AdaBoost

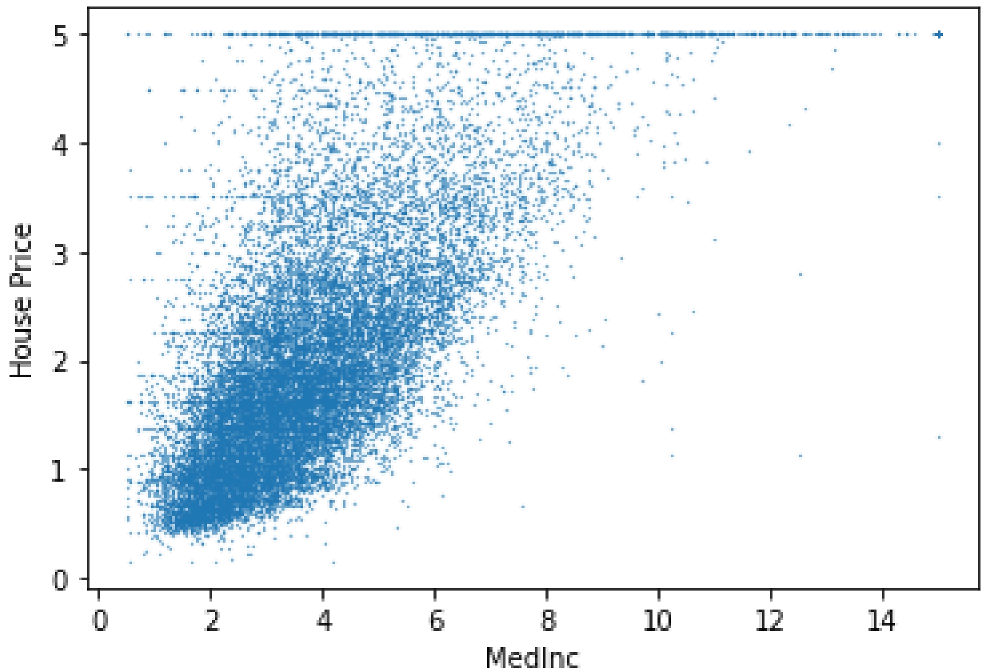
November 9, 2019

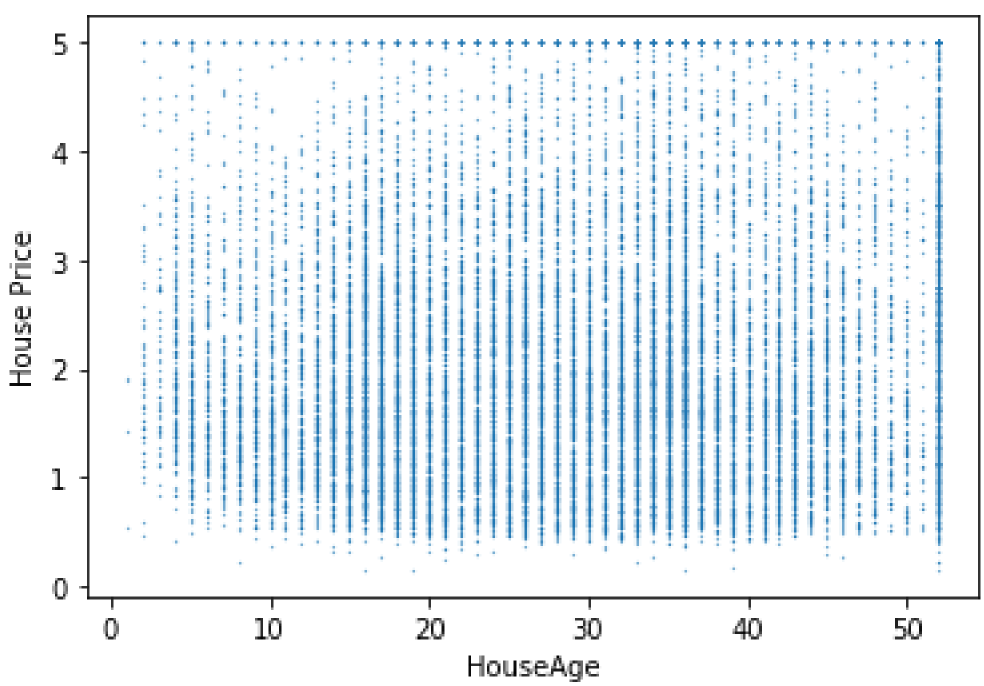
[1]:
```
import matplotlib.pyplot as plt
import numpy as np
import scipy.io as sio
import copy
%matplotlib inline

import sklearn
from sklearn.datasets import fetch_california_housing

plt.rcParams['font.size'] = 14
```

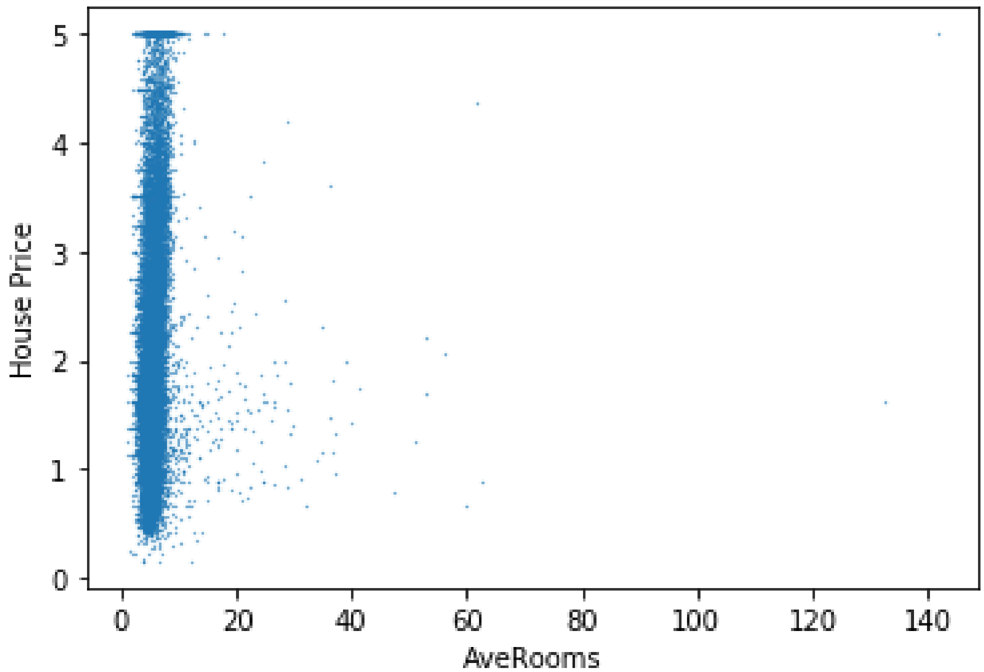
[2]:
```
# Download data

tmp = sklearn.datasets.fetch_california_housing()

num_samples   = tmp['data'].shape[0]
feature_names = tmp['feature_names']
y = tmp['target']
X = tmp['data']

data = {}
for n, feature in enumerate(feature_names):
    data[feature] = tmp['data'][:,n]
```

[3]:
```
plt.plot(data['MedInc'],y,'.',markersize=0.5)
plt.xlabel('MedInc')
plt.ylabel('House Price')
plt.show()
plt.plot(data['HouseAge'],y,'.',markersize=0.5)
plt.xlabel('HouseAge')
plt.ylabel('House Price')
plt.show()
plt.plot(data['AveRooms'],y,'.',markersize=0.5)
plt.xlabel('AveRooms')
plt.ylabel('House Price')
plt.show()
plt.plot(data['AveRooms'],y,'.',markersize=0.5)
plt.xlabel('AveRooms, max room number = 12')
```

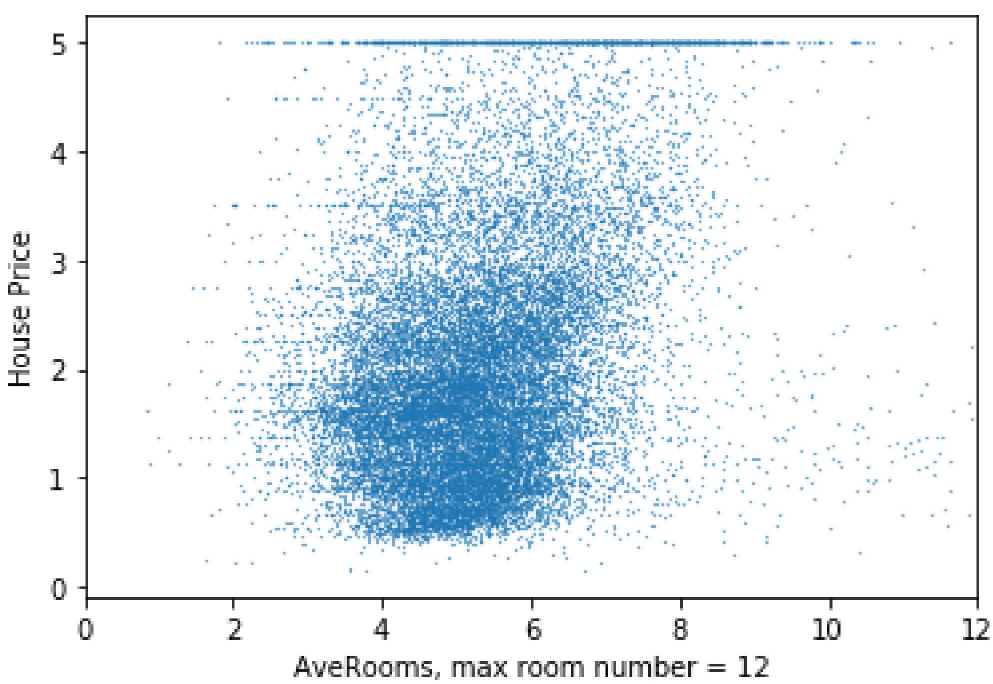
```
plt.ylabel('House Price')
plt.xlim(0,12)
plt.show()
plt.plot(data['AveBedrms'],y,'.',markersize=0.5)
plt.xlabel('AveBedrms')
plt.ylabel('House Price')
plt.show()
plt.plot(data['AveBedrms'],y,'.',markersize=0.5)
plt.xlabel('AveBedrms, min room number = 0.5, max room number = 2')
plt.ylabel('House Price')
plt.xlim(0.5,2)
plt.show()
plt.plot(data['Population'],y,'.',markersize=0.5)
plt.xlabel('Population')
plt.ylabel('House Price')
plt.show()
plt.plot(data['Population'],y,'.',markersize=0.5)
plt.xlabel('Population, max pop = 5000')
plt.ylabel('House Price')
plt.xlim(0,5000)
plt.show()
plt.plot(data['AveOccup'],y,'.',markersize=0.5)
plt.xlabel('AveOccup')
plt.ylabel('House Price')
plt.show()
plt.plot(data['AveOccup'],y,'.',markersize=0.5)
plt.xlabel('AveOccup, max occup = 7')
plt.ylabel('House Price')
plt.xlim(0,7)
plt.show()
plt.plot(data['Latitude'],y,'.',markersize=0.5)
plt.xlabel('Latitude')
plt.ylabel('House Price')
plt.show()
plt.plot(data['Longitude'],y,'.',markersize=0.5)
plt.xlabel('Longitude')
plt.ylabel('House Price')
plt.show()
```


House Price
MedInc
0
1
2
3
4
5
0
2
4
6
8
10
12
14

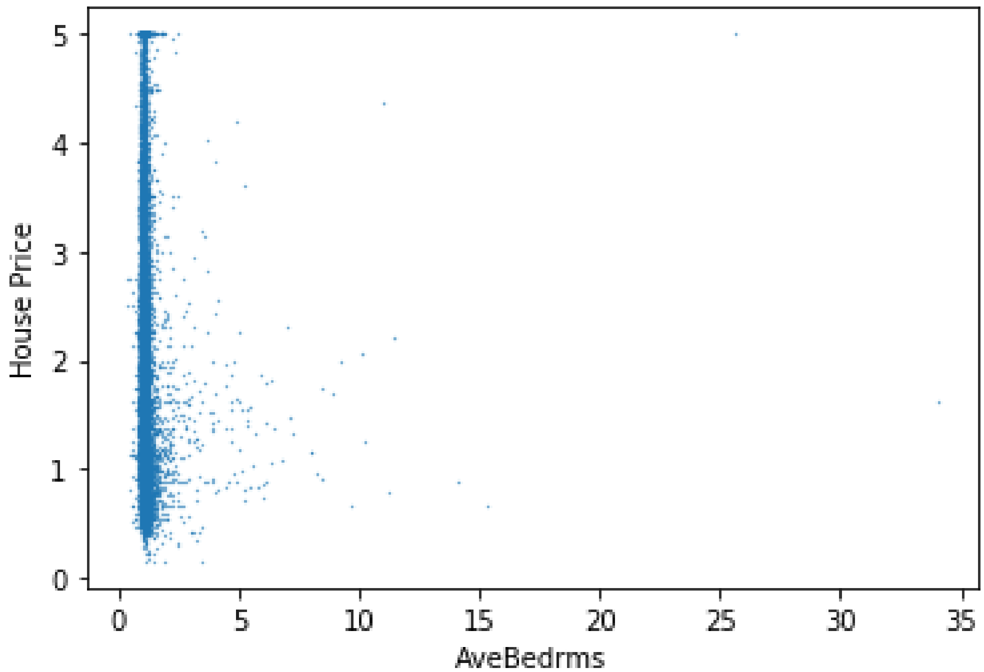

House Price
HouseAge
0
1
2
3
4
5
0
10
20
30
40
50



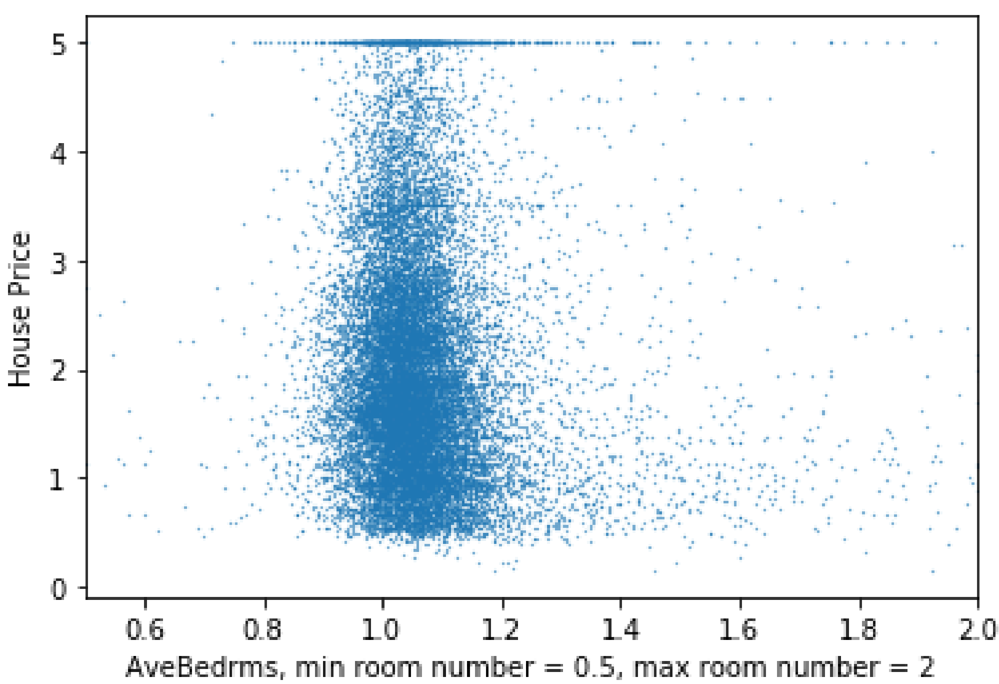
House Price
AveRooms
0
20
40
60
80
100
120
140
0
1
2
3
4
5



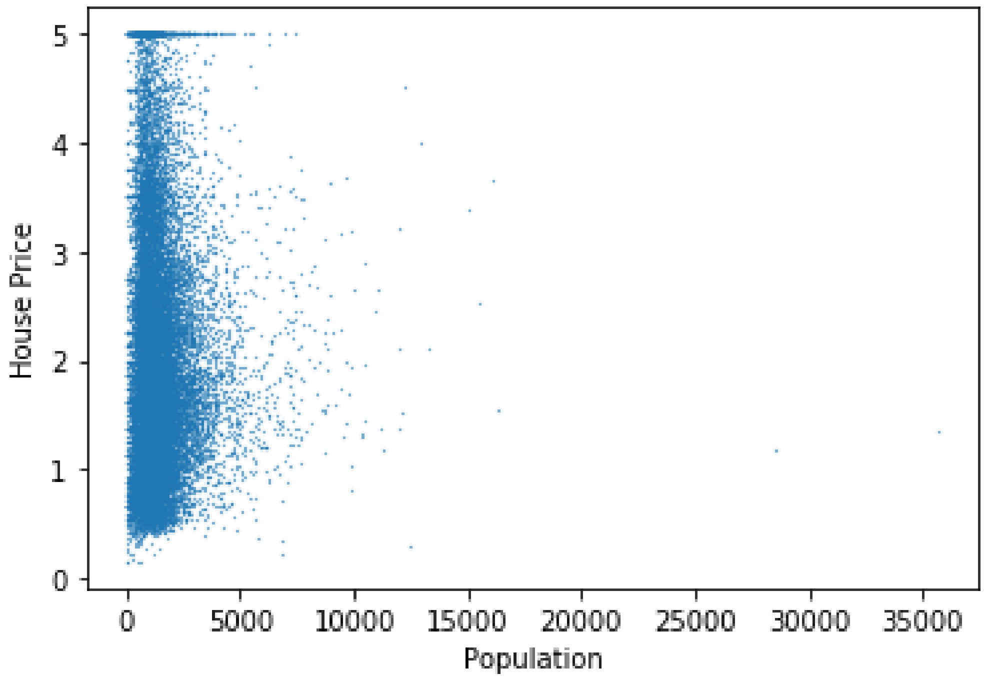
House Price
AveRooms, max room number = 12
0
2
4
6
8
10
12
0
1
2
3
4
5

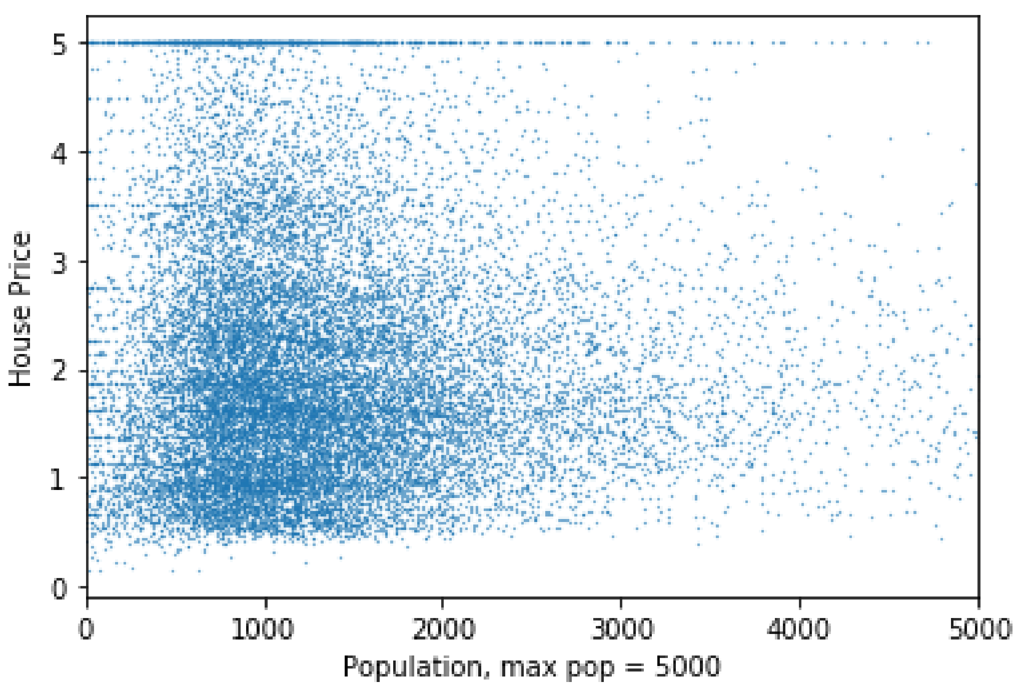


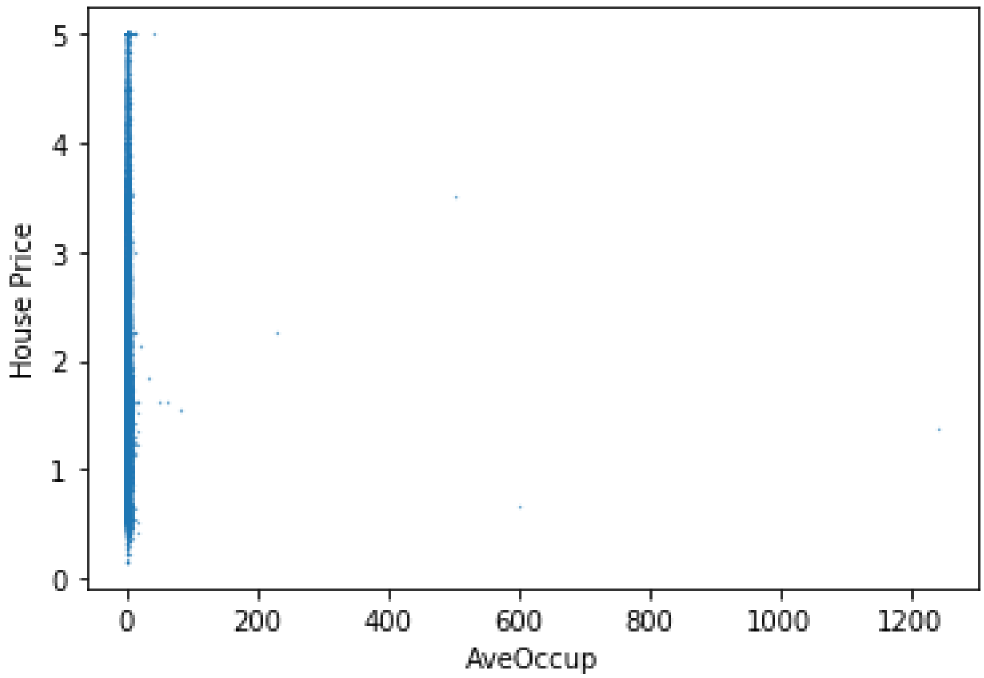
House Price
AveBedrms
0
1
2
3
4
5
0
5
10
15
20
25
30
35

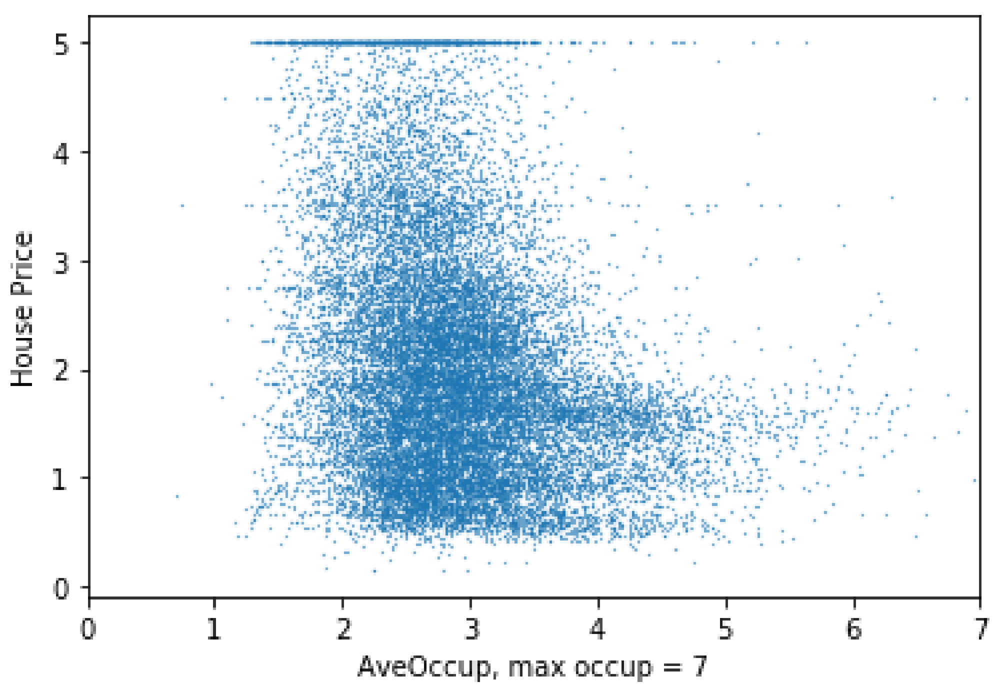


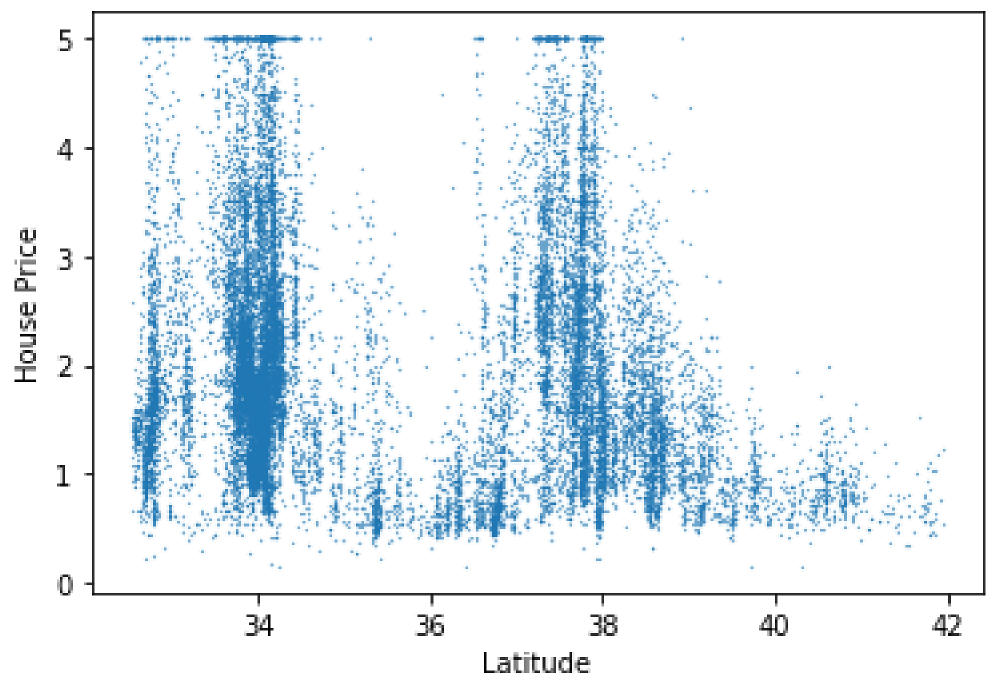
House Price
AveBedrms, min room number = 0.5, max room number = 2
0
1
2
3
4
5
0.6
0.8
1.0
1.2
1.4
1.6
1.8
2.0

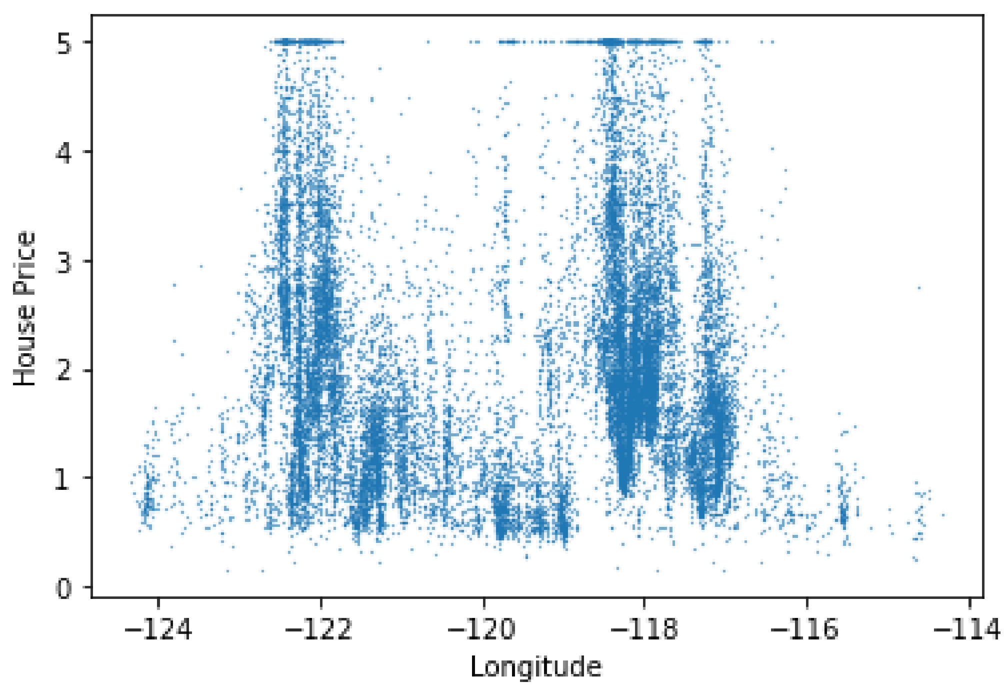

House Price
Population
0
1
2
3
4
5
0
5000
10000
15000
20000
25000
30000
35000


House Price
Population, max pop = 5000
0
1
2
3
4
5
0
1000
2000
3000
4000
5000


House Price
AveOccup
0
1
2
3
4
5
0
200
400
600
800
1000
1200


House Price
AveOccup, max occup = 7
0
1
2
3
4
5
0
1
2
3
4
5
6
7





[4]:
```
# Create stumps
```

```
# bin the data by proportion, 10% in each bin
bins = {}
bin_idx = (np.arange(0,1.1,0.1)*num_samples).astype(np.int16)
bin_idx[-1] = bin_idx[-1]-1
for feature in (feature_names):
    bins[feature] = np.sort(data[feature])[bin_idx]

# decision stumps as weak classifiers
# 0 if not in bin, 1 if in bin
stumps = {}
for feature in feature_names:
    stumps[feature] = np.zeros([num_samples,len(bins[feature])-1])
    for n in range(len(bins[feature])-1):
        stumps[feature][:,n] = data[feature]>bins[feature][n]

# stack the weak classifiers into a matrix
H = np.hstack([stumps[feature] for feature in feature_names])
H = np.hstack([np.ones([num_samples,1]),H])
# prepare the vector for storing weights
alphas = np.zeros(H.shape[1])
```

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[5]:
```
num_iterations = 30
MSE = np.zeros(num_iterations) # track mean square error
```

[6]:
```
alphas = np.zeros(H.shape[1])
for iteration in range(num_iterations):
    f = np.matmul(H,alphas)
    r = y-f; MSE[iteration] = np.mean(r**2) # r = residual
    v = np.matmul(r.transpose(),H)
    idx = np.argmax(abs(v))# optimal direction to move in
    denom = sum(x**2 for x in H[:,idx])
    increment = v[idx]/denom
    alphas[idx] = alphas[idx] + increment # amount to move in optimal direction
```

0.0.2 Plot Results

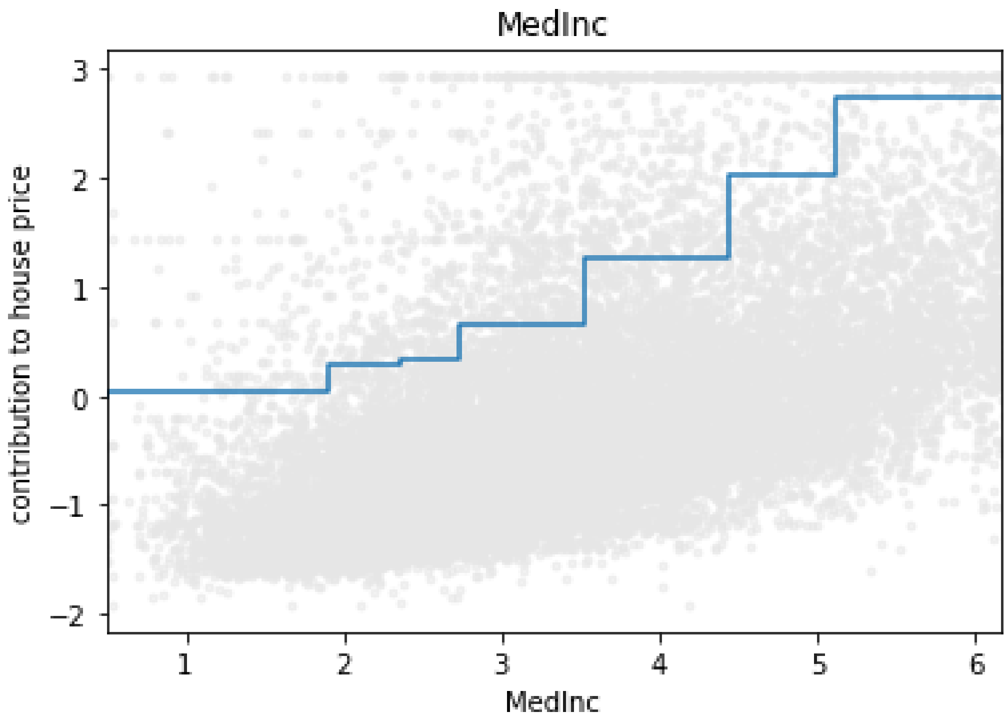
[7]:
```
print(alphas)
print(MSE)
```

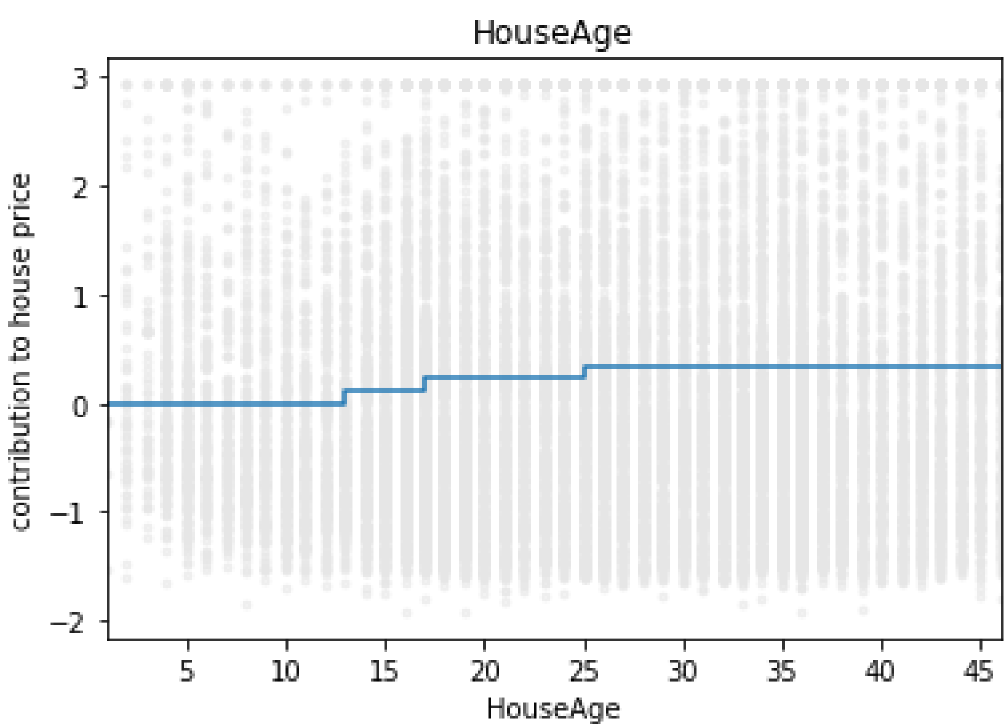
```
[ 2.06855817  0.          0.04532578  0.24035267  0.05170433  0.30840601
  0.          0.61815591  0.          0.7562429   0.70893994  0.
  0.          0.11005079  0.14071509  0.          0.07791702  0.
  0.          0.          0.          0.          0.         -0.05655599
 -0.10539018  0.          0.          0.          0.          0.
  0.          0.          0.          0.04872434  0.1007982   0.
```

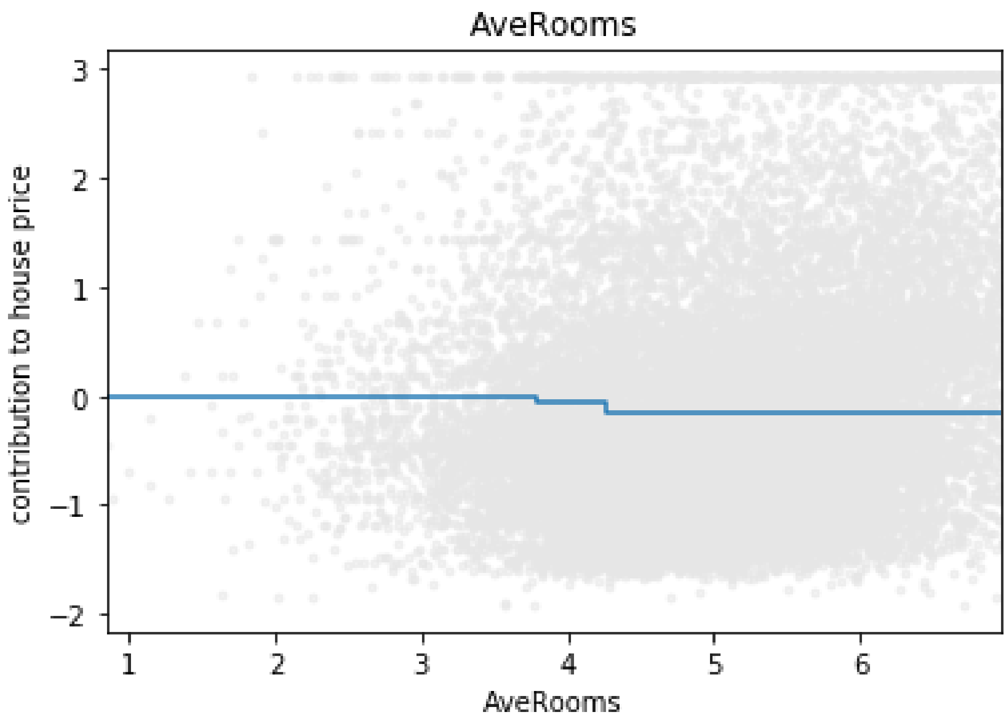
```
  0.          0.          0.          0.          0.          0.
  0.          0.          0.          0.          0.          0.
  0.          0.          0.          0.         -0.172093   -0.42921386
  0.         -0.06917125 -0.19190968  0.          0.          0.
  0.          0.          0.          0.          0.10092535  0.
 -0.30204764  0.          0.         -0.35429535  0.          0.
 -0.09937558 -0.21562125  0.          0.          0.          0.
 -0.24297072  0.          0.        ]
[5.6104832  1.3315503  1.10277822 0.95540752 0.898362   0.86125809
 0.74690513 0.72025217 0.70648854 0.68157957 0.67234355 0.65393067
 0.64461023 0.61988225 0.61281034 0.59516855 0.54493332 0.53715889
 0.53004768 0.52241438 0.51758036 0.51418661 0.5117528  0.50919409
 0.50734531 0.50447474 0.50154187 0.49851258 0.49661344 0.49531801]
```

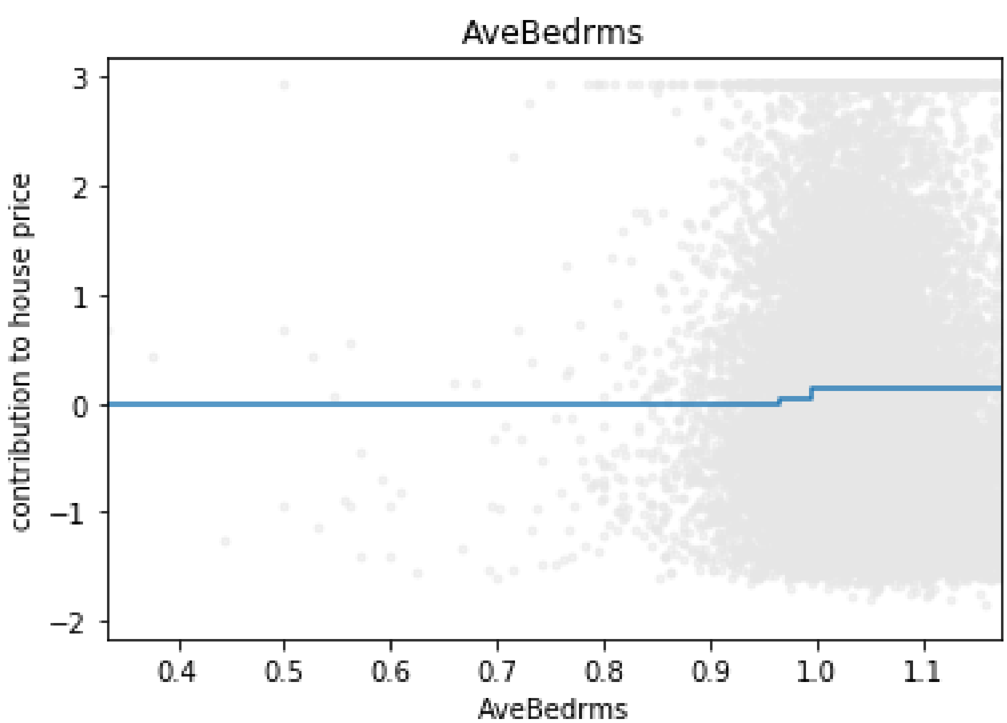
[8]:
```python
alphasf = {}
start = 1
for feature in feature_names:
    alphasf[feature] = alphas[start:(start+stumps[feature].shape[1])]
    start = start + stumps[feature].shape[1]
alphasf['mean'] = alphas[0]
```

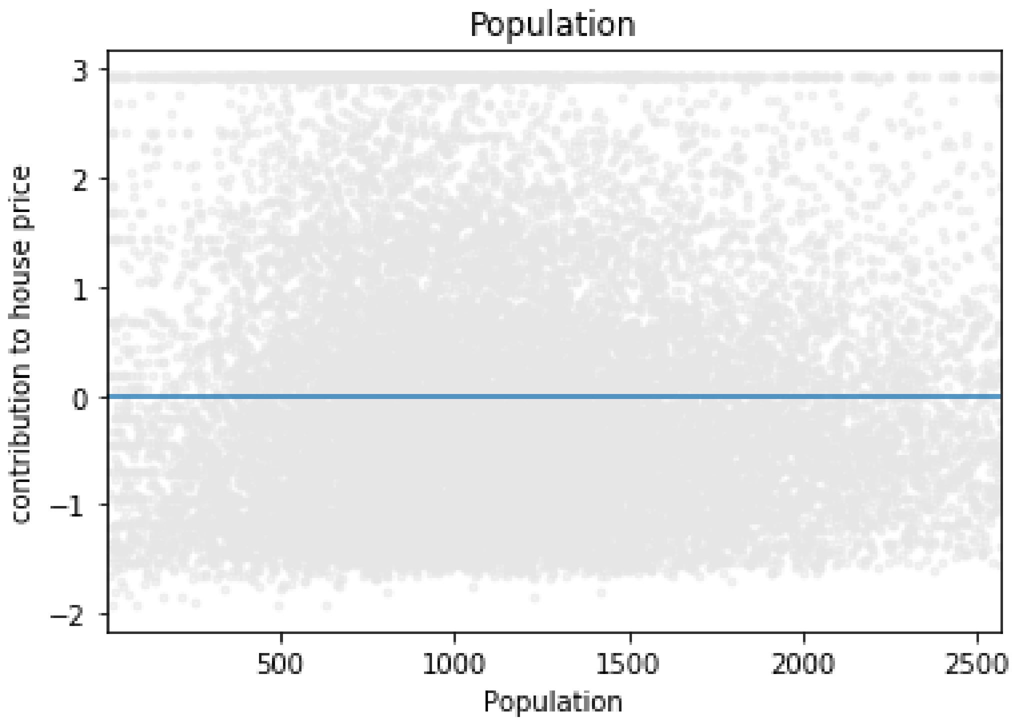
[9]:
```python
for feature in feature_names:
    plt.close("all")
    plt.plot(data[feature],y-np.mean(y),'.',alpha=0.5,color=[0.9,0.9,0.9])
    # plot stuff
    plt.title(feature)
    plt.xlim([bins[feature][0],bins[feature][-2]])
    plt.xlabel(feature)
    plt.ylabel('contribution to house price')
    plt.step(bins[feature][:-1],np.cumsum(alphasf[feature]))
    plt.show()
```

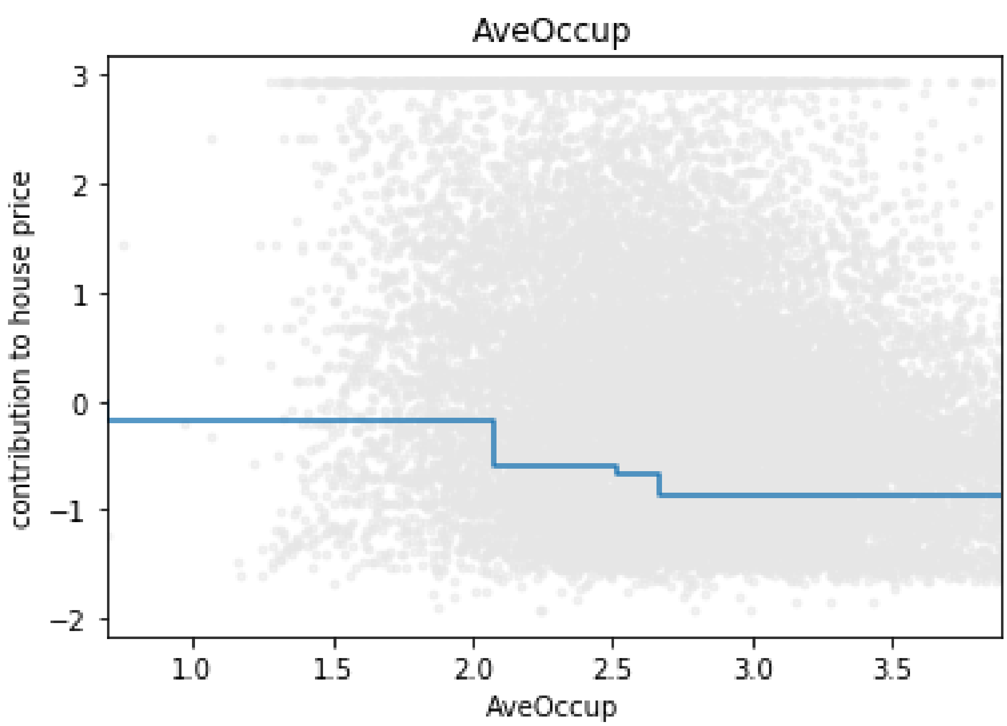

MedInc
contribution to house price
3
2
1
0
−1
−2
1
2
3
4
5
6
MedInc

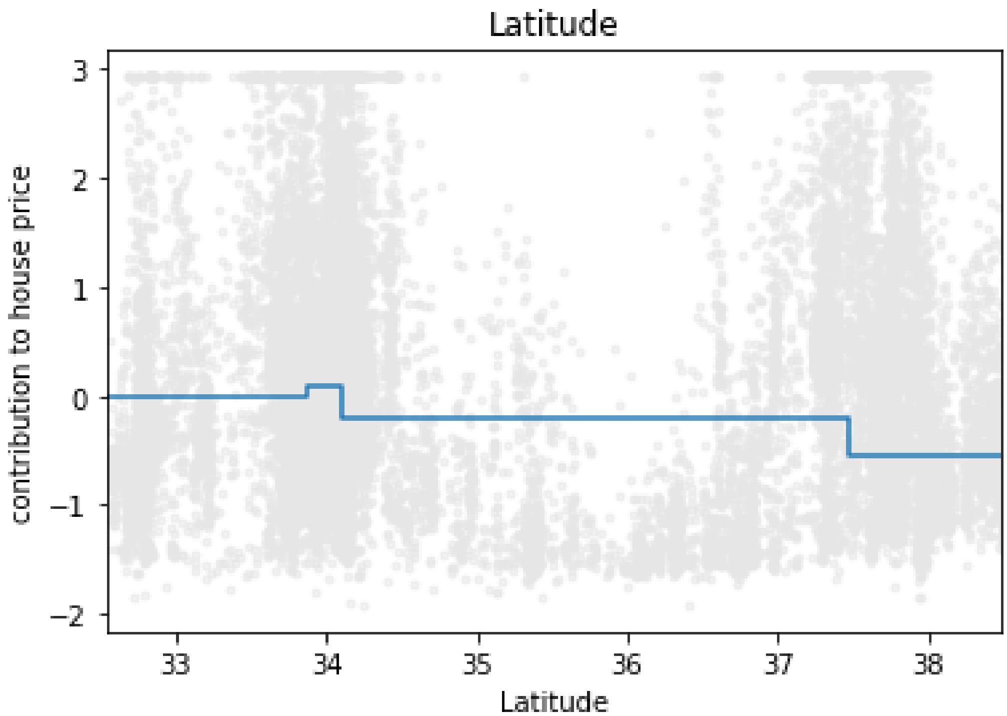

HouseAge
contribution to house price
3
2
1
0
−1
−2
5
10
15
20
25
30
35
40
45
HouseAge

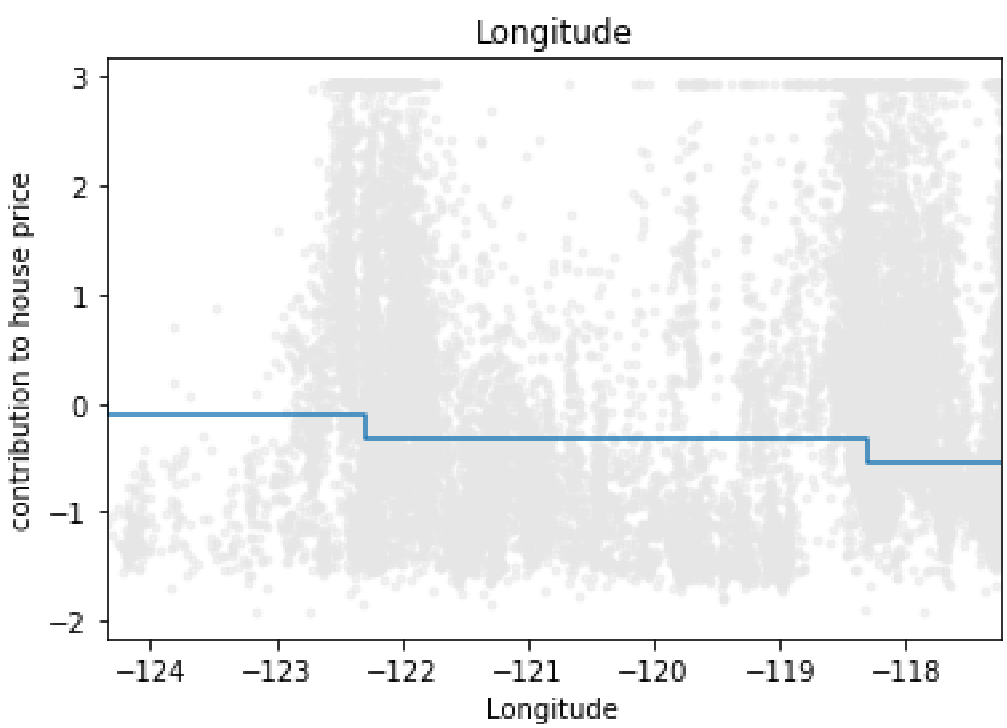

AveRooms
contribution to house price
3
2
1
0
−1
−2
1
2
3
4
5
6
AveRooms


AveBedrms
contribution to house price
3
2
1
0
−1
−2
0.4
0.5
0.6
0.7
0.8
0.9
1.0
1.1
AveBedrms


Population
contribution to house price
3
2
1
0
−1
−2
500
1000
1500
2000
2500
Population


AveOccup
contribution to house price
3
2
1
0
−1
−2
1.0
1.5
2.0
2.5
3.0
3.5
AveOccup


Latitude
contribution to house price
3
2
1
0
−1
−2
33
34
35
36
37
38
Latitude


Longitude
contribution to house price
3
2
1
0
−1
−2
−124
−123
−122
−121
−120
−119
−118
Longitude

0.0.3 Variable Importance

[10]:
```
ret = {}
for feature in feature_names:
    fdata= copy.copy(data[feature])
    np.random.shuffle(fdata)
    gdata = data[feature]
    data[feature] = fdata
    stumps = {}
    for f in feature_names:
        stumps[f] = np.zeros([num_samples,len(bins[f])-1])
        for n in range(len(bins[f])-1):
            stumps[f][:,n] = data[f]>bins[f][n]
    H = np.hstack([stumps[feature] for feature in feature_names])
    H = np.hstack([np.ones([num_samples,1]),H])
    alphas = np.zeros(H.shape[1])
    num_iterations = 30
    MSE1 = np.zeros(num_iterations)
    for iteration in range(num_iterations):
        f = np.matmul(H,alphas)
        r = y-f; MSE1[iteration] = np.mean(r**2) # r = residual
        v = np.matmul(r.transpose(),H)
        idx = np.argmax(abs(v))# optimal direction to move in
        denom = sum(x**2 for x in H[:,idx])
        increment = v[idx]/denom
        alphas[idx] = alphas[idx] + increment # amount to move in optimal␣
 ↪direction
    ret[feature]=MSE1[-1]-MSE[-1]
    print('The importance of feature', feature, 'is', ret[feature])
    data[feature]=gdata
```

```
The importance of feature MedInc is 0.2824472910265669
The importance of feature HouseAge is 0.008949444593040645
The importance of feature AveRooms is -0.002363527425400136
The importance of feature AveBedrms is 0.001626570973289776
The importance of feature Population is 0.0
The importance of feature AveOccup is 0.05980418168746443
The importance of feature Latitude is 0.03252112351794906
The importance of feature Longitude is 0.03351336756346507
```

0.0.4 Boosted Decision Trees

[11]:
```
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.ensemble.partial_dependence import plot_partial_dependence
```

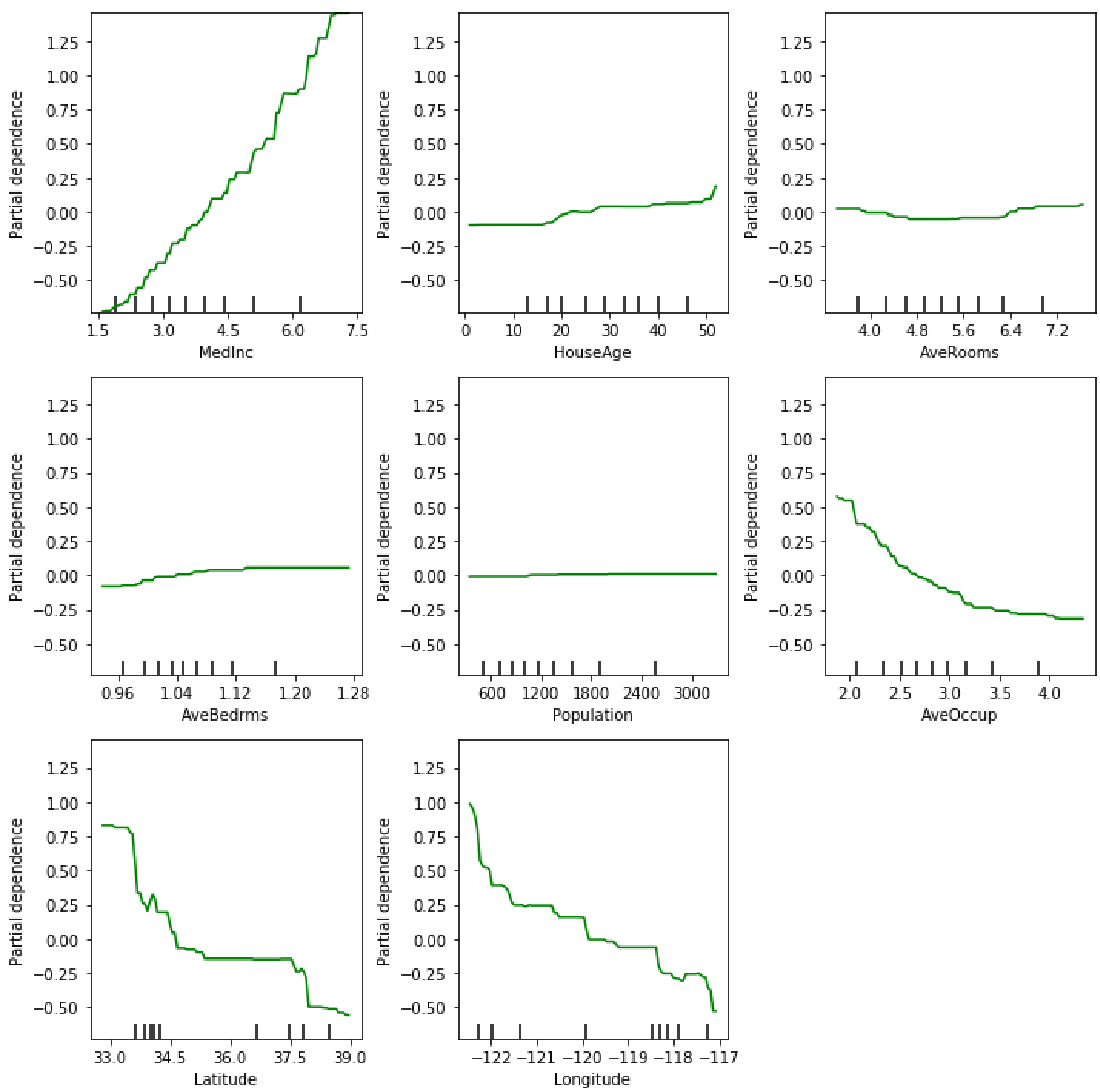
[12]:
```
clf = GradientBoostingRegressor(loss="ls")
clf.fit(X,y)
```

[12]:
```
GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=None,
                          learning_rate=0.1, loss='ls', max_depth=3,
                          max_features=None, max_leaf_nodes=None,
                          min_impurity_decrease=0.0, min_impurity_split=None,
                          min_samples_leaf=1, min_samples_split=2,
                          min_weight_fraction_leaf=0.0, n_estimators=100,
                          n_iter_no_change=None, presort='auto',
                          random_state=None, subsample=1.0, tol=0.0001,
                          validation_fraction=0.1, verbose=0, warm_start=False)
```

[13]:
```
plt.close("all")
plt.figure(figsize=[10,10])
ax = plt.gca()
plot_partial_dependence(clf, X, feature_names, feature_names, n_cols=3, ax=ax)
plt.tight_layout()
plt.show()
```

```
//anaconda3/lib/python3.7/site-packages/sklearn/utils/deprecation.py:85:
DeprecationWarning: Function plot_partial_dependence is deprecated; The function
ensemble.plot_partial_dependence has been deprecated in favour of
sklearn.inspection.plot_partial_dependence in  0.21 and will be removed in 0.23.
  warnings.warn(msg, category=DeprecationWarning)
//anaconda3/lib/python3.7/site-packages/sklearn/utils/deprecation.py:85:
DeprecationWarning: Function partial_dependence is deprecated; The function
ensemble.partial_dependence has been deprecated in favour of
inspection.partial_dependence in 0.21 and will be removed in 0.23.
  warnings.warn(msg, category=DeprecationWarning)
//anaconda3/lib/python3.7/site-packages/sklearn/utils/deprecation.py:85:
DeprecationWarning: Function partial_dependence is deprecated; The function
ensemble.partial_dependence has been deprecated in favour of
inspection.partial_dependence in 0.21 and will be removed in 0.23.
  warnings.warn(msg, category=DeprecationWarning)
//anaconda3/lib/python3.7/site-packages/sklearn/utils/deprecation.py:85:
DeprecationWarning: Function partial_dependence is deprecated; The function
ensemble.partial_dependence has been deprecated in favour of
inspection.partial_dependence in 0.21 and will be removed in 0.23.
  warnings.warn(msg, category=DeprecationWarning)
//anaconda3/lib/python3.7/site-packages/sklearn/utils/deprecation.py:85:
DeprecationWarning: Function partial_dependence is deprecated; The function
ensemble.partial_dependence has been deprecated in favour of
inspection.partial_dependence in 0.21 and will be removed in 0.23.
  warnings.warn(msg, category=DeprecationWarning)
//anaconda3/lib/python3.7/site-packages/sklearn/utils/deprecation.py:85:
DeprecationWarning: Function partial_dependence is deprecated; The function
ensemble.partial_dependence has been deprecated in favour of
inspection.partial_dependence in 0.21 and will be removed in 0.23.
  warnings.warn(msg, category=DeprecationWarning)
//anaconda3/lib/python3.7/site-packages/sklearn/utils/deprecation.py:85:
```

```
DeprecationWarning: Function partial_dependence is deprecated; The function
ensemble.partial_dependence has been deprecated in favour of
inspection.partial_dependence in 0.21 and will be removed in 0.23.
  warnings.warn(msg, category=DeprecationWarning)
//anaconda3/lib/python3.7/site-packages/sklearn/utils/deprecation.py:85:
DeprecationWarning: Function partial_dependence is deprecated; The function
ensemble.partial_dependence has been deprecated in favour of
inspection.partial_dependence in 0.21 and will be removed in 0.23.
  warnings.warn(msg, category=DeprecationWarning)
//anaconda3/lib/python3.7/site-packages/sklearn/utils/deprecation.py:85:
DeprecationWarning: Function partial_dependence is deprecated; The function
ensemble.partial_dependence has been deprecated in favour of
inspection.partial_dependence in 0.21 and will be removed in 0.23.
  warnings.warn(msg, category=DeprecationWarning)
```



0.0.5 Linear Regression

[14]:
```
from sklearn.linear_model import LinearRegression
```

[15]:
```
clf2 = LinearRegression()
clf2.fit(X,y)
```

[15]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

Comparison in MSE

[16]:
```
np.mean((y-clf2.predict(X))**2)
```

[16]:
```
0.5243209861846071
```

[17]:
```
np.mean((y-clf.predict(X))**2)
```

[17]:
```
0.26188431965892933
```

[18]:
```
print(MSE[-1])
```

```
0.4953180130155929
```