Grashof_David_Assignment4

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0.0.1 1.0 | Assignment 4: Evaluating Random Forest and Gradient Boosting Regressors

0.0.2 Overview:

The management team of a real state company is interested in understanding if machine learning techniques can accurately predict residential housing market values to supplement more conventional methods. Using a sample of labeled real estate data for the city of Boston as training data, models will be assessed based on the minimzed RMSE acheived.

As with any machine learning model build, the data must be first analyzed, scaled, encoded and imputed, if necassary. An initial analysis of the data showed that the number of rooms in a given house and the % of local poplation in a lower economic class had the strongest correlation to the response variable, median house value. Next, the data was scaled across all continuous variables and cateogrical variables were encoded. No values needed to be imputed.

Previous attempts were made to generate a meaningful predictive model using linear regression methods. The results indicated that linear regression was a viable option with an RMSE of 4.87. In this phase of the project, tree-based methods were evaluated to determine if they provided greater predictive power, as measured by a lower RMSE. Four models were considered: Random Forest Regression, Gradient Boosting Regression, Ada Boost Regression and Extra Gradient Boosting Regression. All four models showed a significant improvement in performance compared to the linear models with RMSE values ranging from 3.75 (Gradient Boosting) to 3.29 (Extra Gradie Boosting). In addition, an average of all four model's predicted values was considered with the idea being that the aggregated estimators would cancel out any weaknesses in each individual model. This aggregated model beat all 4 of the individual models with an RMSE value of 3.08. It is recommended that the aggregate model be used. Combining all 4 models into a stacked model is likely to be more robust in evaluating future test values than relying on a single model.

0.0.3 1.1 | Load Modules

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        from sklearn.preprocessing import StandardScaler #scale any continuous fields
        from sklearn.preprocessing import Imputer #impute any missing values
        from sklearn.preprocessing import LabelBinarizer
        ################################################
        from sklearn.model_selection import GridSearchCV
        from sklearn.ensemble import GradientBoostingRegressor
        from sklearn.ensemble import AdaBoostRegressor
```

```
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
from sklearn import metrics #to evaluate model performances

import warnings
warnings.filterwarnings("ignore")
```

0.0.4 1.2 | Import Data

```
In [2]: file = "C:/Users/David/OneDrive/MSDS/MSDS422/Week4/boston.csv"
        df = pd.read_csv(file,sep = ',')
        print('df rows:',len(df))
        df.head()
```

```
df rows: 506
```

```
Out[2]:   neighborhood     crim    zn  indus  chas    nox  rooms   age     dis  rad  \
        0       Nahant  0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900    1
        1   Swampscott  0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671    2
        2   Swanpscott  0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671    2
        3   Marblehead  0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622    3
        4   Marblehead  0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622    3

           tax  ptratio  lstat    mv
        0  296     15.3   4.98  24.0
        1  242     17.8   9.14  21.6
        2  242     17.8   4.03  34.7
        3  222     18.7   2.94  33.4
        4  222     18.7   5.33  36.2
```

0.0.5 1.3 | Data Pre-Processing

```
In [3]: #convert dependent variable to log value
        #df['mv'] = np.log(df['mv'])

        #isolate cat/cont/response fields
        cat_fields = ['chas']
        cont_fields = ['crim','zn','indus','nox','rooms','age','dis','rad','tax','ptratio','ls
        response_fields = ['mv']

        df[cat_fields+cont_fields+response_fields].head()
```

```
Out[3]:    chas     crim    zn  indus    nox  rooms   age     dis  rad  tax  ptratio  \
        0     0  0.00632  18.0   2.31  0.538  6.575  65.2  4.0900    1  296     15.3
        1     0  0.02731   0.0   7.07  0.469  6.421  78.9  4.9671    2  242     17.8
        2     0  0.02729   0.0   7.07  0.469  7.185  61.1  4.9671    2  242     17.8
        3     0  0.03237   0.0   2.18  0.458  6.998  45.8  6.0622    3  222     18.7
        4     0  0.06905   0.0   2.18  0.458  7.147  54.2  6.0622    3  222     18.7
```

```
   lstat    mv
0   4.98  24.0
1   9.14  21.6
2   4.03  34.7
3   2.94  33.4
4   5.33  36.2
```

In [4]:
```
#describe cat fields
df[cat_fields].describe()
```

Out[4]:

	chas
count	506.000000
mean	0.069170
std	0.253994
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	1.000000

In [5]:
```
#describe cont fields
df[cont_fields+response_fields].describe()
```

Out[5]:

	crim	zn	indus	nox	rooms	age
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	3.613524	11.363636	11.136779	0.554695	6.284634	68.574901
std	8.601545	23.322453	6.860353	0.115878	0.702617	28.148861
min	0.006320	0.000000	0.460000	0.385000	3.561000	2.900000
25%	0.082045	0.000000	5.190000	0.449000	5.885500	45.025000
50%	0.256510	0.000000	9.690000	0.538000	6.208500	77.500000
75%	3.677082	12.500000	18.100000	0.624000	6.623500	94.075000
max	88.976200	100.000000	27.740000	0.871000	8.780000	100.000000

\

	dis	rad	tax	ptratio	lstat	mv
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	3.795043	9.549407	408.237154	18.455534	12.653063	22.528854
std	2.105710	8.707259	168.537116	2.164946	7.141062	9.182176
min	1.129600	1.000000	187.000000	12.600000	1.730000	5.000000
25%	2.100175	4.000000	279.000000	17.400000	6.950000	17.025000
50%	3.207450	5.000000	330.000000	19.050000	11.360000	21.200000
75%	5.188425	24.000000	666.000000	20.200000	16.955000	25.000000
max	12.126500	24.000000	711.000000	22.000000	37.970000	50.000000

0.0.6 1.3 | Split into Training and Test Data

In [6]:
```
from sklearn.model_selection import train_test_split

RANDOM_STATE = 42
```

```
TEST_SIZE = .3

#split data into train and test sets
xtrain,xtest,ytrain,ytest=train_test_split(df[cat_fields+cont_fields],df['mv'],
                                            test_size = TEST_SIZE, random_state = RA
```

In [7]:
```
#confirm split went according to plan. both y values are close to the mean value
print("Row count of Xtrain:",len(xtrain))
print("Row count of Ytrain:",len(ytrain),"/ Avg Market Value: ",np.mean(ytrain))
print("Row count of Xtest:",len(xtest))
print("Row count of Ytest:",len(ytest),"/ Avg Market Value: ",np.mean(ytest))
```

```
Row count of Xtrain: 354
Row count of Ytrain: 354 / Avg Market Value:  23.023163841807907
Row count of Xtest: 152
Row count of Ytest: 152 / Avg Market Value:  21.377631578947362
```

0.0.7 1.4 | Scale Test and Training Data

In [19]:
```
#scale training data separate from test so as to not influence scaling
train_scaled = pd.DataFrame(StandardScaler().fit_transform(xtrain[cont_fields]),
                   columns = xtrain[cont_fields].columns, index = xtrain.index)

xtrain = pd.concat([xtrain[cat_fields],train_scaled],axis = 1)

#scale test data likewise
test_scaled = pd.DataFrame(StandardScaler().fit_transform(xtest[cont_fields]),
                   columns = xtest[cont_fields].columns, index = xtest.index)

xtest = pd.concat([xtest[cat_fields],test_scaled],axis = 1)

print("Test Data shape:",xtest.shape)
print("Training Data shape: ",xtrain.shape)
xtrain.head()
```

```
Test Data shape: (152, 12)
Training Data shape:  (354, 12)
```

Out[19]:
```
     chas      crim        zn     indus       nox     rooms       age  \
5       0 -0.414259 -0.505125 -1.292142 -0.851085  0.145264 -0.365584
116     0 -0.402008 -0.505125 -0.162083 -0.087967 -0.208401  0.133941
45      0 -0.397211 -0.505125 -0.609489 -0.936828 -0.896237 -1.266900
16      0 -0.290936 -0.505125 -0.431970 -0.165136 -0.543965 -1.429789
468     0  1.457816 -0.505125  1.005500  0.194987 -0.556496  0.079645

          dis       rad       tax   ptratio     lstat
5    1.081628 -0.746179 -1.112790  0.187271 -1.015316
```

```
116 -0.487876 -0.398464  0.150088 -0.212090 -0.053663
45   0.628596 -0.746179 -1.046639 -0.167716 -0.311324
16   0.345133 -0.630274 -0.601625  1.207859 -0.822422
468 -0.403892  1.687825  1.557294  0.852872  0.803800
```

0.0.8 1.5 | One Hot Encoding of Categorical Variables

In [20]:
```
#this method is tricky since I want to one hot encode across a combined test and trai
#and training in isolation then I would run the risk of some values showing up only i
#number of columns

#define variable for identifying test and train
xtrain['train'] = 1
xtest['train'] = 0

#Combine test and train data
combined = pd.concat([xtrain,xtest],axis = 0)

#isolate categorical variables
cat_df = combined[cat_fields]

#one hot encode
cat_df_encoded = pd.get_dummies(cat_df,drop_first = True)

combined_2 = pd.concat([cat_df_encoded,combined[cont_fields],combined['train']],axis =

#split combined data set back to train and test
xtrain = combined_2[combined_2['train'] == 1]
xtest  = combined_2[combined_2['train'] == 0]
#remove train field defined earlier
xtrain.drop('train',axis = 1,inplace = True)
xtest.drop('train',axis = 1, inplace = True)

print("Test Data shape:",xtest.shape)
print("Training Data shape: ",xtrain.shape)
#Check the columns are equal and and the rows counts remained the same
```

```
Test Data shape: (152, 12)
Training Data shape:  (354, 12)
```

0.0.9 1.6 | Model I: Random Forest Regression

In [21]:
```
model1 = RandomForestRegressor(random_state = RANDOM_STATE)

param_grid = [{
    "n_estimators"       :[10, 25, 50, 100,150,200],
    "max_depth"          :[None, 2, 5, 10, 15],
```

```
                "max_features"       :['log2'],
                "min_samples_split"  :[2,4],
                "criterion"          :["mse"],
                "bootstrap"          :[True],
                "warm_start"         :[True, False],
                }]

        grid_search = GridSearchCV(model1,param_grid,cv = 5)
        rf = grid_search.fit(xtrain,ytrain)
        #optimized hyperparameters
        rf.best_params_
```

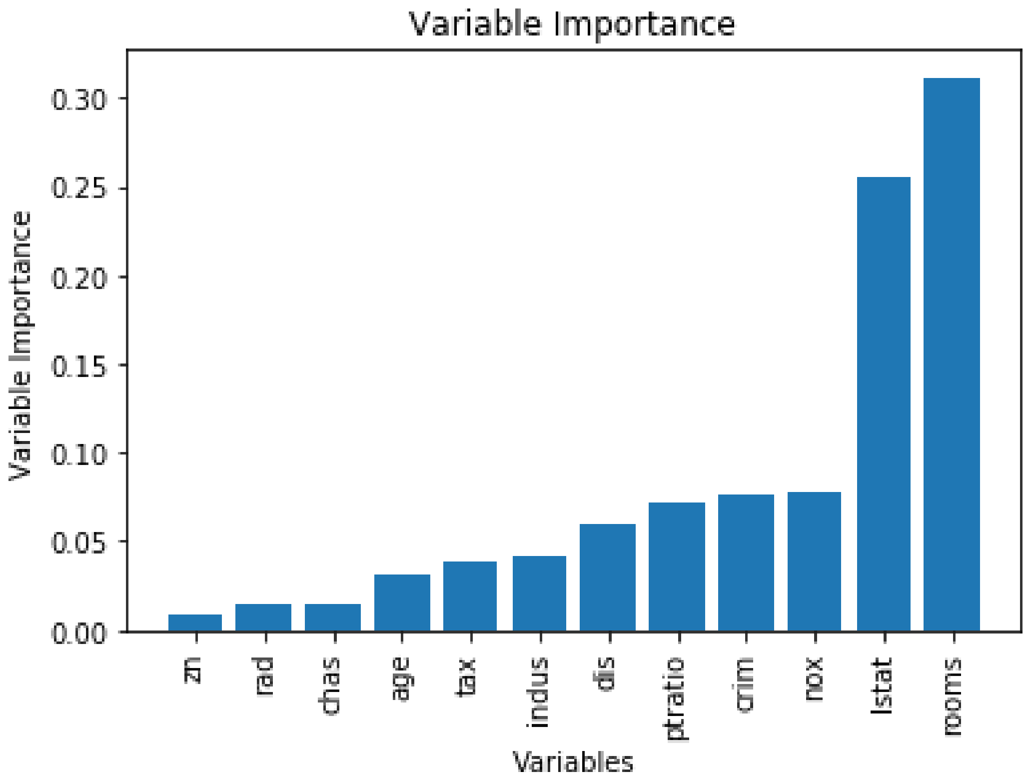
```
Out[21]: {'bootstrap': True,
          'criterion': 'mse',
          'max_depth': 10,
          'max_features': 'log2',
          'min_samples_split': 2,
          'n_estimators': 150,
          'warm_start': True}
```

```
In [22]: best_model_rf = rf.best_estimator_
         rf_pred = best_model_rf.predict(xtest)

         #Examine Results
         print("Random Forest Regressor")
         print("---------------------------")
         print("Number of Features : {}".format(best_model_rf.n_features_))
         print("Root mean squared error : {}".format(np.sqrt(metrics.mean_squared_error(ytest,
         print("R-squared : {}".format(metrics.r2_score(ytest, rf_pred).round(2)))
```

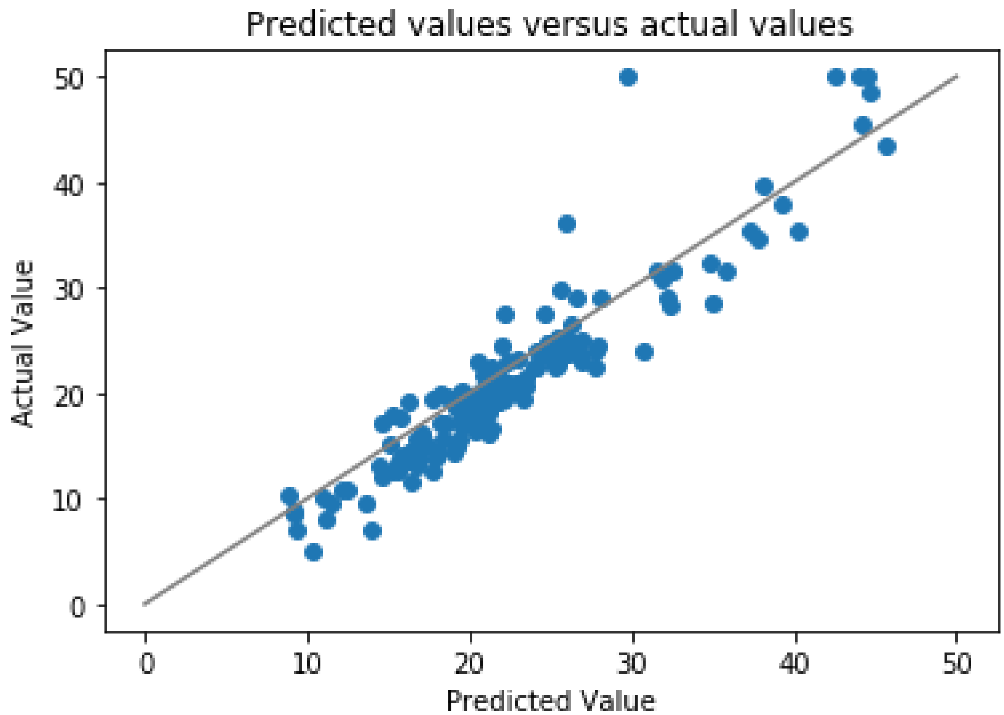
```
Random Forest Regressor
---------------------------
Number of Features : 12
Root mean squared error : 3.29
R-squared : 0.86
```

```
In [24]: coeff = pd.concat([pd.Series(xtrain.columns),pd.Series(best_model_rf.feature_importan
         coeff.columns = ['Variable','Variable Importance']
         coeff = coeff.sort_values('Variable Importance')

         plt.bar(coeff['Variable'],coeff['Variable Importance'])
         plt.title('Variable Importance')
         plt.xticks(rotation = 90)
         plt.ylabel('Variable Importance')
         plt.xlabel('Variables')
```

```
Out[24]: Text(0.5, 0, 'Variables')
```




```
In [43]: #convert back to regular values from log
         plt.scatter(rf_pred,ytest)
         plt.plot([0, 50], [0, 50],'grey')
         plt.title('Predicted values versus actual values')
         plt.xlabel('Predicted Value')
         plt.ylabel('Actual Value')

Out[43]: Text(0, 0.5, 'Actual Value')
```



0.0.10 1.7 | Model II: Gradient Boost Regression

```
In [26]: model2 = GradientBoostingRegressor(random_state = RANDOM_STATE)

         param_grid = [{
             "loss"                  :['ls', 'lad', 'huber', 'quantile'],
             "learning_rate"         :[.50, 1.0, 1.5],
             "max_features"          :['log2'],
             "n_estimators"          :[10, 25, 50, 100],
             "criterion"             :["mse"],
             "warm_start"            :[True, False],
             }]

         grid_search = GridSearchCV(model2,param_grid,cv = 5)
         gb = grid_search.fit(xtrain,ytrain)
         #optimized hyperparameters
         gb.best_params_
```

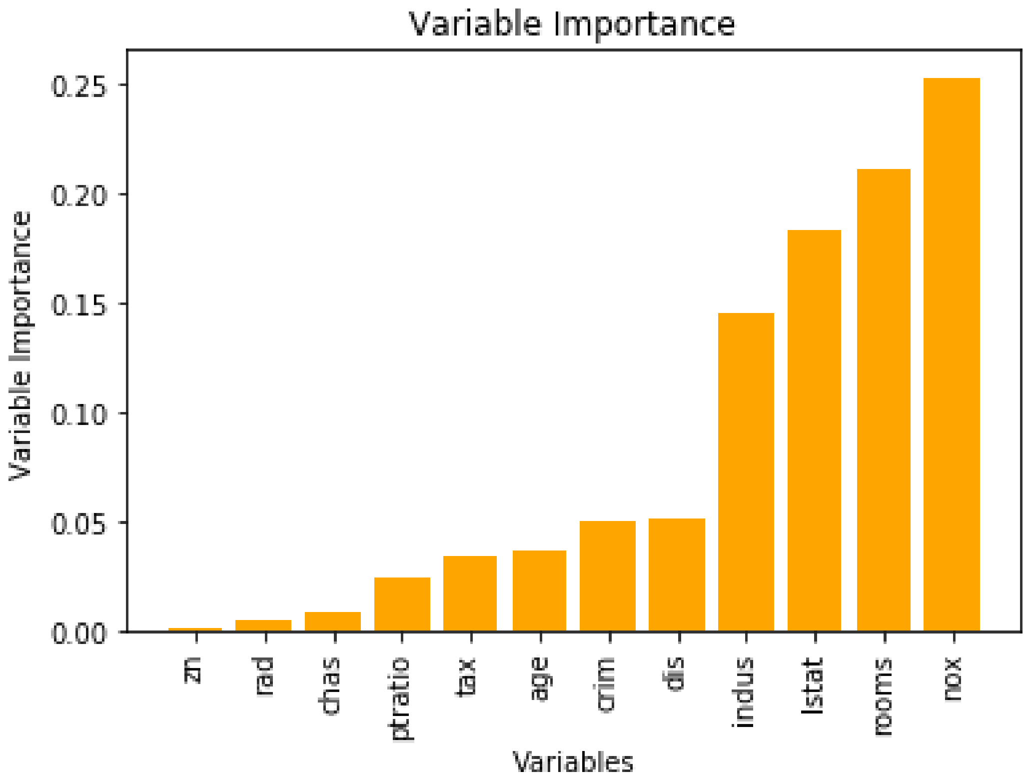
```
Out[26]: {'criterion': 'mse',
          'learning_rate': 0.5,
          'loss': 'huber',
          'max_features': 'log2',
          'n_estimators': 50,
          'warm_start': True}
```

In [27]:
```
best_model_gb = gb.best_estimator_
gb_pred = best_model_gb.predict(xtest)

#Examine Results
print("Gradient Boost Regressor")
print("---------------------------")
print("Number of Features : {}".format(best_model_gb.n_features_))
print("Root mean squared error : {}".format(np.sqrt(metrics.mean_squared_error(ytest,
print("R-squared : {}".format(metrics.r2_score(ytest, gb_pred).round(2)))
```

```
Gradient Boost Regressor
---------------------------
Number of Features : 12
Root mean squared error : 3.75
R-squared : 0.81
```

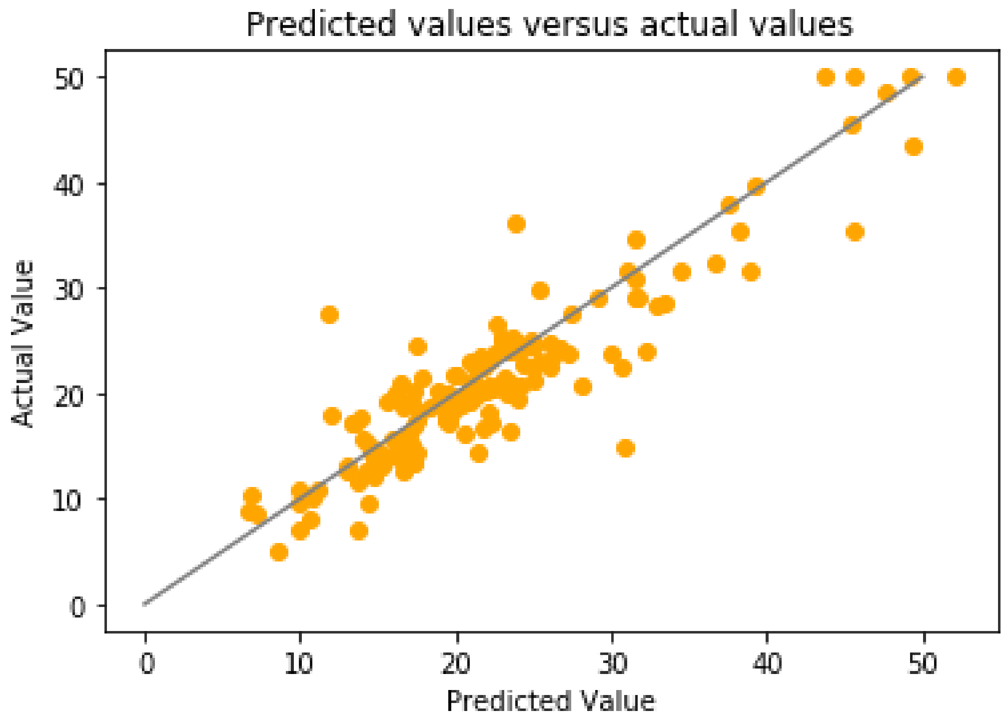
In [28]:
```
coeff = pd.concat([pd.Series(xtrain.columns),pd.Series(best_model_gb.feature_importanc
coeff.columns = ['Variable','Variable Importance']
coeff = coeff.sort_values('Variable Importance')

plt.bar(coeff['Variable'],coeff['Variable Importance'],color = 'Orange')
plt.title('Variable Importance')
plt.xticks(rotation = 90)
plt.ylabel('Variable Importance')
plt.xlabel('Variables')
```

Out[28]:
```
Text(0.5, 0, 'Variables')
```



In [42]:
```
#convert back to regular values from log
plt.scatter(gb_pred,ytest,color = 'Orange')
plt.plot([0, 50], [0, 50],'grey')
plt.title('Predicted values versus actual values')
plt.xlabel('Predicted Value')
plt.ylabel('Actual Value')
```

Out[42]:
```
Text(0, 0.5, 'Actual Value')
```



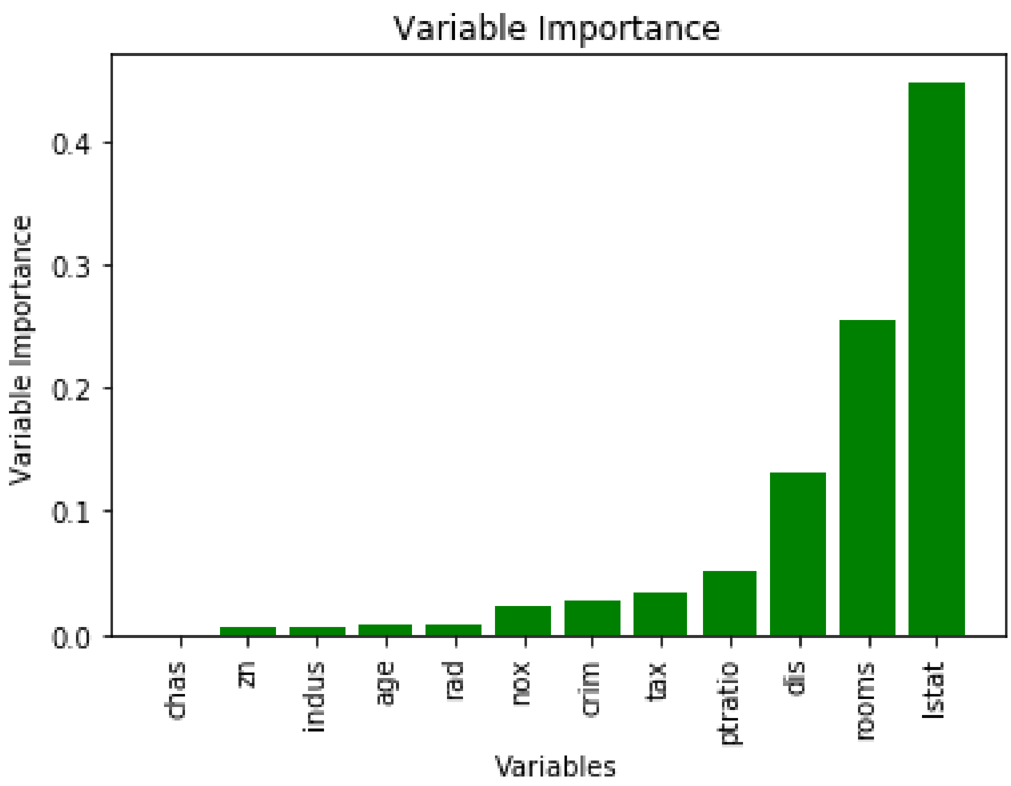
0.0.11 1.8 | Model III: AdaBoost Regression

```
In [30]: model3 = AdaBoostRegressor(random_state = RANDOM_STATE)

         param_grid = [{
             "loss"                 :['linear','square','exponential'],
             "learning_rate"        :[.50, 1.0, 1.5,2],
             "n_estimators"         :[10, 25, 50, 100,150]
             }]

         grid_search = GridSearchCV(model3,param_grid,cv = 5)
         ab = grid_search.fit(xtrain,ytrain)
         #optimized hyperparameters
         ab.best_params_

Out[30]: {'learning_rate': 2, 'loss': 'exponential', 'n_estimators': 100}

In [31]: best_model_ab = ab.best_estimator_
         ab_pred = best_model_ab.predict(xtest)

         #Examine Results
         print("AdaBoost Regressor")
         print("---------------------------")
         print("Root mean squared error : {}".format(np.sqrt(metrics.mean_squared_error(ytest,
         print("R-squared : {}".format(metrics.r2_score(ytest, ab_pred).round(2)))
```

```
AdaBoost Regressor
---------------------------
Root mean squared error : 3.44
R-squared : 0.84
```

In [32]:
```
coeff = pd.concat([pd.Series(xtrain.columns),pd.Series(best_model_ab.feature_importan
coeff.columns = ['Variable','Variable Importance']
coeff = coeff.sort_values('Variable Importance')

plt.bar(coeff['Variable'],coeff['Variable Importance'],color = 'Green')
plt.title('Variable Importance')
plt.xticks(rotation = 90)
plt.ylabel('Variable Importance')
plt.xlabel('Variables')
```

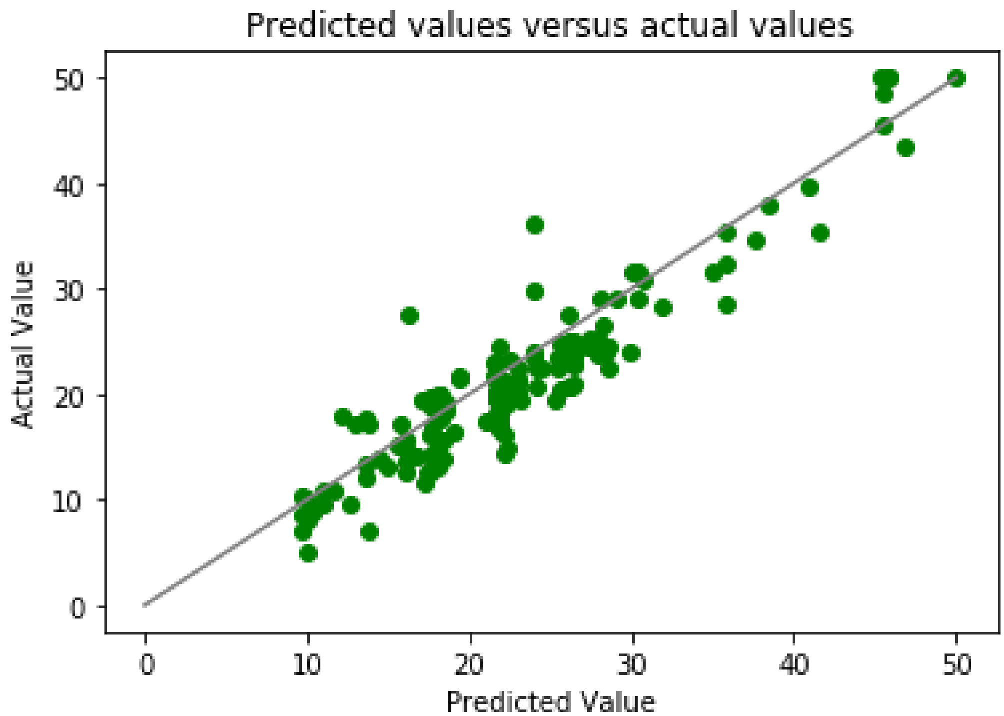
Out[32]:
```
Text(0.5, 0, 'Variables')
```



In [41]:
```
#convert back to regular values from log
plt.scatter(ab_pred,ytest,color = 'Green')
plt.plot([0, 50], [0, 50],'grey')
plt.title('Predicted values versus actual values')
```

```
        plt.xlabel('Predicted Value')
        plt.ylabel('Actual Value')
```

Out[41]: Text(0, 0.5, 'Actual Value')



0.0.12 1.9 | Model IV: XGBoost Regression

In [34]:
```
model4 = XGBRegressor(random_state = RANDOM_STATE)

#param_grid = [{
#    "loss"                :['linear','square','exponential'],
#    "learning_rate"       :[.50, 1.0, 1.5,2],
#    "n_estimators"        :[10, 25, 50, 100,150]
#    }]

#grid_search = GridSearchCV(model3,param_grid,cv = 5)
#xg = model4.fit(xtrain,ytrain)
#optimized hyperparameters
#xg.best_params_


param_grid = [{
    "loss"                :['ls', 'lad', 'huber', 'quantile'],
    "learning_rate"       :[.50, 1.0, 1.5],
```

```
            "max_features"       :['log2'],
            "n_estimators"       :[10, 25, 50, 100],
            "criterion"          :["mse"],
            "warm_start"         :[True, False],
            }]

        grid_search = GridSearchCV(model4,param_grid,cv = 5)
        xg = grid_search.fit(xtrain,ytrain)
        #optimized hyperparameters
        xg.best_params_
```

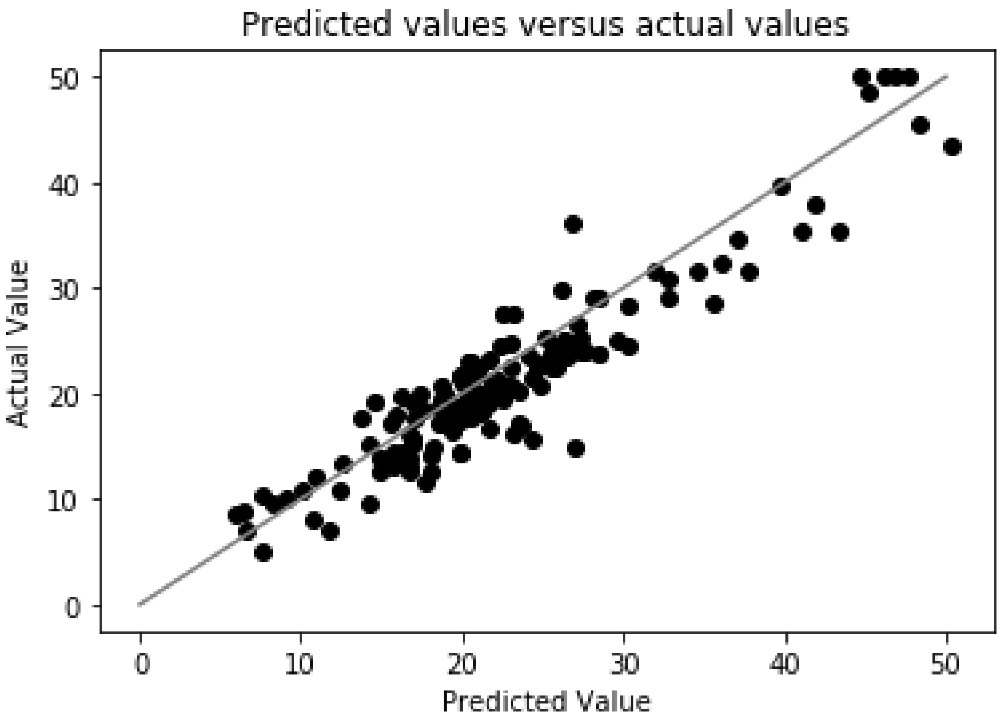
Out[34]:
```
{'criterion': 'mse',
 'learning_rate': 0.5,
 'loss': 'ls',
 'max_features': 'log2',
 'n_estimators': 25,
 'warm_start': True}
```

In [35]:
```
xg_pred = xg.predict(xtest)

#Examine Results
print("AdaBoost Regressor")
print("---------------------------")
print("Root mean squared error : {}".format(np.sqrt(metrics.mean_squared_error(ytest,
print("R-squared : {}".format(metrics.r2_score(ytest, xg_pred).round(2)))
```

```
AdaBoost Regressor
---------------------------
Root mean squared error : 3.29
R-squared : 0.86
```

In [40]:
```
#convert back to regular values from log
plt.scatter(xg_pred,ytest,color = 'black')
plt.plot([0, 50], [0, 50],'grey')
plt.title('Predicted values versus actual values')
plt.xlabel('Predicted Value')
plt.ylabel('Actual Value')
```

Out[40]:
```
Text(0, 0.5, 'Actual Value')
```



0.0.13 2.0 | Analysis of Models

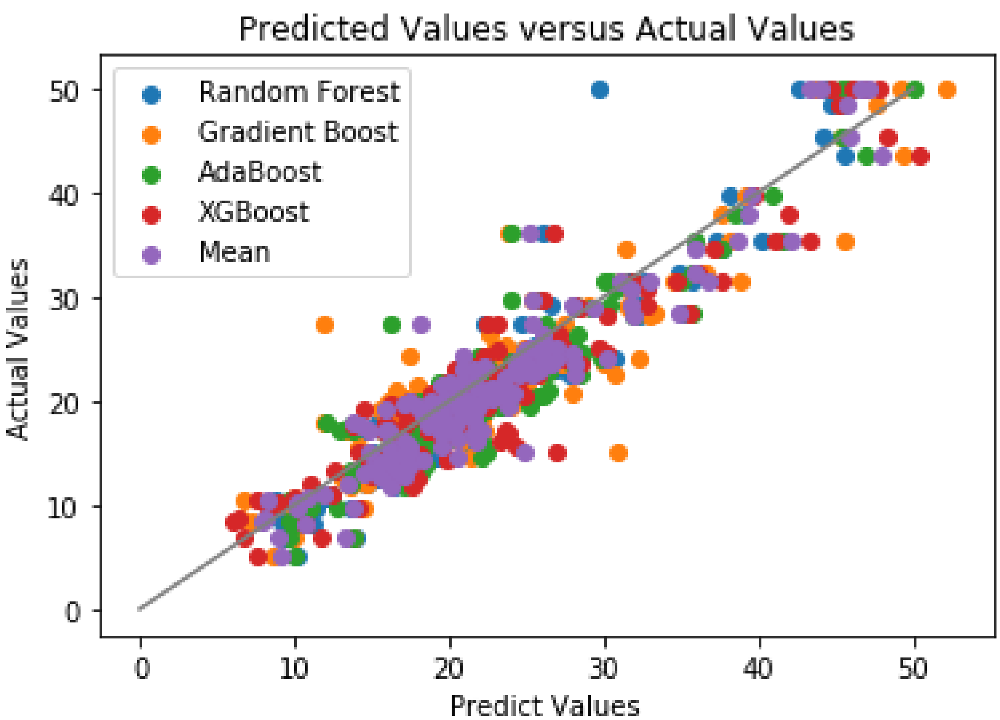
```
In [37]: print('RMSE of Models')
         print('----------------------------------------')
         print("Random Forest  : {}".format(np.sqrt(metrics.mean_squared_error(ytest, rf_pred)
         print("Gradient Boost : {}".format(np.sqrt(metrics.mean_squared_error(ytest, gb_pred)
         print("AdaBoost       : {}".format(np.sqrt(metrics.mean_squared_error(ytest, ab_pred)
         print("XGBoost        : {}".format(np.sqrt(metrics.mean_squared_error(ytest, xg_pred)
         print("----------------------------------------")
         print("Mean of Models : {}".format(np.sqrt(metrics.mean_squared_error(ytest, (rf_pred
```

```
RMSE of Models
----------------------------------------
Random Forest  : 3.29
Gradient Boost : 3.75
AdaBoost       : 3.44
XGBoost        : 3.29
----------------------------------------
Mean of Models : 3.08
```

```
In [44]: mean_pred = (rf_pred+gb_pred+ab_pred+xg_pred)/4
         for i,j in zip([rf_pred,gb_pred,ab_pred,xg_pred,mean_pred],['Random Forest','Gradient
             plt.scatter(i,ytest,label = j)
```

```
plt.plot([0, 50], [0, 50],'grey')
plt.title('Predicted Values versus Actual Values')
plt.xlabel('Predict Values')
plt.ylabel('Actual Values')
plt.legend()
```

Out[44]: <matplotlib.legend.Legend at 0x225cc45f320>



In [ ]: