(X.head())
print('----')
print('Data Type of X is: ',type(X))
print('***********')
print(y.head())
print('----')
print('Data Type of y is: ',type(y))
   Avg._Area_Income Avg._Area_House_Age
                                          Avg._Area_Number_of_Rooms
0
       79545.458574
                                5.682861
                                                           7.009188
1
       79248.642455
                                6.002900
                                                           6.730821
2
       61287.067179
                                5.865890
                                                           8.512727
3
       63345.240046
                                7.188236
                                                           5.586729
4
       59982.197226
                                5.040555
                                                           7.839388
   Avg._Area_Number_of_Bedrooms
                                Area Population
0
                           4.09
                                    23086.800503
1
                           3.09
                                    40173.072174
2
                           5.13
                                    36882.159400
3
                           3.26
                                    34310.242831
4
                           4.23
                                    26354.109472
Data Type of X is: <class 'pandas.core.frame.DataFrame'>
******
a
    1.059034e+06
1
    1.505891e+06
2
    1.058988e+06
3
    1.260617e+06
4
    6.309435e+05
Name: Price, dtype: float64
Data Type of y is: <class 'pandas.core.series.Series'>
```

In [16]:

```
from sklearn.model_selection import train test split
```

In [17]:

```
# unpacking train test split tuple
# This will split the dataset in two groups called training set and test set
# Because we have y which is our target, the model will work with training set and then
we can confirm the accuracy on the test set
X train, X test, y train, y test = train test split(X, y, test size=0.4, random state=1
01)
# Random state is chosen to 101 to get exactly same result what I got last time as last
time also I had chosen 101
```

In [18]:

```
# import the LinearRegression model
from sklearn.linear_model import LinearRegression
# Make an instance of this model or instantiate the model
lm = LinearRegression()
```

In [19]:

```
# Let's fit the training set to the model
lm.fit(X_train, y_train)
```

Out[19]:

LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=F
alse)

In [22]:

```
# We need two important values from this model
# 1. intercept which you can get it from the attribute lm.intercept_
# 2. coefficient which you can get it from the attribute lm.coef_
print('Intercept is: ',lm.intercept_)
print('Set of coefficients is: ',lm.coef_)
```

```
Intercept is: -2640159.796851911
Set of coefficients is: [2.15282755e+01 1.64883282e+05 1.22368678e+05 2.2
3380186e+03
1.51504200e+01]
```

In [23]:

```
# Intercept shown above do not talk to us directly
# So we use a better way of representing them
# Let's make a data frame out of it
# the columns names corresponding to the co-efficients can be index
# The coefficients can be the body of the DataFrame
# and column name can be coeff
Coeff_df = pd.DataFrame(lm.coef_, index=X.columns, columns=['Co-efficients'])
Coeff_df
```

Out[23]:

	Co-efficients
AvgArea_Income	21.528276
AvgArea_House_Age	164883.282027
AvgArea_Number_of_Rooms	122368.678027
AvgArea_Number_of_Bedrooms	2233.801864
Area_Population	15.150420

In [24]:

```
# We still haven't passed the test set to this model
# And we still haven't compared its generation of y values and our already available y
values
pred_values = lm.predict(X_test)
print(type(pred_values))
print('*************')
a = pred_values/y_test
print(a)
```

```
<class 'numpy.ndarray'>
******
1718
        1.007408
2511
        0.947930
345
        1.026779
2521
        0.916032
54
        1.052625
2866
        0.884542
2371
        0.928265
2952
        1.212477
45
        0.963788
4653
        0.933742
891
        1.008175
3011
        1.016302
335
        0.987783
3050
        0.887521
3850
        0.964823
834
        1.094442
3188
        0.849544
4675
        0.848376
2564
        1.136980
1866
        0.865799
1492
        1.263964
3720
        1.218885
        1.044775
618
3489
        0.998544
2145
        0.963020
3200
        0.987091
4752
        0.985603
602
        1.011727
4665
        1.016204
79
        1.035449
4668
        0.923755
3762
        1.342201
236
        1.026918
4897
        0.948148
1283
        1.157236
2443
        1.282226
3600
        1.032961
2138
        1.067112
254
        1.174238
3987
        0.918753
527
        0.977258
1362
        0.988514
4577
        0.940858
2642
        0.984865
4297
        0.967352
1114
        0.971898
1041
        0.984857
3666
        1.055580
4571
        0.926021
3698
        0.955747
412
        0.986969
3385
        0.995617
3057
        0.896668
3863
        1.048679
4165
        1.000425
1776
        1.017135
4269
        0.959212
1661
        2.456270
```

2410 1.0159192302 1.004457

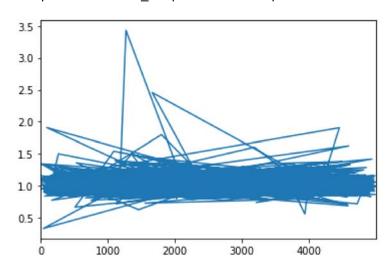
Name: Price, Length: 2000, dtype: float64

In [25]:

a.plot()

Out[25]:

<matplotlib.axes._subplots.AxesSubplot at 0x1fe8b37c7f0>

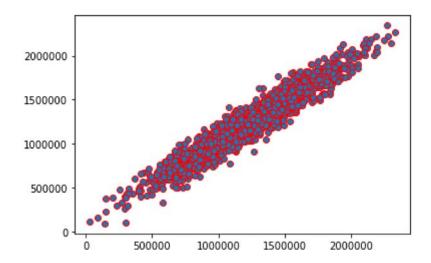


In [26]:

plt.scatter(y_test,pred_values,edgecolors='red')

Out[26]:

<matplotlib.collections.PathCollection at 0x1fe8b73de48>



In [27]:

```
f = (lambda x: x>320000)
above_320T = y_test.apply(f)
print(above_320T)
```

1718

2511

True

True

345	True
2521	True
54	True
2866	True
2371	True
2952	True
45	True
4653	True
891	True
3011 335	True True
3050	True
3850	True
834	True
3188	True
4675	True
2564	True
1866	True
1492	True
3720	True
618	True
3489	True
2145	True
3200	True
4752	True
602 4665	True True
79	True
,,,	•••
4668	True
3762	True
236	True
4897	True
1283	True
2443	True
3600	True
2138	True
254	True
3987	True
527 1362	True True
4577	True
2642	True
4297	True
1114	True
1041	True
3666	True
4571	True
3698	True
412	True
3385	True
3057	True
3863	True
4165 1776	True
1776 4260	True
4269 1661	True False
2410	True
2-710	11 40
:///C:/Users/	vtaor/Dowr

2302 True

Name: Price, Length: 2000, dtype: bool

In [28]:

sns.scatterplot(x=y_test,y=a,hue=above_320T)
To me this is a great plot
This plot explains that the accuracy of the model is better for predicting houses wit
h price above 320,000

Out[28]:

<matplotlib.axes._subplots.AxesSubplot at 0x1fe8b40c390>

