Grashof_David_Assignment3

April 20, 2019

0.0.1 1.0 | Assignment 3: Evaluating Linear Regression Models

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.

The data was split into a training and test data set and then was fed into a Lasso Regression, Ridge Regression and Elastic Regression. One technique applied to the response variable was to apply a log function to it. This was shown to improve performance by reducing the RMSE and improving the r^2 score. The value in using a log value over the actual value in the dependent variable is to normalize the skewed distribution of the response variable and achieve homoscedasticity across residuals at all values. The three models were assesed for performance using a cross-validation design applying a number of different alpha values. It was found that each regression model generated nearly identical RMSE and r^2 scores of .198 (of log value) and .75, respectively.

The recommendation to the managmen team is that they consider additional model types beyond linear models. While the results produced by any of the three linear models provide some predictive power, it would be expected that considering additional modeling options would likely result in an improved outcome and minimized RMSE.

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.linear_model import ElasticNetCV
        from sklearn.linear_model import LassoCV
```

```
from sklearn.linear_model import RidgeCV
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/Week3/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','nox','rooms','dis','rad','tax','ptratio','lstat']
        response_fields = ['mv']

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

```
Out[3]:    chas     crim    zn    nox  rooms     dis  rad  tax  ptratio  lstat  \
        0     0  0.00632  18.0  0.538  6.575  4.0900    1  296     15.3   4.98
        1     0  0.02731   0.0  0.469  6.421  4.9671    2  242     17.8   9.14
        2     0  0.02729   0.0  0.469  7.185  4.9671    2  242     17.8   4.03
        3     0  0.03237   0.0  0.458  6.998  6.0622    3  222     18.7   2.94
        4     0  0.06905   0.0  0.458  7.147  6.0622    3  222     18.7   5.33
```

```
         mv
0  3.178054
1  3.072693
2  3.546740
3  3.508556
4  3.589059
```

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	nox	rooms	dis	rad \
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	3.613524	11.363636	0.554695	6.284634	3.795043	9.549407
std	8.601545	23.322453	0.115878	0.702617	2.105710	8.707259
min	0.006320	0.000000	0.385000	3.561000	1.129600	1.000000
25%	0.082045	0.000000	0.449000	5.885500	2.100175	4.000000
50%	0.256510	0.000000	0.538000	6.208500	3.207450	5.000000
75%	3.677082	12.500000	0.624000	6.623500	5.188425	24.000000
max	88.976200	100.000000	0.871000	8.780000	12.126500	24.000000

	tax	ptratio	lstat	mv
count	506.000000	506.000000	506.000000	506.000000
mean	408.237154	18.455534	12.653063	3.034558
std	168.537116	2.164946	7.141062	0.408275
min	187.000000	12.600000	1.730000	1.609438
25%	279.000000	17.400000	6.950000	2.834680
50%	330.000000	19.050000	11.360000	3.054001
75%	666.000000	20.200000	16.955000	3.218876
max	711.000000	22.000000	37.970000	3.912023

In [6]:
```
# check for any NA values to determine whether imputing is necassary
for i in cat_fields+cont_fields:
    print('NA count for',i,':',len(df[df[i].isna() == True]))
```

```
NA count for chas : 0
NA count for crim : 0
```

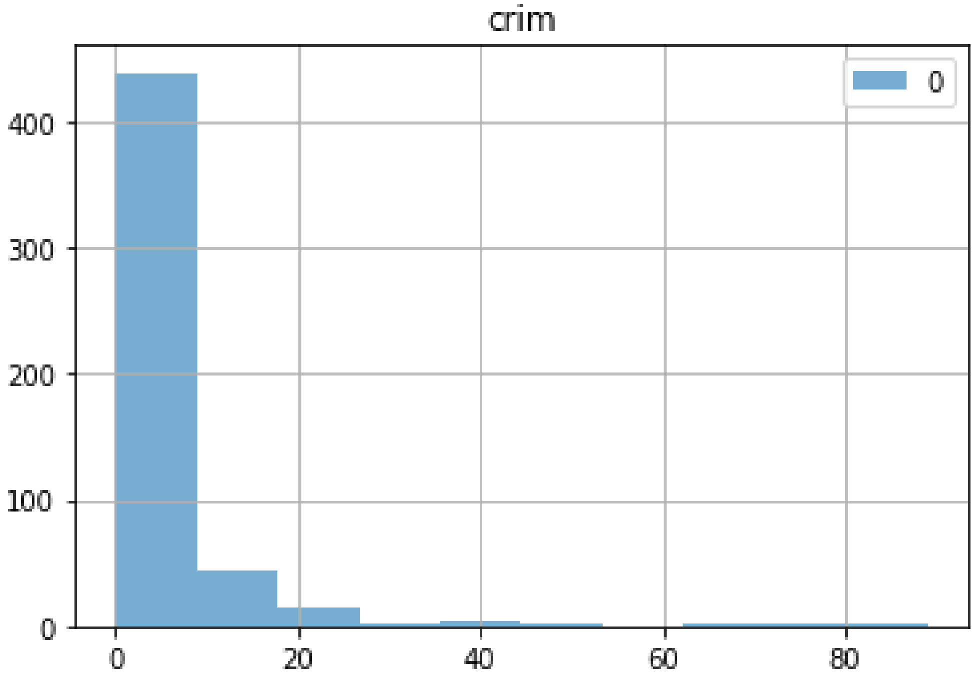
```
NA count for zn : 0
NA count for nox : 0
NA count for rooms : 0
NA count for dis : 0
NA count for rad : 0
NA count for tax : 0
NA count for ptratio : 0
NA count for lstat : 0
```

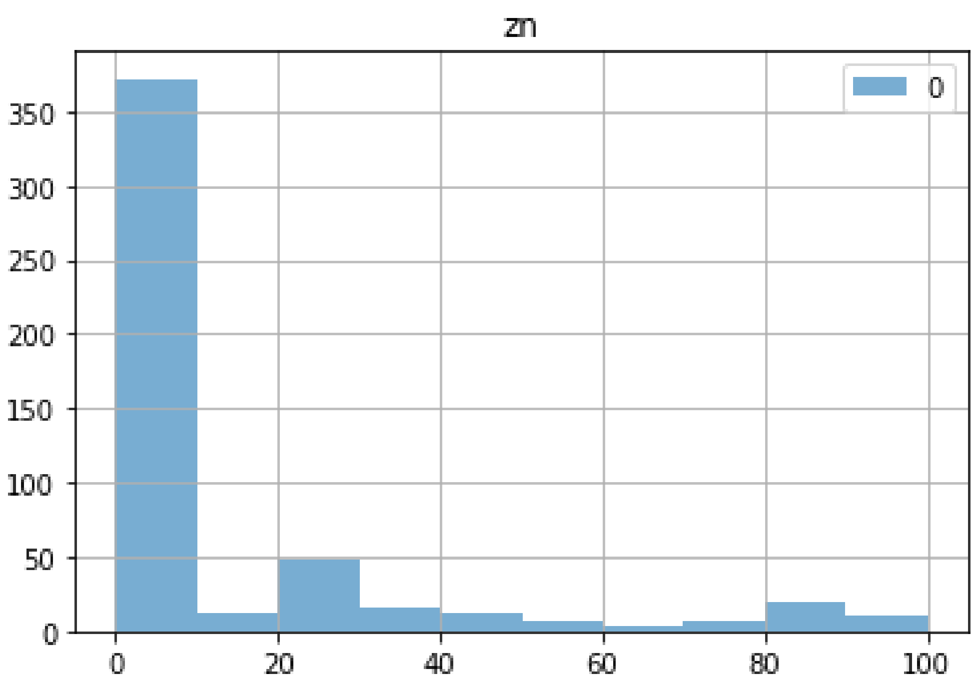
0.0.6 1.4 | EDA

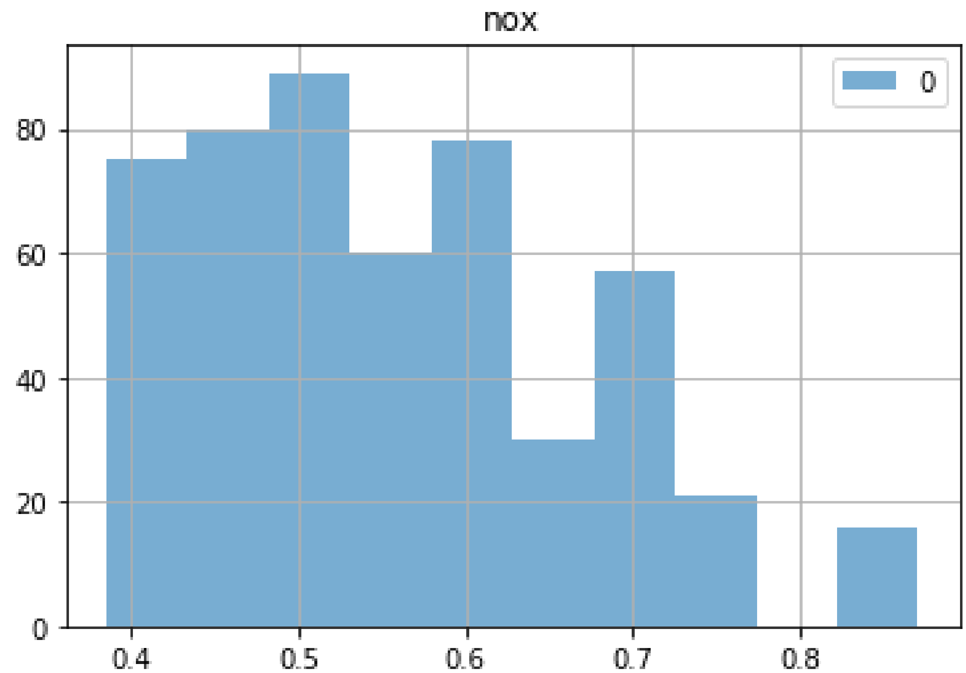
```
In [7]: #create binary variable for comparing distributions of cont fields across above averag
        def mv_split(i):
            i = int(i)
            if i > df['mv'].mean(): cat = 1
            if i <= df['mv'].mean(): cat = 0
            return(cat)

        df['mv_cat'] = df['mv'].map(mv_split)
        df[['mv_cat','mv']].head()
```

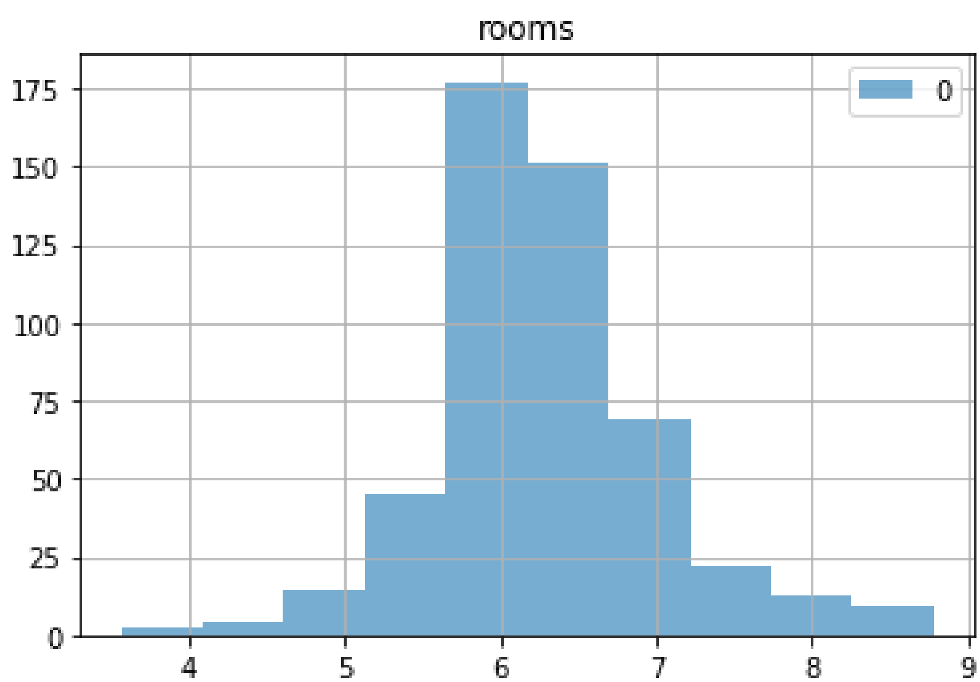
```
Out[7]:    mv_cat        mv
        0       0  3.178054
        1       0  3.072693
        2       0  3.546740
        3       0  3.508556
        4       0  3.589059
```

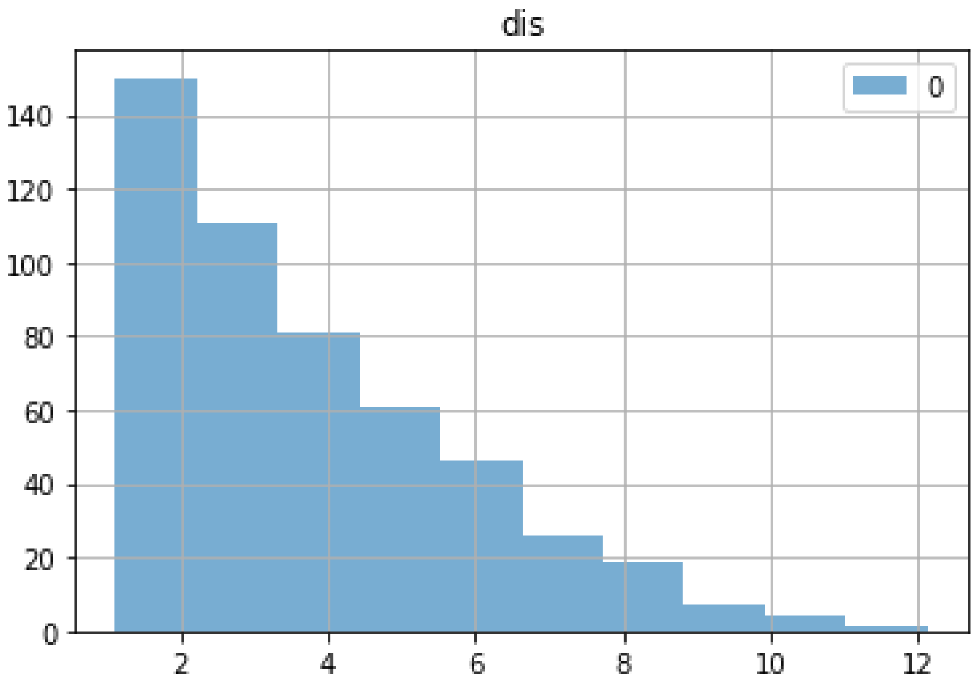
```
In [8]: #Distribution of continuous fields separated by mv_cat
        for i in cont_fields:
            plt.figure(i)
            df.groupby('mv_cat')[i].hist(alpha = .6)
            plt.title(i)
            plt.legend('01')
        #Views gives some insight into which variables follow distinct distributions for above
```

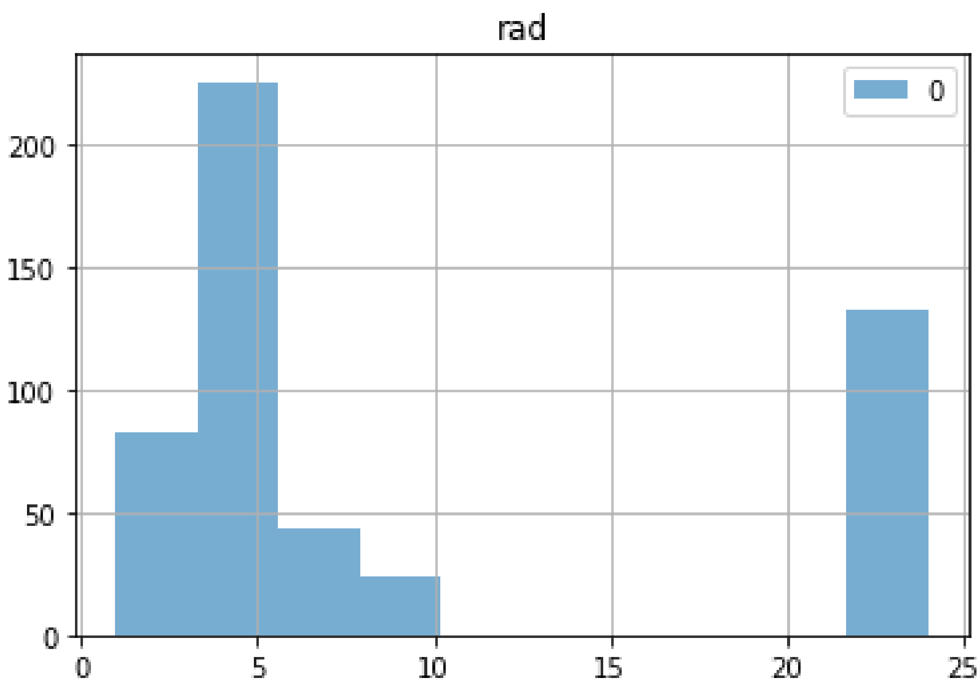

crim
0
400
300
200
100
0
0
20
40
60
80

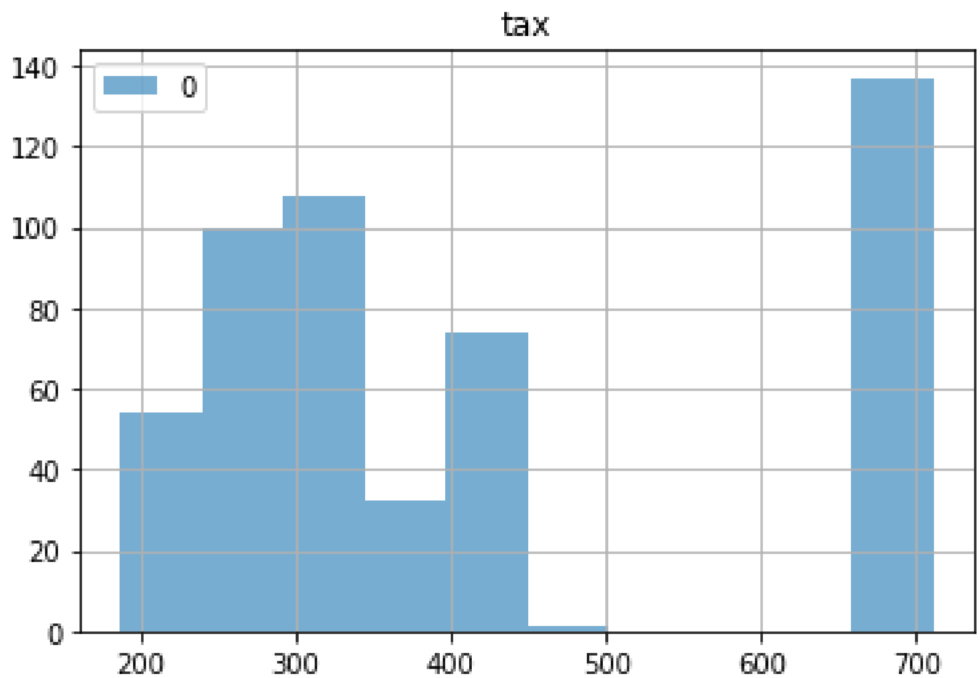

zn
0
350
300
250
200
150
100
50
0
0
20
40
60
80
100

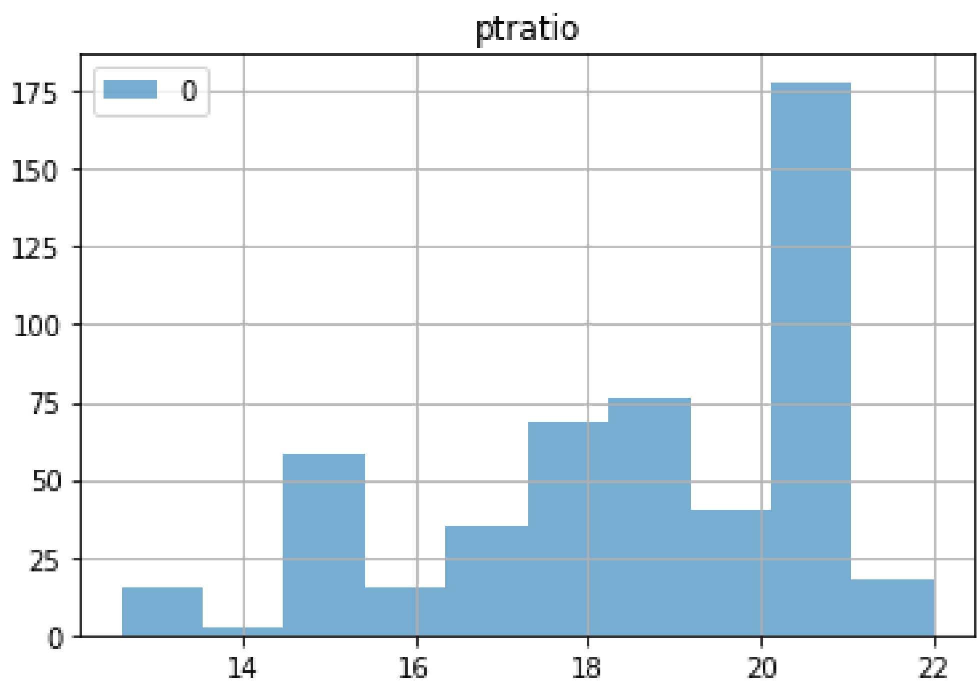

nox
0
80
60
40
20
0
0.4
0.5
0.6
0.7
0.8

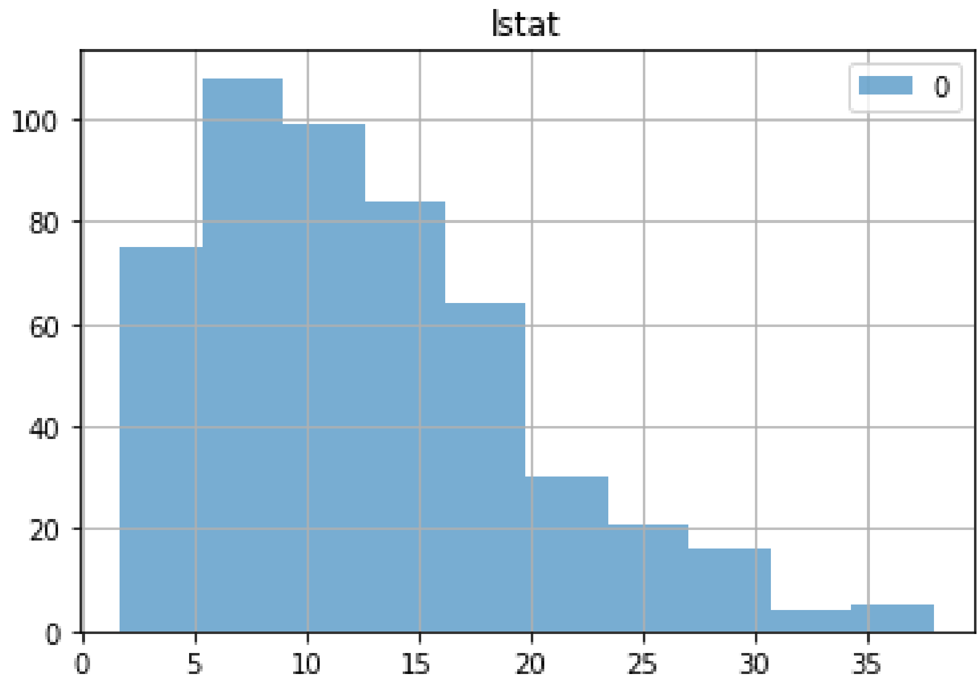

rooms
0
175
150
125
100
75
50
25
0
4
5
6
7
8
9


dis
0
140
120
100
80
60
40
20
0
2
4
6
8
10
12


rad
0
200
150
100
50
0
0
5
10
15
20
25

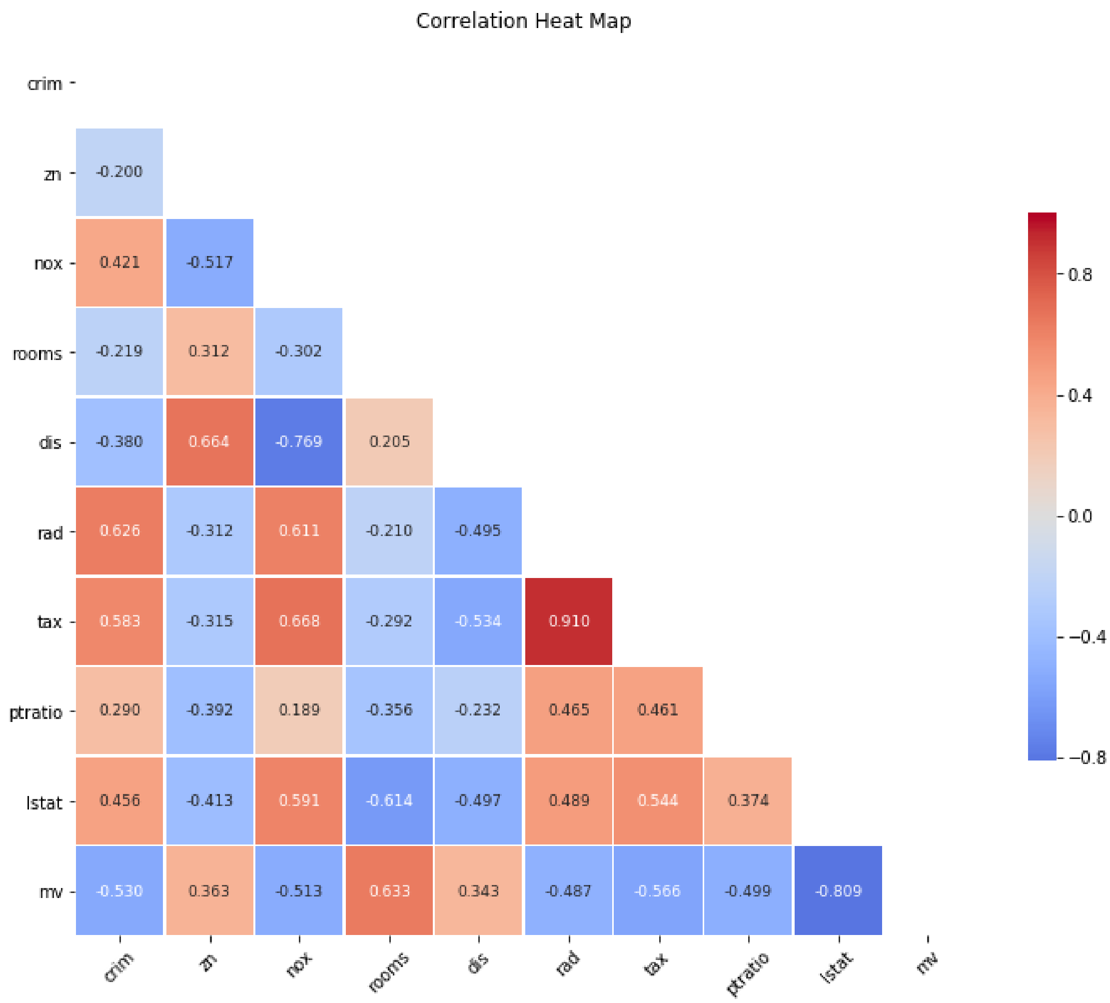

tax
0
140
120
100
80
60
40
20
0
200
300
400
500
600
700


ptratio
0
175
150
125
100
75
50
25
0
14
16
18
20
22

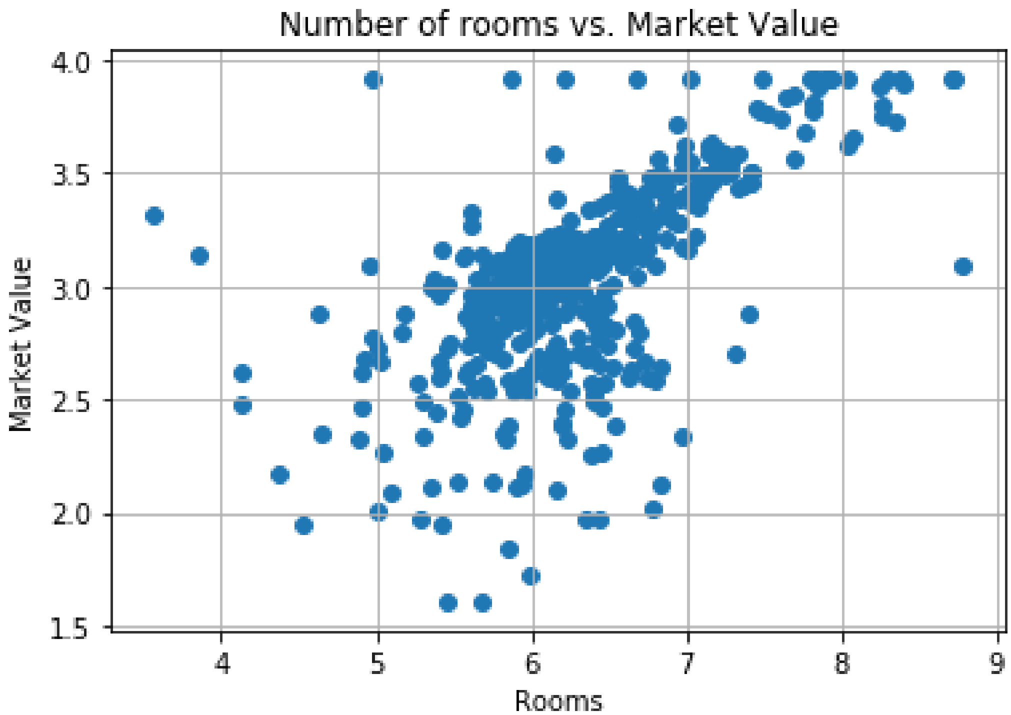



```
In [9]: import seaborn as sns

        def corr_chart(df_corr):
            corr=df_corr.corr()
            #screen top half to get a triangle
            top = np.zeros_like(corr, dtype=np.bool)
            top[np.triu_indices_from(top)] = True
            fig=plt.figure()
            fig, ax = plt.subplots(figsize=(12,12))
            sns.heatmap(corr, mask=top, cmap='coolwarm',
                center = 0, square=True,
                linewidths=.5, cbar_kws={'shrink':.5},
                annot = True, annot_kws={'size': 9}, fmt = '.3f')
            plt.xticks(rotation=45) # rotate variable labels on columns (x axis)
            plt.yticks(rotation=0) # use horizontal variable labels on rows (y axis)
            plt.title('Correlation Heat Map')

        for i in [cont_fields+response_fields]:
            corr_chart(df_corr = df[i])

        #this visual confirms that none of the variables are correlated with one another. In o
        # loan is not also equal to one
```

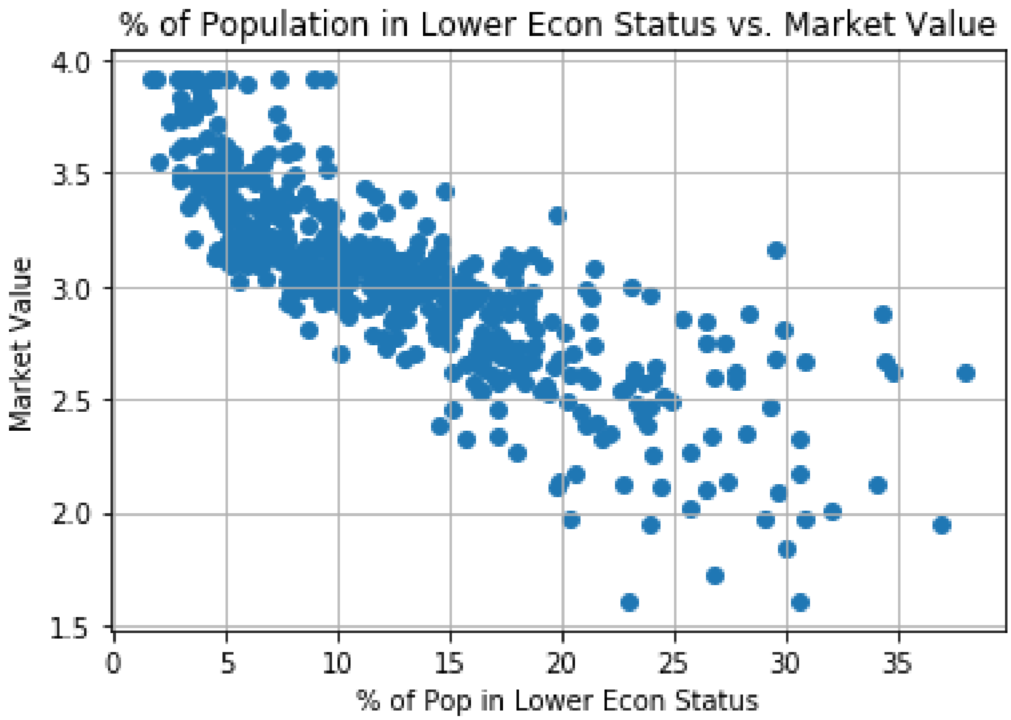
```
<Figure size 432x288 with 0 Axes>
```



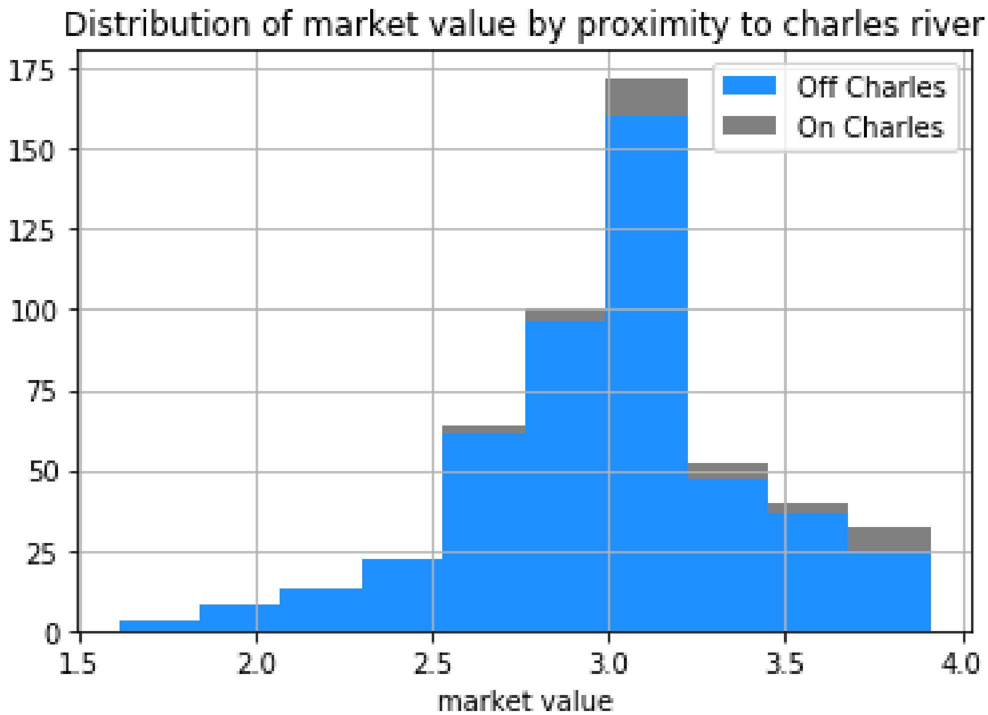

```
In [10]: #plot rooms versus market value since this variable shows the strongest positive indi
         plt.scatter(df['rooms'],df['mv'])
         plt.title('Number of rooms vs. Market Value')
         plt.xlabel('Rooms')
         plt.ylabel('Market Value')
         plt.grid()
         #number of rooms shows a strong positive correlation to market value with a consisten
         #only a medium amount of rooms but a high market value
```



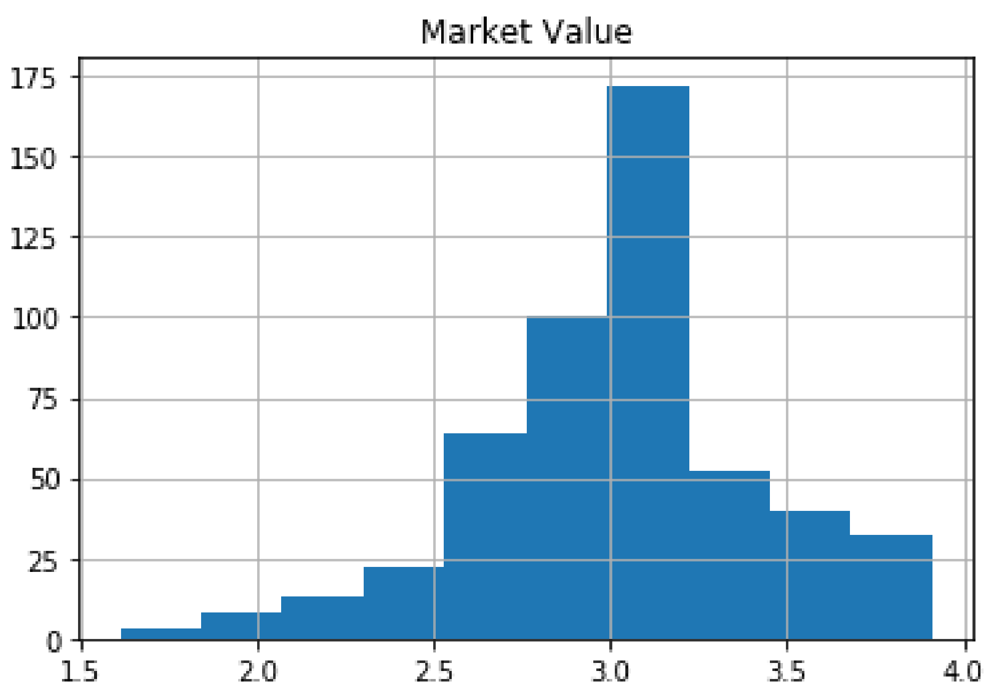
In [11]:
```
#plot lstat versus market value since this variable shows the strongest negative indi
plt.scatter(df['lstat'],df['mv'])
plt.title('% of Population in Lower Econ Status vs. Market Value')
plt.xlabel('% of Pop in Lower Econ Status')
plt.ylabel('Market Value')
plt.grid()
#it looks like once the lstat drops below 5% it begins to increase the market value a
#there are also fewer values here.
```



In [12]:
```
#isolate market value by on the charles river or not
x1 = df['mv'][df['chas']==0]
x2 = df['mv'][df['chas']==1]

#combine threads and plot
plt.hist([x1,x2],stacked = True,color = ["dodgerblue","grey"])
plt.title("Distribution of market value by proximity to charles river")
plt.xlabel("market value")
plt.legend({'Off Charles':'dodgerblue','On Charles':"grey"})
plt.grid(True)
plt.show()

#Based on this view it doesn't appear that this variable will be valuable
```




```
In [13]: #Distribution of log response field
         df['mv'].hist()
         plt.title('Market Value')
         plt.show()
```



0.0.7 1.5 | Split into Training and Test Data

```
In [14]: 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 = R
```

```
In [15]: #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:  3.0553049800143626
Row count of Xtest: 152
Row count of Ytest: 152 / Avg Market Value:  2.9862393689329636
```

0.0.8 1.6 | Scale Test and Training Data

```
In [16]: #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, 10)
Training Data shape:  (354, 10)
```

```
C:\Users\David\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:625: DataConversionWa
  return self.partial_fit(X, y)
C:\Users\David\Anaconda3\lib\site-packages\sklearn\base.py:462: DataConversionWarning: Data wi
  return self.fit(X, **fit_params).transform(X)
C:\Users\David\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:625: DataConversionWa
  return self.partial_fit(X, y)
C:\Users\David\Anaconda3\lib\site-packages\sklearn\base.py:462: DataConversionWarning: Data wi
  return self.fit(X, **fit_params).transform(X)
```

Out[16]:

```
     chas      crim        zn       nox     rooms       dis       rad  \
5       0 -0.414259 -0.505125 -0.851085  0.145264  1.081628 -0.746179
116     0 -0.402008 -0.505125 -0.087967 -0.208401 -0.487876 -0.398464
45      0 -0.397211 -0.505125 -0.936828 -0.896237  0.628596 -0.746179
16      0 -0.290936 -0.505125 -0.165136 -0.543965  0.345133 -0.630274
468     0  1.457816 -0.505125  0.194987 -0.556496 -0.403892  1.687825

          tax   ptratio     lstat
5   -1.112790  0.187271 -1.015316
116  0.150088 -0.212090 -0.053663
45  -1.046639 -0.167716 -0.311324
16  -0.601625  1.207859 -0.822422
468  1.557294  0.852872  0.803800
```

0.0.9 1.7 | One Hot Encoding of Categorical Variables

In [17]:

```
#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, 10)
Training Data shape:  (354, 10)
```

0.0.10 1.8 | Model I: ElasticNet Regression

```
In [18]: #apply different alpha values for best result
         for i in range(1,10):
                 model1 = ElasticNetCV(n_alphas = i,l1_ratio = .5,selection = 'random',copy_X=
                 # Evaluate performance of optimal model on test data
                 model1.fit(xtrain, ytrain)
                 # Apply model1 to out-of-sample test data `xtest`.
                 model1_pred = model1.predict(xtest)
                 print("---------------------------")
                 print("n_alphas: ",i," performance")
                 print("Root mean squared error : {}".format(np.sqrt(metrics.mean_squared_erro
                 print("R-squared : {}".format(metrics.r2_score(ytest, model1_pred).round(2)))
         #looks like a lower n_alpha value produces a lower RMSE
```

```
---------------------------
n_alphas:  1  performance
Root mean squared error : 0.198
R-squared : 0.75
---------------------------
n_alphas:  2  performance
Root mean squared error : 0.198
R-squared : 0.75
---------------------------
n_alphas:  3  performance
Root mean squared error : 0.198
R-squared : 0.75
---------------------------
n_alphas:  4  performance
Root mean squared error : 0.198
R-squared : 0.75
---------------------------
n_alphas:  5  performance
Root mean squared error : 0.201
R-squared : 0.74
---------------------------
```

```
n_alphas:  6  performance
Root mean squared error : 0.2
R-squared : 0.74
---------------------------
n_alphas:  7  performance
Root mean squared error : 0.2
R-squared : 0.74
---------------------------
n_alphas:  8  performance
Root mean squared error : 0.202
R-squared : 0.74
---------------------------
n_alphas:  9  performance
Root mean squared error : 0.201
R-squared : 0.74
```

In [19]:
```
model1 = ElasticNetCV(n_alphas = 2,l1_ratio = .5,copy_X=True,normalize = False, cv=5,
# Evaluate performance of optimal model on test data
model1.fit(xtrain, ytrain)
# Apply model1 to out-of-sample test data `xtest`.
model1_pred = model1.predict(xtest)

#examine coefficients
coeff = pd.concat([pd.Series(xtest.columns),pd.Series(model1.coef_)],axis = 1)
coeff.columns = ['Predictor','Coefficient']
coeff
```

Out[19]:

	Predictor	Coefficient
0	chas	0.115005
1	crim	-0.091546
2	zn	0.020784
3	nox	-0.070323
4	rooms	0.062328
5	dis	-0.099548
6	rad	0.071343
7	tax	-0.068338
8	ptratio	-0.071714
9	lstat	-0.227003

0.0.11 1.9 | Model II: Lasso Regression

In [20]:
```
#apply different alpha values for best result
for i in range(1,10):
        model2 = LassoCV(n_alphas = i,selection = 'random',copy_X=True,normalize = Fa
        # Evaluate performance of optimal model on test data
        model2.fit(xtrain, ytrain)
        # Apply model1 to out-of-sample test data `xtest`.
```

```
                model2_pred = model2.predict(xtest)
                print("----------------------------")
                print("n_alphas: ",i," performance")
                print("Root mean squared error : {}".format(np.sqrt(metrics.mean_squared_erro
                print("R-squared : {}".format(metrics.r2_score(ytest, model2_pred).round(2)))
        #looks like a lower n_alpha value produces a lower RMSE
```

```
---------------------------
n_alphas:  1  performance
Root mean squared error : 0.198
R-squared : 0.75
---------------------------
n_alphas:  2  performance
Root mean squared error : 0.198
R-squared : 0.75
---------------------------
n_alphas:  3  performance
Root mean squared error : 0.198
R-squared : 0.75
---------------------------
n_alphas:  4  performance
Root mean squared error : 0.198
R-squared : 0.75
---------------------------
n_alphas:  5  performance
Root mean squared error : 0.201
R-squared : 0.74
---------------------------
n_alphas:  6  performance
Root mean squared error : 0.2
R-squared : 0.74
---------------------------
n_alphas:  7  performance
Root mean squared error : 0.2
R-squared : 0.74
---------------------------
n_alphas:  8  performance
Root mean squared error : 0.199
R-squared : 0.74
---------------------------
n_alphas:  9  performance
Root mean squared error : 0.201
R-squared : 0.74
```

```
In [21]: model2 = LassoCV(n_alphas = 1,copy_X=True,normalize = False, cv=5, random_state = RANI
         # Evaluate performance of optimal model on test data
         model2.fit(xtrain, ytrain)
```

```
# Apply model1 to out-of-sample test data `xtest`.
model2_pred = model2.predict(xtest)

#examine coefficients
coeff = pd.concat([pd.Series(xtest.columns),pd.Series(model1.coef_)],axis = 1)
coeff.columns = ['Predictor','Coefficient']
coeff
```

Out[21]:

	Predictor	Coefficient
0	chas	0.115005
1	crim	-0.091546
2	zn	0.020784
3	nox	-0.070323
4	rooms	0.062328
5	dis	-0.099548
6	rad	0.071343
7	tax	-0.068338
8	ptratio	-0.071714
9	lstat	-0.227003

0.0.12 2.0 | Model III: Ridge Regression

In [22]:
```
#apply different alpha values for best result
model3 = RidgeCV(alphas = [1e-3, 1e-2, 1e-1, 1],scoring = 'neg_mean_squared_error',no
# Evaluate performance of optimal model on test data
model3.fit(xtrain, ytrain)
# Apply model1 to out-of-sample test data `xtest`.
model3_pred = model3.predict(xtest)
print("---------------------------")
print("Root mean squared error : {}".format(np.sqrt(metrics.mean_squared_error(ytest,
print("R-squared : {}".format(metrics.r2_score(ytest, model3_pred).round(2)))
#looks like a lower n_alpha value produces a lower RMSE
```

```
---------------------------
Root mean squared error : 0.198
R-squared : 0.75
```

In [23]:
```
#examine coefficients
coeff = pd.concat([pd.Series(xtest.columns),pd.Series(model3.coef_)],axis = 1)
coeff.columns = ['Predictor','Coefficient']
coeff
```

Out[23]:

	Predictor	Coefficient
0	chas	0.115523
1	crim	-0.092013
2	zn	0.021538
3	nox	-0.071127
4	rooms	0.062539

```
5        dis    -0.100575
6        rad     0.073395
7        tax    -0.070202
8    ptratio    -0.071904
9      lstat    -0.226086
```

0.1 2.1 | Analysis of Results

```
In [24]: #convert back to regular values from log
         plt.scatter(np.exp(model3_pred),np.exp(ytest))
         plt.title('Predicted values versus actual values')
         plt.xlabel('Predicted Value')
         plt.ylabel('Actual Value')

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