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

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, Ridge, Lasso, ElasticNet
from sklearn.model_selection import cross_val_score

from sklearn.preprocessing import StandardScaler
```

In [2]:
```
from sklearn.datasets import fetch_california_housing
cal = fetch_california_housing()
```

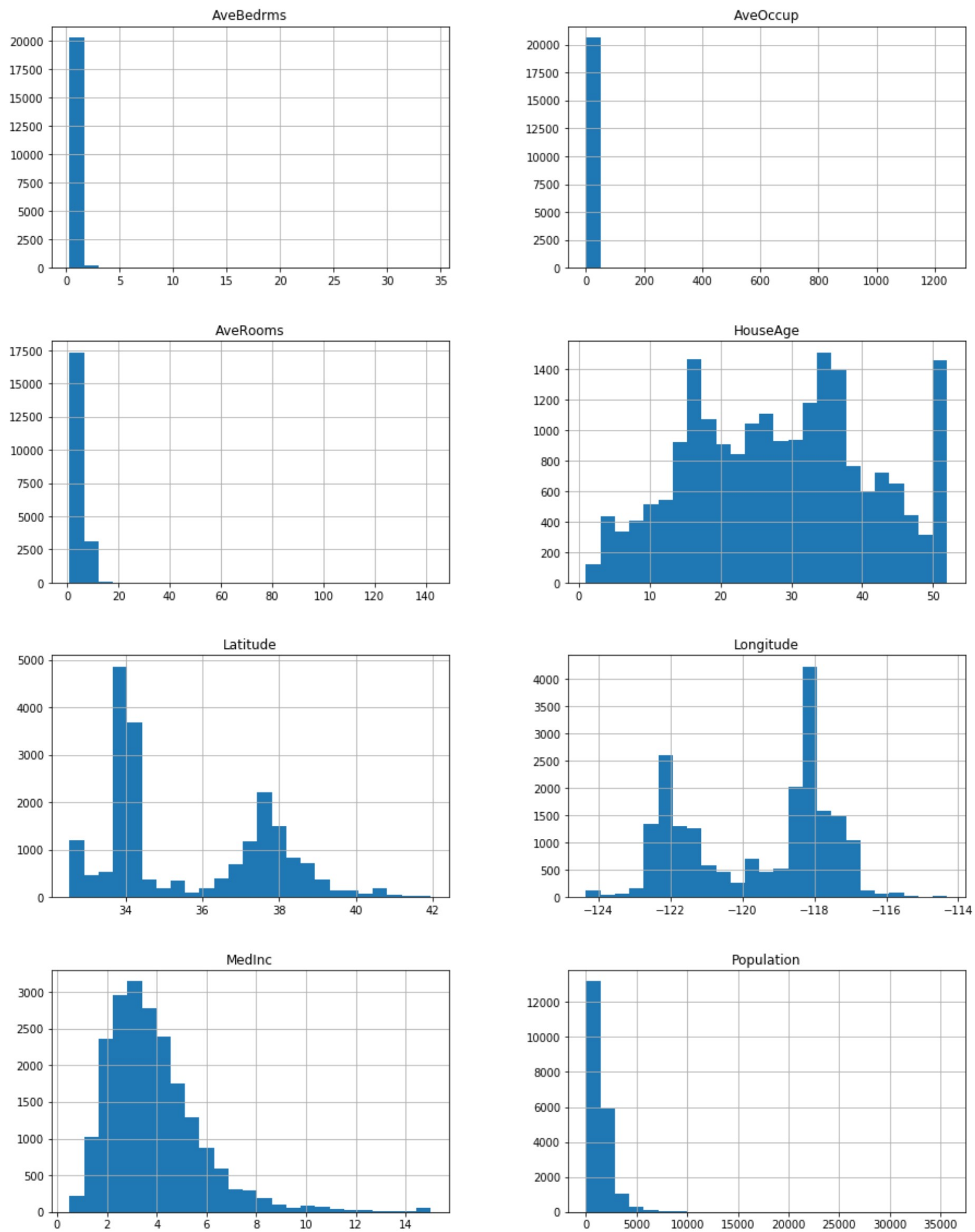
In [3]:
```
print(cal.feature_names)
```

```
['MedInc', 'HouseAge', 'AveRooms', 'AveBedrms', 'Population', 'AveOccup', 'Latit
ude', 'Longitude']
```

In [4]:
```
cal_df = pd.DataFrame(cal.data)
cal_df.columns = cal.feature_names
```

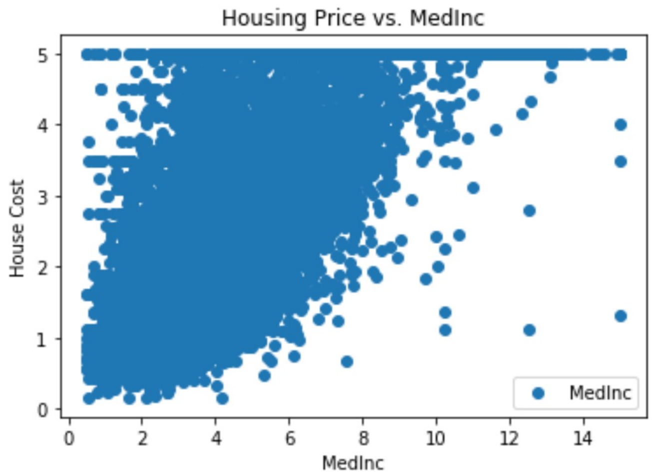
In [5]:
```
fig = plt.figure(figsize = (15,20))
ax = fig.gca()
cal_df.hist(ax = ax, bins = 25, layout=(-1, 2))
plt.show()
```

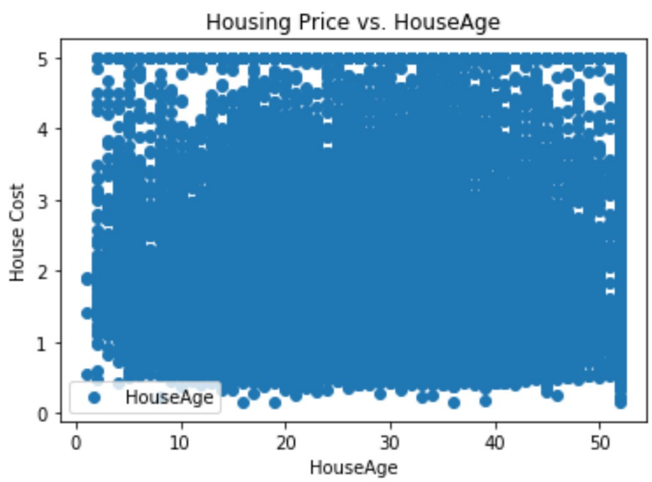
```
C:\Users\grech\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:2961
: UserWarning: To output multiple subplots, the figure containing the passed axe
s is being cleared
  exec(code_obj, self.user_global_ns, self.user_ns)
```

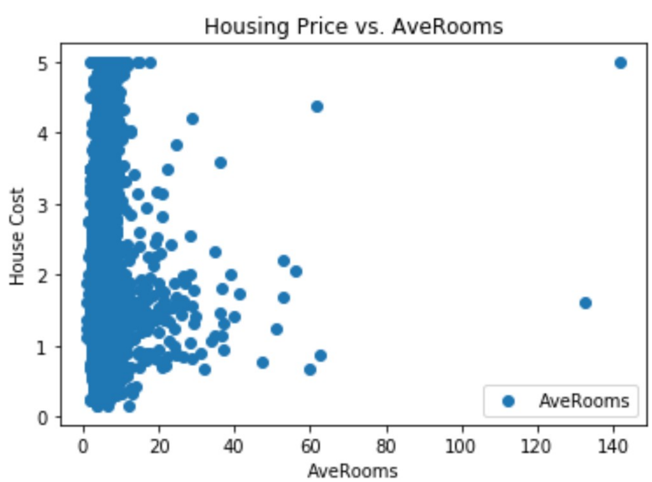


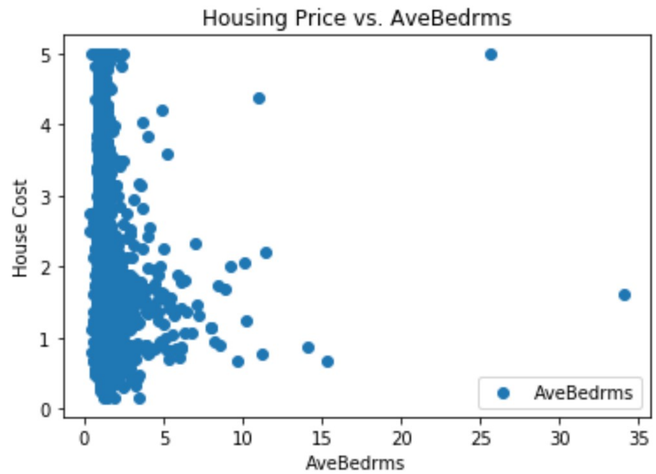
In [6]:
```
X = cal_df.values
y = cal.target
```

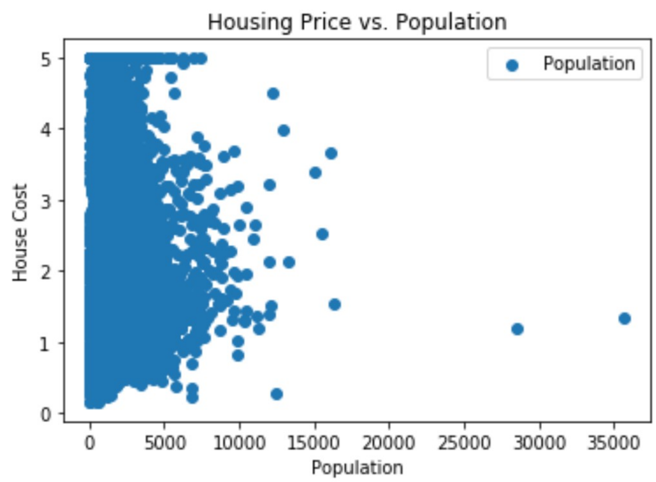
In [7]:
```
for column in cal_df:
    x = cal_df[column]
    plt.scatter(x, y, label = column)
    plt.ylabel('House Cost')
    plt.xlabel(column)
    plt.title('Housing Price vs. ' + column)
    plt.legend()
    plt.show()
```

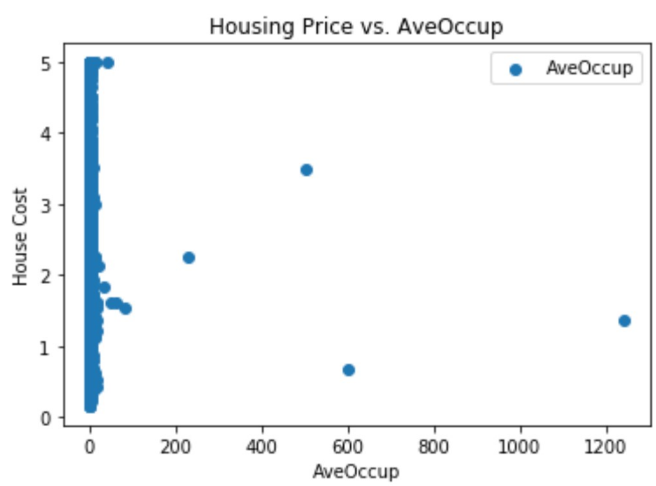

Housing Price vs. MedInc
House Cost
MedInc
MedInc

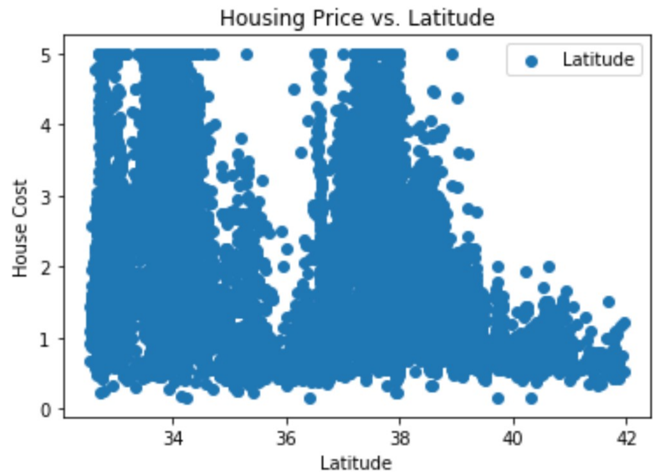

Housing Price vs. HouseAge
House Cost
HouseAge
HouseAge

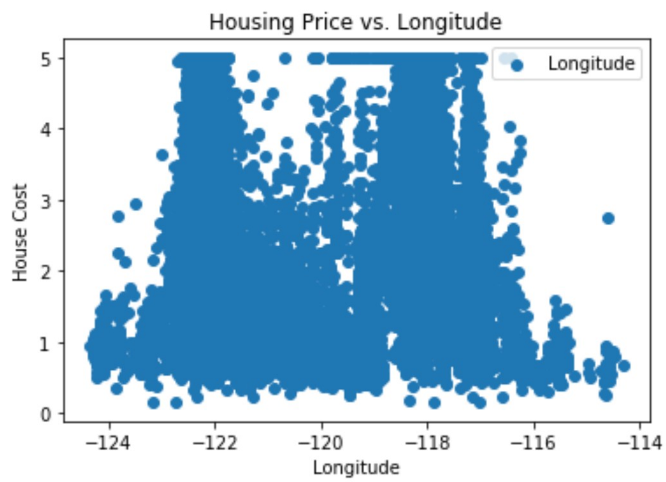

Housing Price vs. AveRooms
House Cost
AveRooms
AveRooms


Housing Price vs. AveBedrms
House Cost
AveBedrms
AveBedrms
0
1
2
3
4
5
0
5
10
15
20
25
30
35


Housing Price vs. Population
House Cost
Population
Population
0
1
2
3
4
5
0
5000
10000
15000
20000
25000
30000
35000


Housing Price vs. AveOccup
House Cost
AveOccup
AveOccup
0
1
2
3
4
5
0
200
400
600
800
1000
1200





In [8]:
```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.33, random_
state = 5)
```

In [9]:
```
models = [LinearRegression(), Ridge(), Lasso(), ElasticNet()]
def run_cases(X, y):
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.33, ran
dom_state = 5)
    for model in models:
        scores = cross_val_score(model, X_train, y_train, cv=5, scoring= 'neg_mean_
absolute_error')
        print(str(model).split('(')[0] + ' R^2', abs(scores).mean())
```

In [10]:
```
#Not scaled features
run_cases(X, y)
```

```
LinearRegression R^2 0.5279879232838869
Ridge R^2 0.5280051865749653
Lasso R^2 0.7697898067409374
ElasticNet R^2 0.678966818346656
```

In [11]:
```
#Scaled features
run_cases(X_scaled, y)
```

```
LinearRegression R^2 0.5279879232838481
Ridge R^2 0.5279818561729331
Lasso R^2 0.9024655367185686
ElasticNet R^2 0.80950549909697
```

Scaling the data significantly improved the accuracy for the Lasso and the Elastic Net. It did not affect the performance of the linear regression model. The Ridge Regression model stays basically the same.

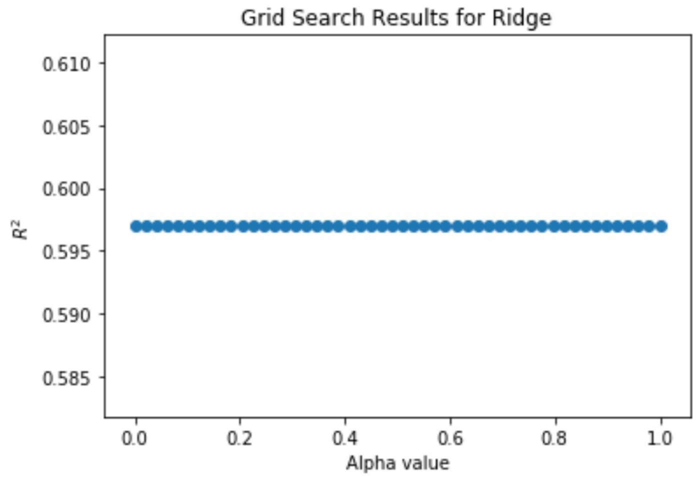
In [12]:
```
def run_grid_search(model, params):
    grid = GridSearchCV(model, params, cv=5)
    grid.fit(X_train, y_train)
    results = grid.grid_scores_

    params = []
    scores = []
    for score in results:
        mean = score[1]
        param = score[0]['alpha']
        scores.append(abs(mean))
        params.append(param)


    ax = plt.subplot(111)
    ax.scatter(params, scores)
    ax.set_title('Grid Search Results for ' + str(model).split('(')[0])
    ax.set_xlabel('Alpha value')
    ax.set_ylabel('$R^2$')
    plt.show()
    return params, scores
```

In [13]:
```
equal_spacing = np.linspace(1e-8, 1, 50)
```

In [14]:
```
from sklearn.model_selection import GridSearchCV
ridge_param = {'alpha':equal_spacing}
lasso_param = {'alpha':equal_spacing}
elstic_param = {'alpha':equal_spacing} #, 'l1_ratio':(0, 0.25, 0.5, 0.75, 1.0)
```

In [15]:
```
params1, scores1 = run_grid_search(models[1], ridge_param)
params2, scores2 = run_grid_search(models[2], lasso_param)
params3, scores3 = run_grid_search(models[3], elstic_param)
```

```
C:\Users\grech\Anaconda3\lib\site-packages\sklearn\model_selection\_search.py:76
2: DeprecationWarning: The grid_scores_ attribute was deprecated in version 0.18
in favor of the more elaborate cv_results_ attribute. The grid_scores_ attribute
will not be available from 0.20
  DeprecationWarning)
```




```
C:\Users\grech\Anaconda3\lib\site-packages\sklearn\model_selection\_search.py:76
2: DeprecationWarning: The grid_scores_ attribute was deprecated in version 0.18
in favor of the more elaborate cv_results_ attribute. The grid_scores_ attribute
will not be available from 0.20
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```


```
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will not be available from 0.20
  DeprecationWarning)
```
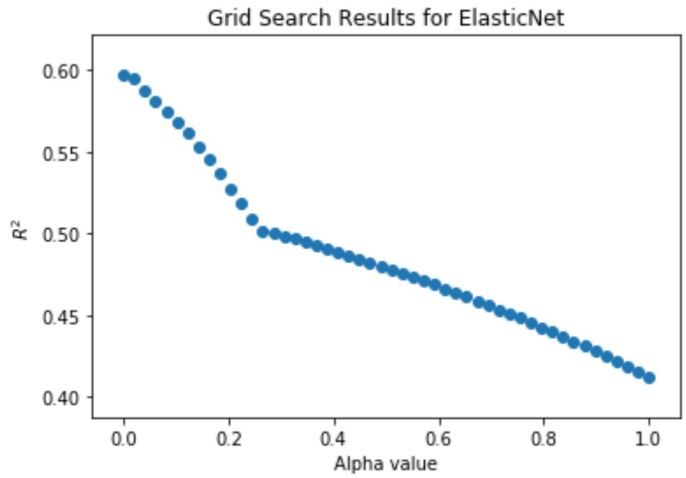



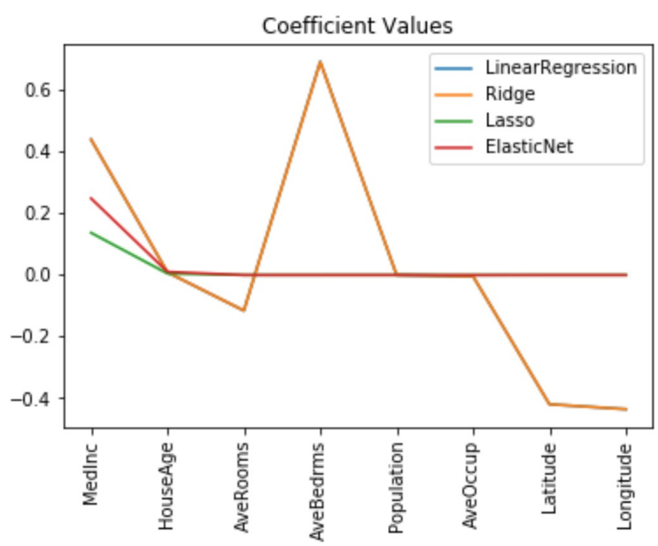
Intrestingly all of the models perform better with lower reguralization as can be seen by the models having the highest R^2 value near the origin. The Ridge Regression model does not change as you change the alpha value.

In [16]:

```
imps = []
for model in models:
    model.fit(X_train, y_train)
    feature_imp = model.coef_
    imps.append(feature_imp)
```

In [17]:

```
feature_names = list(cal.feature_names)
for i, imp in enumerate(imps):
    plt.plot(imp, label = str(models[i]).split('(')[0])
    plt.legend()
plt.title('Coefficient Values')
locs, labels = plt.xticks()
plt.xticks(np.arange(len(feature_names)), feature_names, rotation = 90)
plt.show()
```



In [ ]: