In [ ]:

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Laboratory 29: Multiple Regression

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ENGR 1330 Laboratory 29 - In Lab

Background

Download the data set ca_housing.csv and describe its contents (no not the describe function, but words - what does it appear to contain)

In [1]:

```
# Load the necessary packages
import numpy as np
import pandas as pd
import seaborn as sns
import statistics
import math
from matplotlib import pyplot as plt
import statsmodels.formula.api as smf
```

Get the datafile

In [2]:

```
import requests # Module to process http/https requests
remote_url="http://54.243.252.9/engr-1330-webroot/8-Labs/Lab29/ca_housing.csv"  # set t
rget = requests.get(remote_url, allow_redirects=True)  # get the remote resource, follo
open('ca_housing.csv','wb').write(rget.content); # extract from the remote the contents
```

Read the datafile into a dataframe

In [3]:

```
housing = pd.read_csv('ca_housing.csv')
housing.describe() # verify the read
```

Out[3]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitud
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.00000
mean	3.870671	28.639486	5.429000	1.096675	1425.476744	3.070655	35.63186
std	1.899822	12.585558	2.474173	0.473911	1132.462122	10.386050	2.13595
min	0.499900	1.000000	0.846154	0.333333	3.000000	0.692308	32.54000
25%	2.563400	18.000000	4.440716	1.006079	787.000000	2.429741	33.93000
50%	3.534800	29.000000	5.229129	1.048780	1166.000000	2.818116	34.26000
75%	4.743250	37.000000	6.052381	1.099526	1725.000000	3.282261	37.71000

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitud
max	15.000100	52.000000	141.909091	34.066667	35682.000000	1243.333333	41.95000

Data preprocessing

After loading the data, it's a good practice to see if there are any missing values in the data. Count the number of missing values for each feature using isnull() .

In [4]:
```
housing.isnull().sum()
```

Out[4]:
```
MedInc         0
HouseAge       0
AveRooms       0
AveBedrms      0
Population     0
AveOccup       0
Latitude       0
Longitude      0
AveHouseVal    0
dtype: int64
```

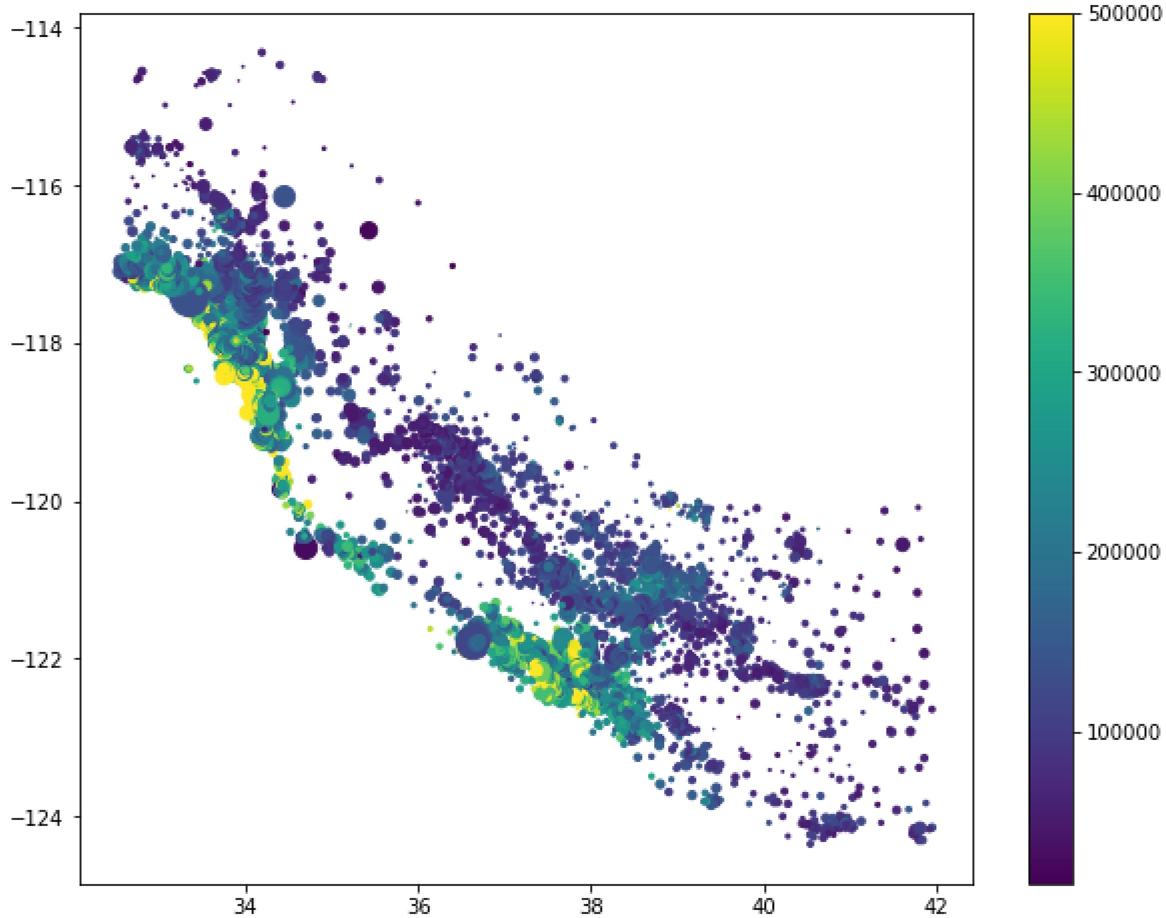
It appears that all values have non-null entries, so no cleaning necessary.

Exploratory Data Analysis

Plot the distribution of the target variable AveHouseVal depending on Latitude and Longitude. The code below should get the following figure (assuming you named your dataframe "housing")

In [5]:
```
plt.figure(figsize=(10,8))
plt.scatter(housing['Latitude'], housing['Longitude'], c=housing['AveHouseVal'], s=hous
plt.colorbar()
```

Out[5]:
```
<matplotlib.colorbar.Colorbar at 0x1fdcb6a2a30>
```



So it sort of looks like Callyfornia, notice the high value homes are along the coast, and get cheaper as one moves inland. Aslo note we are not correctly projecting the Lat-Lon values, so we should not use our script as a GIS-type tool just yet.

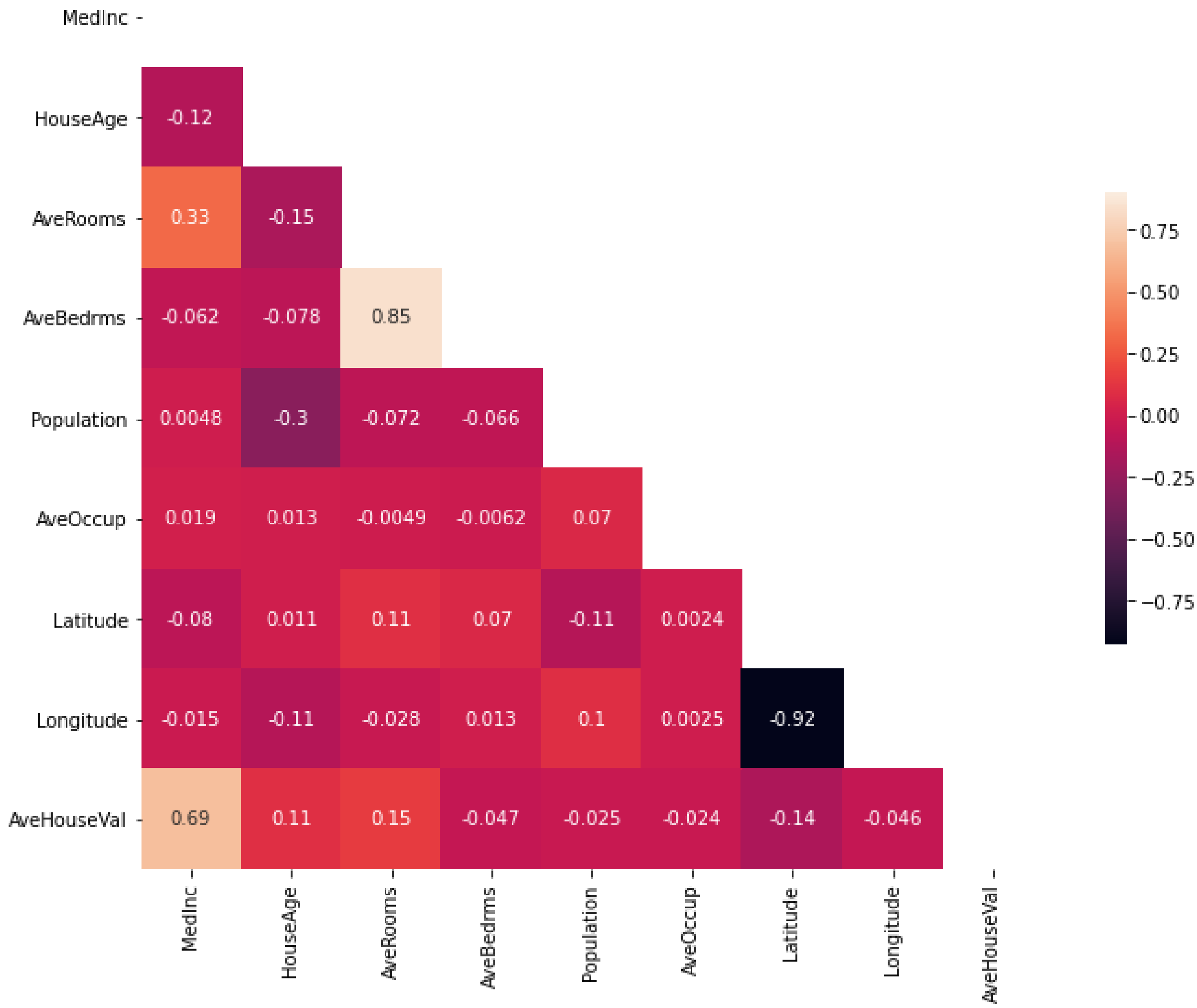
Correlation map

Next, we create a correlation matrix that measures the linear relationships between the variables.

The script below should produce a correlation map that prints the off-diagional correlation matrix terms, and color codes them/

In [6]:
```
corrmat = housing.corr()
plt.subplots(figsize=(12,9))
mask = np.zeros_like(corrmat, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True
sns.heatmap(corrmat, vmax=0.9, square=True, annot=True, mask=mask, cbar_kws={"shrink":
```

Out[6]: <AxesSubplot:>



Build a Multiple-variable Model

The script below uses all the variables (its a dumb model but illustrates the syntax and package warnings we can use to improve the model)

In [8]:
```
# Initialise and fit linear regression model using `statsmodels`
model = smf.ols('AveHouseVal ~ MedInc + AveRooms + HouseAge + AveRooms + Latitude + Lon
model = model.fit()
pred = model.predict()
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            AveHouseVal   R-squared:                       0.606
Model:                            OLS   Adj. R-squared:                  0.606
Method:                 Least Squares   F-statistic:                     3970.
Date:                Sat, 30 Jul 2022   Prob (F-statistic):               0.00
Time:                        21:39:34   Log-Likelihood:            -2.6025e+05
No. Observations:               20640   AIC:                         5.205e+05
Df Residuals:                   20631   BIC:                         5.206e+05
Df Model:                           8
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept  -3.694e+06   6.59e+04    -56.067      0.000   -3.82e+06   -3.57e+06
```

```
MedInc      4.367e+04    419.680    104.054      0.000    4.28e+04    4.45e+04
AveRooms   -1.073e+04    588.538    -18.235      0.000   -1.19e+04   -9578.623
HouseAge     943.5778     44.628     21.143      0.000     856.104    1031.052
Latitude   -4.213e+04    719.687    -58.541      0.000   -4.35e+04   -4.07e+04
Longitude  -4.345e+04    753.289    -57.682      0.000   -4.49e+04    -4.2e+04
AveOccup    -378.6543     48.741     -7.769      0.000    -474.191    -283.117
AveBedrms   6.451e+04   2813.494     22.928      0.000      5.9e+04       7e+04
Population    -0.3976      0.475     -0.837      0.402      -1.329       0.533
==============================================================================
Omnibus:                     4393.650   Durbin-Watson:                   0.885
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            14087.596
Skew:                           1.082   Prob(JB):                         0.00
Kurtosis:                       6.420   Cond. No.                     2.38e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
[2] The condition number is large, 2.38e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Select Useable Variables

To fit a linear regression model, we want to select those features that have a high correlation with our dependent variable **AveHouseVal**.

By looking at the correlation matrix we can see that MediaInc has a strong positive correlation with AverageHouseVal (0.69). The other two variables with highest correlation are HouseAge and AveRooms.

We should drop population as it could include zero (and its coefficient is already small). An important point when selecting features for a linear regression model is to check for multicollinearity. For example, the features Latitude and Longitude have 0.92 correlation with each other, so we should **not** include **both** of them simultaneously in our regression model.

Because the correlation between the variables MediaInc , HouseAve and AveRooms is not high, yet they have good correlation with **AveHouseVal** , we consider those three variables for our regression model.

Exercise 1

Build a model to predict **AveHouseVal** based on

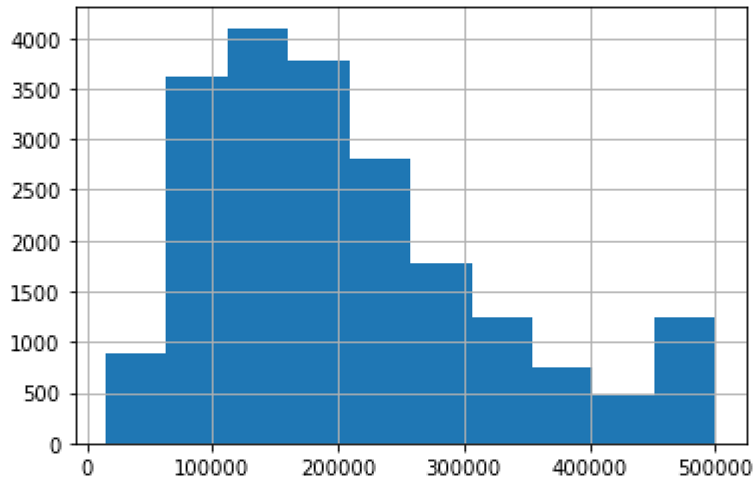
- **MediaInc**
- **HouseAge**
- **AveRooms**

1. Report the equation of the model.
2. Produce a histogram of **AveHouseVal**.
3. Produce a histogram of the residuals.
4. What is the mean value of the residuals?

5. Do the residuals seem to be normally distributed? How will you assess?
6. Are the residuals homoscedastic? (Yep you're gonna have to look that up)

In [27]:
```
import statsmodels.api as sm
(housing['AveHouseVal']).hist()
```

Out[27]: <AxesSubplot:>

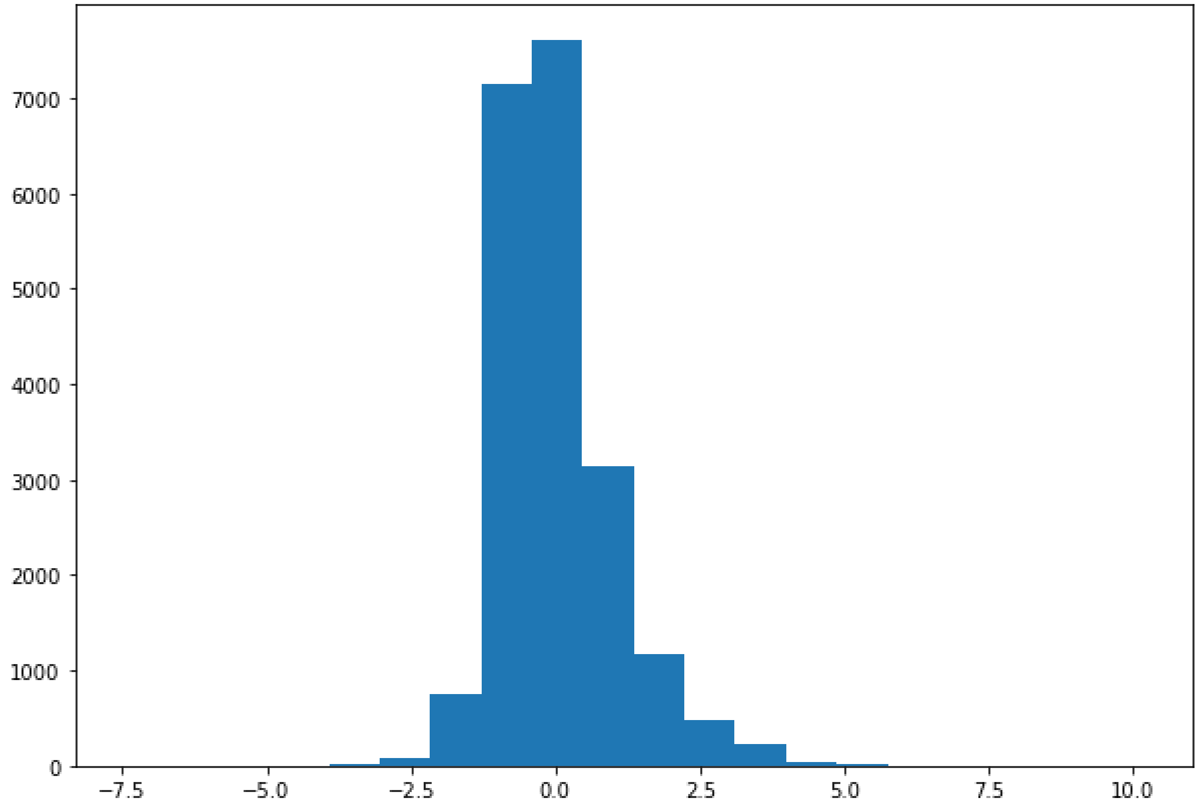


In [28]:
```
model = smf.ols('AveHouseVal ~ MedInc + HouseAge + AveRooms', data = housing)
model = model.fit()
slope = model.params[1]
Rsquare = model.rsquared
intercept = model.params[0]
RMSE = math.sqrt(model.mse_total)
infl = model.get_influence()
res = infl.resid_studentized_internal
print(res)
p = res
print('===============================')

fig, ax = plt.subplots(figsize = (10, 7))
ax.hist(p, bins = 20)
```

```
[ 0.39635562 -0.36582416 -0.44969507 ...  0.00653609 -0.19629183
 -0.38516945]
===============================
```

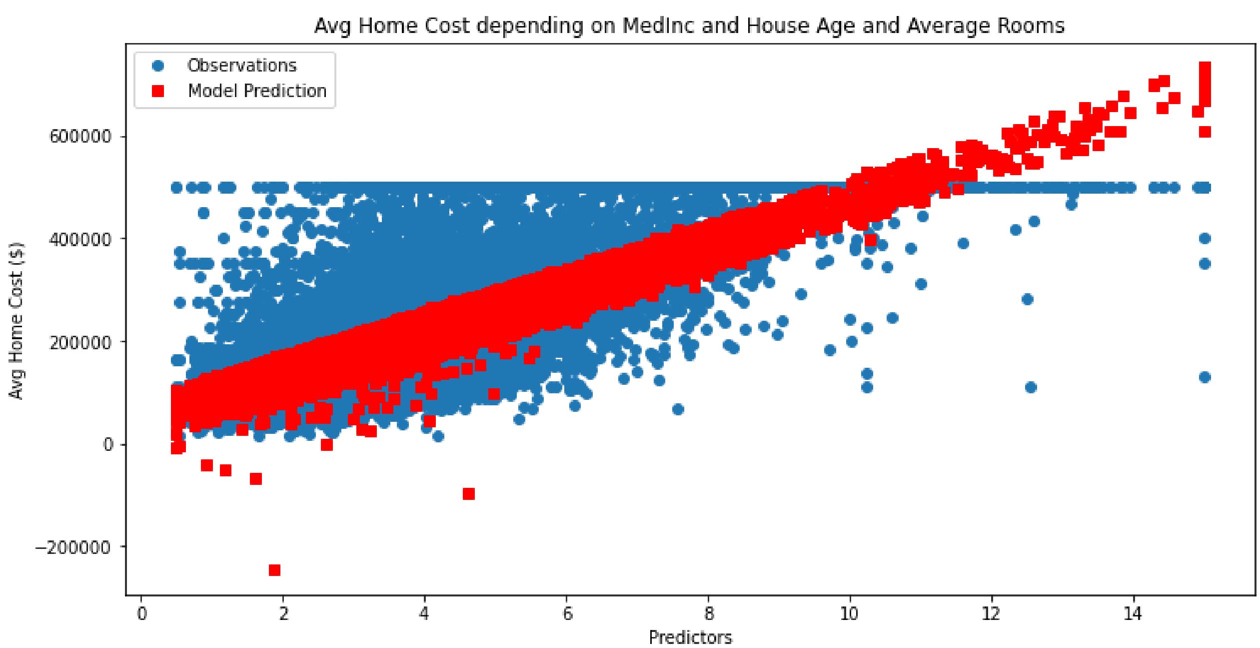
Out[28]:
```
(array([1.000e+00, 1.000e+00, 1.000e+00, 2.000e+00, 8.000e+00, 7.200e+01,
        7.480e+02, 7.139e+03, 7.601e+03, 3.138e+03, 1.169e+03, 4.830e+02,
        2.210e+02, 4.700e+01, 8.000e+00, 0.000e+00, 0.000e+00, 0.000e+00,
        0.000e+00, 1.000e+00]),
 array([-7.4433225 , -6.5641189 , -5.6849153 , -4.80571169, -3.92650809,
        -3.04730448, -2.16810088, -1.28889727, -0.40969367,  0.46950993,
         1.34871354,  2.22791714,  3.10712075,  3.98632435,  4.86552795,
         5.74473156,  6.62393516,  7.50313877,  8.38234237,  9.26154598,
        10.14074958]),
 <BarContainer object of 20 artists>)
```



In [32]:
```
hVal = model.predict()

plt.figure(figsize=(12, 6))
plt.plot(housing['MedInc'], housing['AveHouseVal'], 'o')
plt.plot(housing['MedInc'], hVal, marker = 's' ,color ='r', linewidth=0)
plt.xlabel('Predictors')
plt.ylabel('Avg Home Cost ($)')
plt.legend(['Observations','Model Prediction'])
plt.title('Avg Home Cost depending on MedInc and House Age and Average Rooms')

plt.show()
```



As we can see the observations are not homoscendastic, whilst the prediction is

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Exercise 2

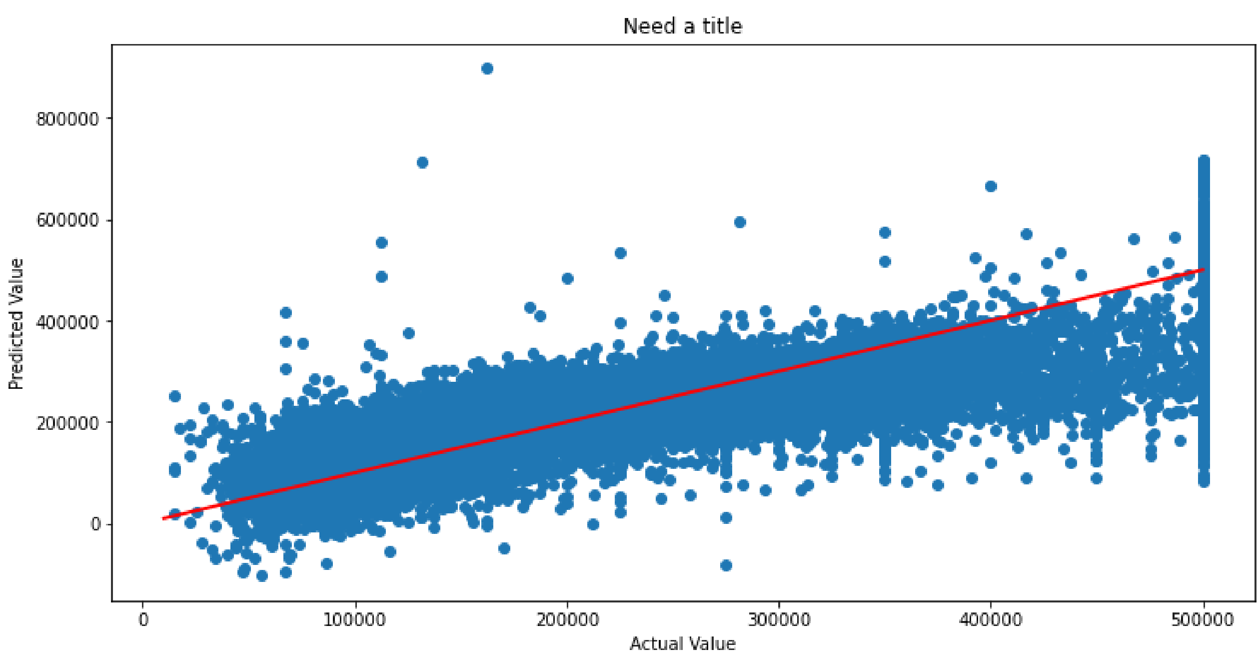
Build a plot of AveHouseValue on the x-axis, and the predicted HouseValue on the y-axis. Add an equal value line (i.e. [10000,500000],[10000,500000] in a second plot call).

Something like:

```
# Plot regression against actual data - What do we see?
plt.figure(figsize=(12, 6))
plt.plot(housing['AveHouseVal'], pred, 'o')          # scatter plot
actual vs model
plt.plot([10000,500000],[10000,500000] , 'r', linewidth=2)   # equal
value line
plt.xlabel('Actual Value')
plt.ylabel('Predicted Value')
plt.title('Need a title')
plt.show();
```

If your model estimates a value of \$200,000 or less is your model over- or under-predicting?

In [33]:
```
plt.figure(figsize=(12, 6))
plt.plot(housing['AveHouseVal'], pred, 'o')
plt.plot([10000,500000],[10000,500000] , 'r', linewidth=2)
plt.xlabel('Actual Value')
plt.ylabel('Predicted Value')
plt.title('Need a title')
plt.show();
```



According to the model it demonstrates that it is overpredicting