Predicting Crime Rates Based on Population Demographics and Environmental Factors

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Abstract

Predicting crime rates based on various factors within a population has the potential of helping law enforcement allocate resources efficiently. Investigating correlations of factors and crime rates are also of interest to decipher their importance. Population demographics and environmental factors have been measured previously as a function of crime rate. Aspects investigated in this paper include nitrogen oxide concentration, transportation, education, and median values of homes within the Boston area.

A backward stepwise linear regression approach was employed to predict the power-transformed crime rate. Five statistically significant regression coefficients were used to measure their importance and influence on the model. Model assumptions, outliers, distributions of variables, and relationships were inspected graphically.

Nitrogen oxide concentrations showed to have the greatest impact. Availability of education to the local population also presented to be a substantial factor. Housing values influenced the model the least, which was contrary to other studies. Positive correlations were found between highway accessibility and crime rate, which affirms that transportation is a factor when predicting crime rates. Future work includes the application of a model that evaluates crime at an individual basis rather than at a population level to effectively predict crime rates in real time.

Introduction

Analyzing demographics within a specific geographic location has many uses. Investigating how population demographics are related to crime rates is one of them. This type of analysis is useful for making real-time predictions as to what the crime rate would be in a specific area. Generating models would also aid in the allocation of resources regarding crime prevention in specific areas [1].

Narrowing down which factors are responsible for crime is not a new idea. Educational factors such as percent of people with less than a high school education have been modeled to have a significant positive impact on crime rates [2]. The distance traveled to the crime scene has also been of interest but was shown to be statistically insignificant [3]. The inverse relationship between crime and housing values has always been a topic of interest and has been researched thoroughly [4] [5]. Additionally, evidence has been provided that air pollution (from nitrogen oxides and carbon monoxide) has a direct effect on crime [6].

Deciphering which factors impact crime rate the most would aid in the decision making as to where police resources should be deployed. Modeling crime rates based on housing and neighborhood characteristics would be beneficial to the police force as it would increase visibility on the whereabouts of crime. This analysis will model crime rates within different areas of Boston using characteristics of each neighborhood [5]. It will investigate which factors are impact the crime rate the most and propose a tool to predict the crime rate given characteristics of a neighborhood.

Methods

A backwards stepwise multiple linear regression approach was employed to fit the crime rate to regressor variables in the model. The response variable was transformed by finding the power at which the log-likelihood function is maximized, which is known as the BoxCox method [7]. Each of the regressor variables were deemed to not be colinear after showing they have a variance inflation factor less than four, with the exception of the interaction term. The intercept was removed from the model because it did not make sense to have a negative crime rate, which improved the adjusted R^2. **Table 1** below shows all variables used in the model as well as their explanation [5].

Table 1: Variables Utilized in Regression Model

Variable Name	Explanation	Type
Crime Rate	Per capita crime rate per town	Response
Radial Highway Accessibility	Measures how accessible the highway is within the specific town	Regressor
Employment Distance	Weighted distance to five employment centers in the Boston region	Regressor
Pupil Teacher Ratio	The ratio of students to teachers within the town's school district	Regressor
Median Value of Home (in $1000's)	Median value of owner-occupied homes in 1978	Regressor
NO_x Concentration (in parts per ten million)	Nitrogen oxides concentration in the air of the town	Regressor

Figure 1 depicts the distribution of each of these variables where the median is depicted by the dashed red line.

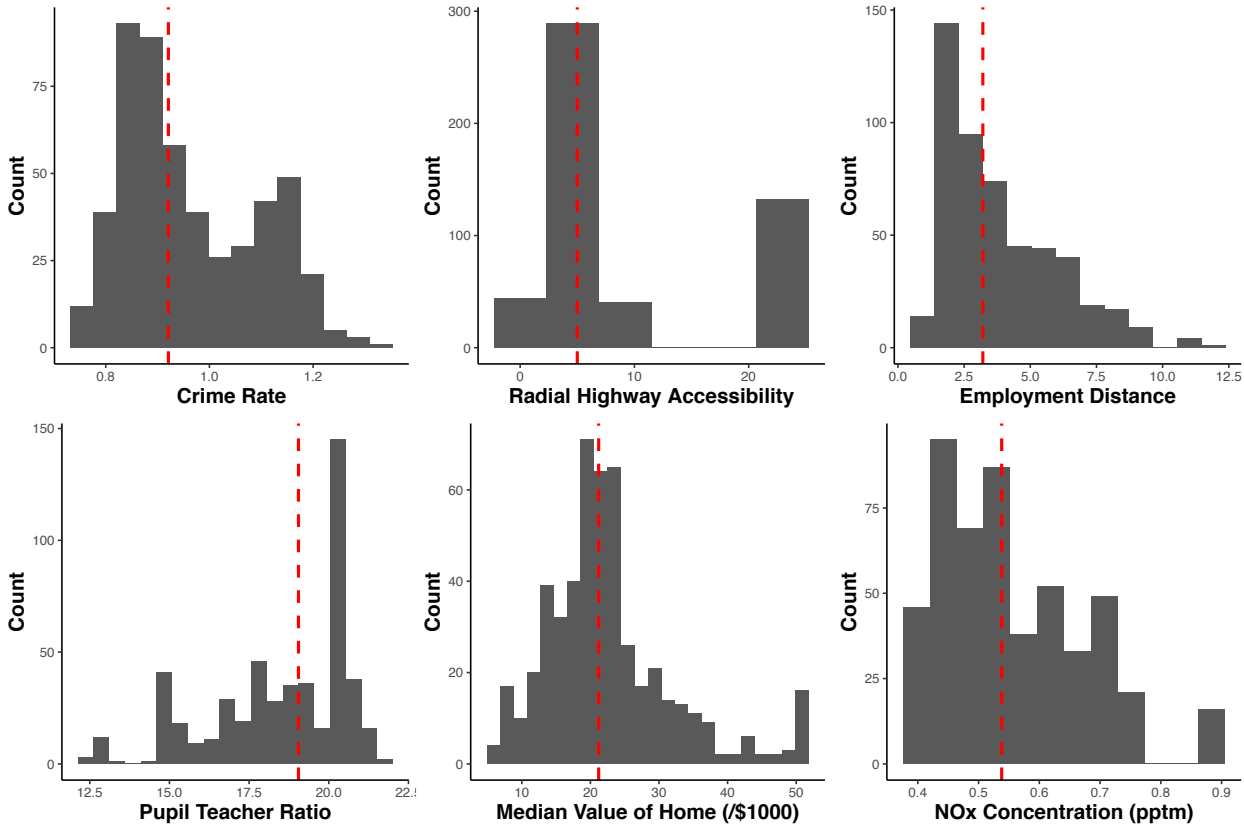

Figure 1: Distribution of Model Variables

Crime rate has a distinct subpopulation which causes the right skew in the distribution, which indicates there are a group of towns which have a high crime rate. Interestingly, there is a group of towns where poor highway accessibility is prevalent. There is a subpopulation of towns that have a short (2.0-2.5) distance to the employment centers, perhaps this is in the downtown Boston area. A pupil teacher ratio of 20-21 also frequently occurs for a group of towns, maybe this is representative of the downtown area as well. Additionally, a cluster of towns where the median house value is $50,000+ in 1978 dollars is revealed in the histogram.

The independence of errors, linearity, bias, scedasticity, and normality of residuals assumptions were all checked via visual inspection of **Figure 2** on the succeeding page. The figure displays plots that check the assumptions of the regression model of the transformed response variable.

The errors do not appear to be independent where the index is around 300 for employment distance regressor. There are mild groupings in the independence of errors plot in radial highway accessibility, NO_x concentration, and pupil teacher ratio. The model violates the linearity assumption for employment distance after 8.0 because of the residuals all being below zero. When the pupil teacher ratio is equal to 12.7, there appears to be a weighted mean above zero. Additionally, the NO_x concentration is weighted below zero around the maximum. The model appears to be mostly unbiased and homoscedastic. Errors appear to be normal in the qqplot, but the Shapiro Wilks [8] test fails with $p <= 0.05$.

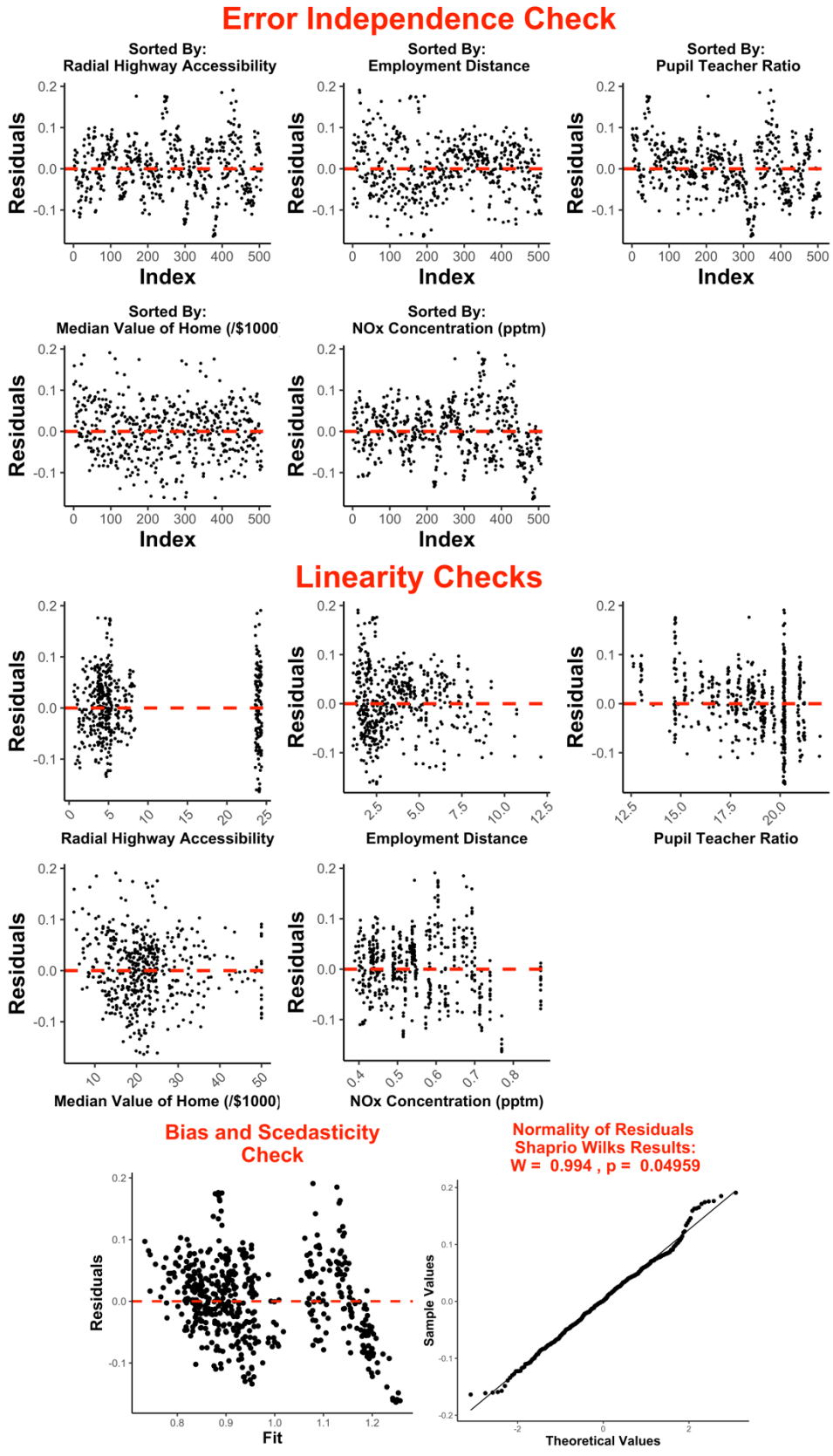

Figure 2: Depiction of Model Assumption Inspection

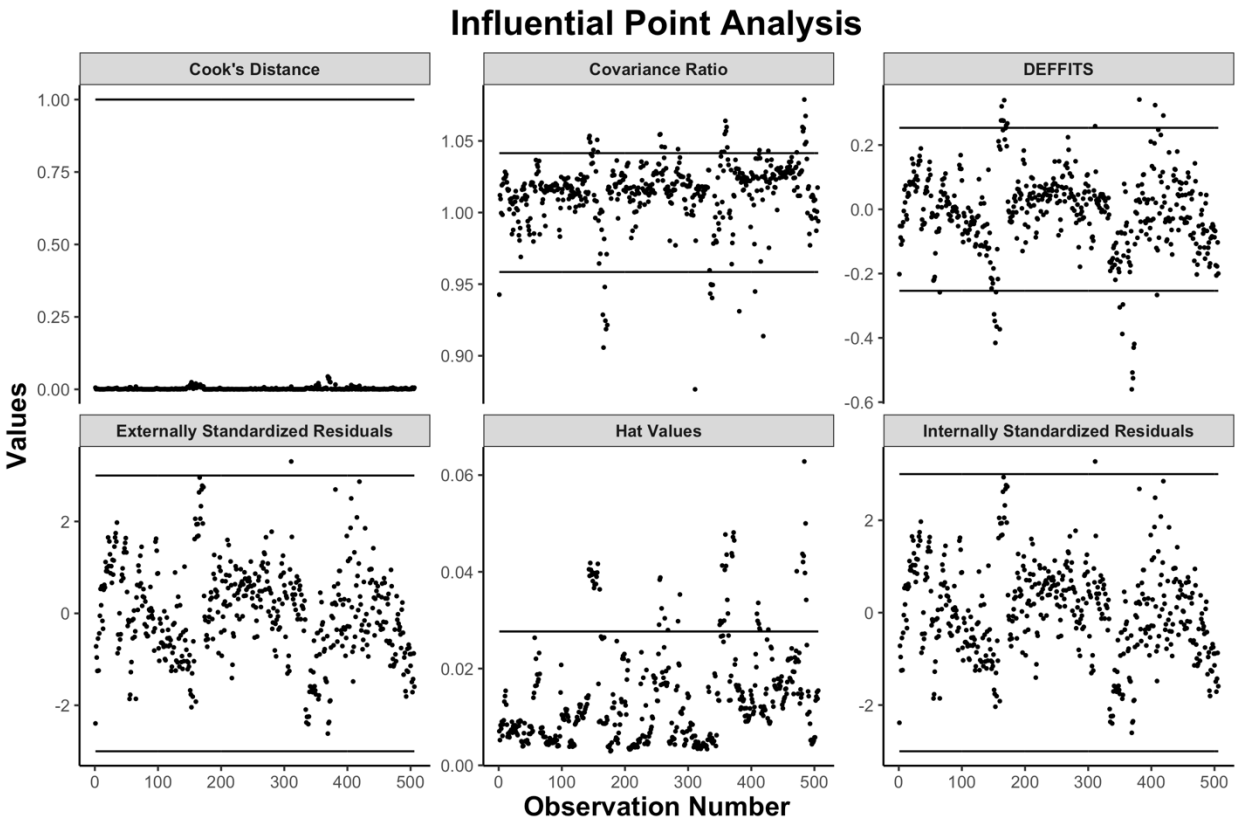

Figure 3: Influential Point Analysis

Figure 3 illustrates leverage, outlier, and influential points based on their evaluation above or below thresholds indicated by the black horizontal line. Several leverage points appear to be in clusters above the hat value threshold. Outlier wise, there appears to be one observation that is above both thresholds for the standardized residuals. The covariance ratio and DEFFITS depict several points as influential. These points could be caused by the irregular distributions seen in **Figure 1**.

Results

Table 2 below displays the statistics and metrics for model evaluation and **Figure 4** depicts the relationship between each regressor variable and the power transformed crime rate.

Table 2: Regressor Estimates of Crime Rate

Regressor	**Point Estimate**	**t-value**	**P-value**	**95% C.I.**
NO_x Concentration	0.8209	29.447	$< 2*10^{-16}$	(0.7662, 0.8757)
Pupil Teacher Ratio	0.0187	18.712	$< 2*10^{-16}$	(0.0168, 0.0207)
Employment Distance	0.0104	6.295	$6.73*10^{-10}$	(0.0072, 0.0137)
Radial Highway Accessibility	0.0066	15.622	$< 2*10^{-16}$	(0.0057, 0.0074)
Median Value of Home	0.0025	8.498	$2.23*10^{-16}$	(0.0019, 0.0031)

R^2 adj. = 0.9958; RMSE = 0.0623; AIC = -1360.626; BIC = -1335.257

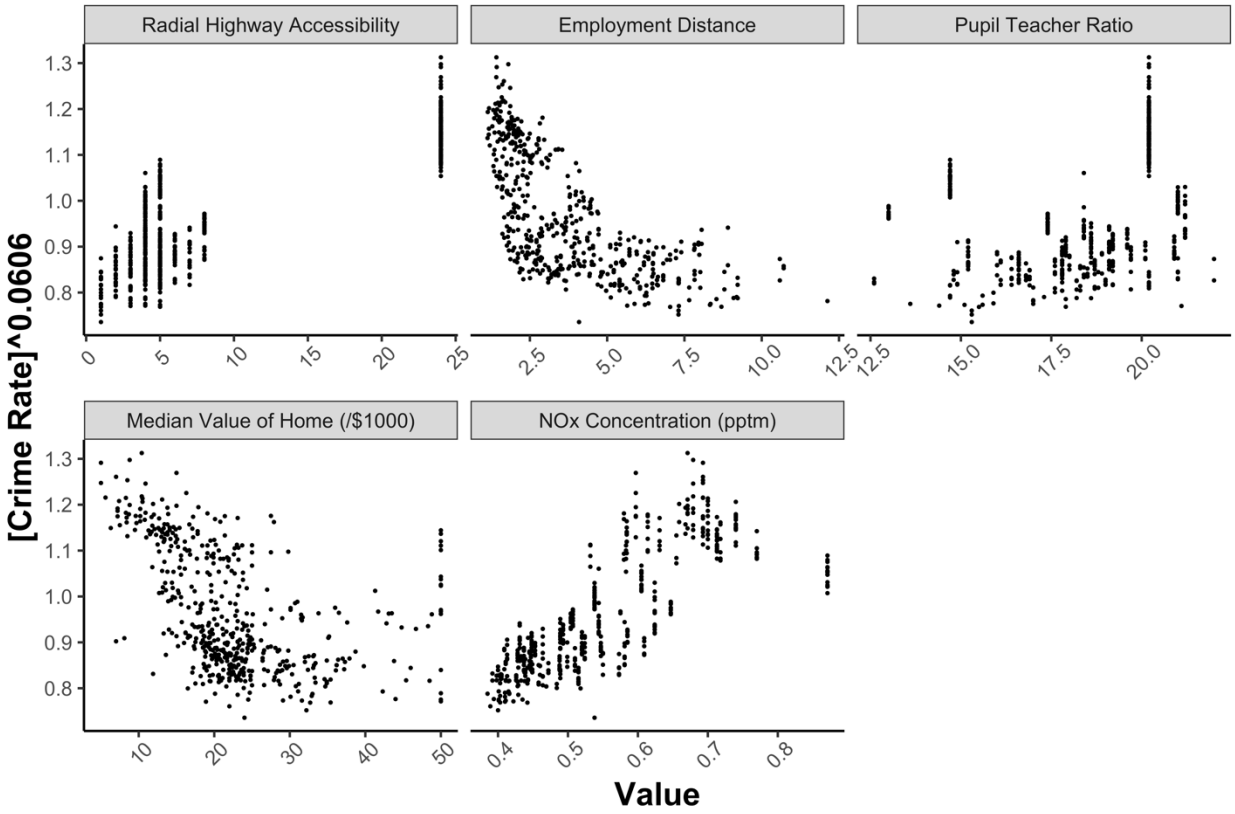

Figure 4: Relationships Between Regressor Variables and Crime Rate

NO_x concentration has the largest linear impact on the crime rate for this study. Additionally, there is a subpopulation where NO_x concentration is maximum where the transformed crime rate is not maximum. **Figure 4** reveals that there is an asymptotic relationship between the transformed crime rate and employment distance. The median value of homes appears to have the least impact in the model however, there may be a non-linear relationship as shown in **Figure 4**.

Discussion

The strong linear relationship NO_x emissions in this model parallel with the findings that air pollution have an effect on crime rates [6]. Since this has been found in two different studies, one could question as to why this is occurring. Do the emissions have a physiological effect on individuals that make them more likely to commit a crime? Or do crimes just happen in areas where emissions are elevated?

In this study as well as in [2], the crime rate and availability of education are linearly associated. Is this because the local population is less educated on the impact of crime on their communities? Do teachers not want to live in the high crime areas because of their own safety concerns? One invested in this area could survey individuals to dig deeper.

Surprisingly, the median value of the homes showed to have little to no linear influence on crime rate based on the model coefficient. However, there appears to be a non-linear inverse relationship shown in **Figure 4**. Since the findings in **Table 2** and **Figure 4** conflict with each other, a

conclusion cannot be reached and the anticipated anticorrelated relationship found in [4] [5]. This could be because the strength of the other regressor variables, as well as the groupings of leverage points.

A positive correlation was found between crime rate and radial highway accessibility. This finding may confirm the idea that crime rates are influenced by the ease of travel to and from the crime scene [3]. Does readily available highway access make it easier for the perpetrators to commit the crimes? Is there a distance component to and from crime scenes that is missing from this study? These questions could be investigated further to develop a story.

Conclusion

Five regressor variables were found to be statistically significant in the model to predict crime rates in Boston. NO_x concentration showed to have the greatest impact, which replicated the findings that air emissions are correlated with crime rate [6]. Availability of education to the local population also showed that it was substantial factor in this model and in [2]. Housing values displayed the least significant impact, contrary to what was found in other studies [4] [5]. A positive correlation was found between the accessibility of highways and crime rate, which reintroduces the idea that transportation is a factor when predicting crime rates.

Further work includes the investigation of the factors discussed in this paper but at an individual level. Data in this study were binned at a population basis and did not include specific crimes or individuals. Additional data including the specific individual involved in the crime, geographic coordinates of places involved, distance traveled, level of education of perpetrator, employment status of individual, and NO_x emissions specific to the place at which the culprit decided to commit the crime would be ideal. A real-time model (such as logistic regression) that has the ability to predict the probability based on attributes at an individual level would be helpful to law enforcement efficiently allocate resources.

References

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[8] P. Royston, "An extension of Shapiro and Wilk's W test for normality to large samples," *Applied Statistics,* no. 31, pp. 115-124.

Appendix: R Code Utilized in Crime Rate Analysis

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Loading and Inspecting

```
data(Boston)
df                                  =                                  Boston
for                  (col                  in                  colnames(df)){
  cat("Number of Missing values in ", col,": ", as.character(length(which(is.
na(df[,col])))),                                                      "\n")
}
```

```
##     Number     of     Missing     values     in          crim     :          0
##     Number     of     Missing     values     in          zn     :          0
##     Number     of     Missing     values     in          indus     :          0
##     Number     of     Missing     values     in          chas     :          0
##     Number     of     Missing     values     in          nox     :          0
##     Number     of     Missing     values     in          rm     :          0
##     Number     of     Missing     values     in          age     :          0
##     Number     of     Missing     values     in          dis     :          0
##     Number     of     Missing     values     in          rad     :          0
##     Number     of     Missing     values     in          tax     :          0
##     Number     of     Missing     values     in          ptratio     :          0
##     Number     of     Missing     values     in          black     :          0
##     Number     of     Missing     values     in          lstat     :          0
## Number of Missing values in  medv :  0
```

```
str(df)
```

```
##    'data.frame':                 506    obs.    of        14    variables:
##    $  crim      :  num    0.00632  0.02731  0.02729  0.03237  0.06905  ...
##    $  zn          :  num    18  0  0  0  0  0  12.5  12.5  12.5  12.5  ...
##   $ indus   : num   2.31  7.07  7.07  2.18  2.18  2.18  7.87  7.87  7.87  7.87  ...
##      $   chas        :   int      0   0   0   0   0   0   0   0   0   0   ...
##  $ nox    : num  0.538 0.469 0.469 0.458 0.458 0.458 0.524 0.524 0.524 0.5
24                                                                          ...
##      $   rm              :   num      6.58   6.42   7.18   7   7.15   ...
##   $ age     : num   65.2  78.9  61.1  45.8  54.2  58.7  66.6  96.1  100  85.9  ...
##      $   dis           :   num      4.09   4.97   4.97   6.06   6.06   ...
##     $   rad          :   int      1   2   2   3   3   3   5   5   5   5   ...
##    $  tax       :  num    296  242  242  222  222  222  311  311  311  311  ...
##   $ ptratio:  num   15.3  17.8  17.8  18.7  18.7  18.7  15.2  15.2  15.2  15.2  ...
##       $    black       :    num       397    397    393    395    397    ...
##      $   lstat       :   num       4.98   9.14   4.03   2.94   5.33   ...
##  $ medv   : num  24 21.6 34.7 33.4 36.2 28.7 22.9 27.1 16.5 18.9 ...
```

```
df                              =                              as.data.frame(df)
head(df)
```

```
##      crim zn indus chas   nox    rm  age    dis rad tax ptratio  black lst
at
## 1 0.00632 18  2.31    0 0.538 6.575 65.2 4.0900   1 296    15.3 396.90  4.
98
## 2 0.02731  0  7.07    0 0.469 6.421 78.9 4.9671   2 242    17.8 396.90  9.
14
## 3 0.02729  0  7.07    0 0.469 7.185 61.1 4.9671   2 242    17.8 392.83  4.
03
## 4 0.03237  0  2.18    0 0.458 6.998 45.8 6.0622   3 222    18.7 394.63  2.
94
## 5 0.06905  0  2.18    0 0.458 7.147 54.2 6.0622   3 222    18.7 396.90  5.
33
## 6 0.02985  0  2.18    0 0.458 6.430 58.7 6.0622   3 222    18.7 394.12  5.
21
##                                                                      medv
##                                  1                                   24.0
##                                  2                                   21.6
##                                  3                                   34.7
##                                  4                                   33.4
##                                  5                                   36.2
## 6 28.7
```

Model Fitting

```
mlr              =              lm(crim~.,              data              =df)
summary(mlr)

##
##                                                                   Call:
##      lm(formula      =      crim      ~      .,      data      =      df)
##
##                                                                Residuals:
##             Min                1Q    Median                3Q             Max
##        -9.924        -2.120        -0.353                1.019        75.051
##
##                                                             Coefficients:
##                                  Estimate  Std.  Error  t  value  Pr(>|t|)
##   (Intercept)      17.033228         7.234903         2.354   0.018949   *
##  zn                          0.044855      0.018734      2.394  0.017025  *
##   indus                     -0.063855        0.083407     -0.766   0.444294
##   chas                       -0.749134        1.180147     -0.635   0.525867
##   nox                     -10.313535       5.275536     -1.955   0.051152  .
##   rm                           0.430131       0.612830       0.702   0.483089
##   age                          0.001452       0.017925       0.081   0.935488
##   dis                      -0.987176       0.281817    -3.503   0.000502  ***
##   rad                       0.588209      0.088049      6.680   6.46e-11  ***
##   tax                         -0.003780       0.005156     -0.733   0.463793
##   ptratio                   -0.271081         0.186450      -1.454   0.146611
##   black                     -0.007538       0.003673     -2.052   0.040702  *
##   lstat                      0.126211       0.075725       1.667   0.096208  .
##   medv                      -0.198887       0.060516     -3.287   0.001087  **
```

```
##                                                                      ---
##  Signif.  codes:    0  '***'  0.001  '**'  0.01  '*'  0.05  '.'  0.1  ' '  1
##
##   Residual   standard   error:   6.439   on   492   degrees   of   freedom
##   Multiple   R-squared:      0.454,      Adjusted   R-squared:      0.4396
## F-statistic: 31.47 on 13 and 492 DF,  p-value: < 2.2e-16
```

Stepwise Regression

```
sbi = stepwise(df, y = 'crim', selection = "backward", select = 'AIC')
sbi$variate
```

```
## [1] "intercept" "zn"        "nox"       "dis"       "rad"       "ptratio"
## [7] "black"     "lstat"     "medv"
```

```
mlr2 = lm(crim~ zn + nox + dis + rad + ptratio + black + lstat + medv, data =
df                                                                          )
summary(mlr2)
```

```
##
##                                                                  Call:
##  lm(formula  =  crim  ~  zn  +  nox  +  dis  +  rad  +  ptratio  +  black  +
##                            lstat      +      medv,      data      =      df)
##
##                                                               Residuals:
##            Min                 1Q   Median                 3Q            Max
##        -9.860        -2.102        -0.363                0.895        75.702
##
##                                                            Coefficients:
##                                  Estimate  Std.  Error  t  value  Pr(>|t|)
##   (Intercept)      19.683128         6.086010         3.234   0.001301   **
##  zn                          0.043293      0.017977      2.408  0.016394  *
##  nox                      -12.753708       4.760157     -2.679  0.007623  **
##  dis                       -0.918318       0.261932     -3.506  0.000496  ***
##  rad                        0.532617      0.049727    10.711    <  2e-16  ***
##   ptratio                 -0.310541        0.182941     -1.697   0.090229   .
##  black                     -0.007922       0.003615     -2.191   0.028897  *
##  lstat                        0.110173       0.069219       1.592   0.112097
##  medv                      -0.174207       0.053988     -3.227   0.001334  **
##                                                                      ---
##  Signif.  codes:    0  '***'  0.001  '**'  0.01  '*'  0.05  '.'  0.1  ' '  1
##
##   Residual   standard   error:   6.428   on   497   degrees   of   freedom
##   Multiple   R-squared:      0.4505,    Adjusted   R-squared:      0.4416
## F-statistic: 50.92 on 8 and 497 DF,  p-value: < 2.2e-16
```

Colinearity Check

```
vif(mlr2)
```

```
##       zn      nox      dis      rad  ptratio    black    lstat     medv
## 2.148871 3.719176 3.718604 2.291669 1.917428 1.331764 2.986626 3.013693
```

Correlation between regressors:

```
cor(df[,which(colnames(df)%in%sbi$variate)])
```

```
##                  zn        nox        dis        rad    ptratio      black
## zn        1.0000000 -0.5166037  0.6644082 -0.3119478 -0.3916785  0.1755203
## nox      -0.5166037  1.0000000 -0.7692301  0.6114406  0.1889327 -0.3800506
## dis       0.6644082 -0.7692301  1.0000000 -0.4945879 -0.2324705  0.2915117
## rad      -0.3119478  0.6114406 -0.4945879  1.0000000  0.4647412 -0.4444128
## ptratio -0.3916785  0.1889327 -0.2324705  0.4647412  1.0000000 -0.1773833
## black     0.1755203 -0.3800506  0.2915117 -0.4444128 -0.1773833  1.0000000
## lstat    -0.4129946  0.5908789 -0.4969958  0.4886763  0.3740443 -0.3660869
## medv      0.3604453 -0.4273208  0.2499287 -0.3816262 -0.5077867  0.3334608
##                                                lstat                   medv
##      zn                                       -0.4129946            0.3604453
##       nox                                           0.5908789       -0.4273208
##       dis                                     -0.4969958            0.2499287
##       rad                                           0.4886763       -0.3816262
##            ptratio                           0.3740443            -0.5077867
##         black                           -0.3660869                  0.3334608
##         lstat                                   1.0000000         -0.7376627
## medv    -0.7376627  1.0000000
```

We see that the intercept is not statistically significant and it doesnt make any sense to have a negative crime rate, so we remove it.

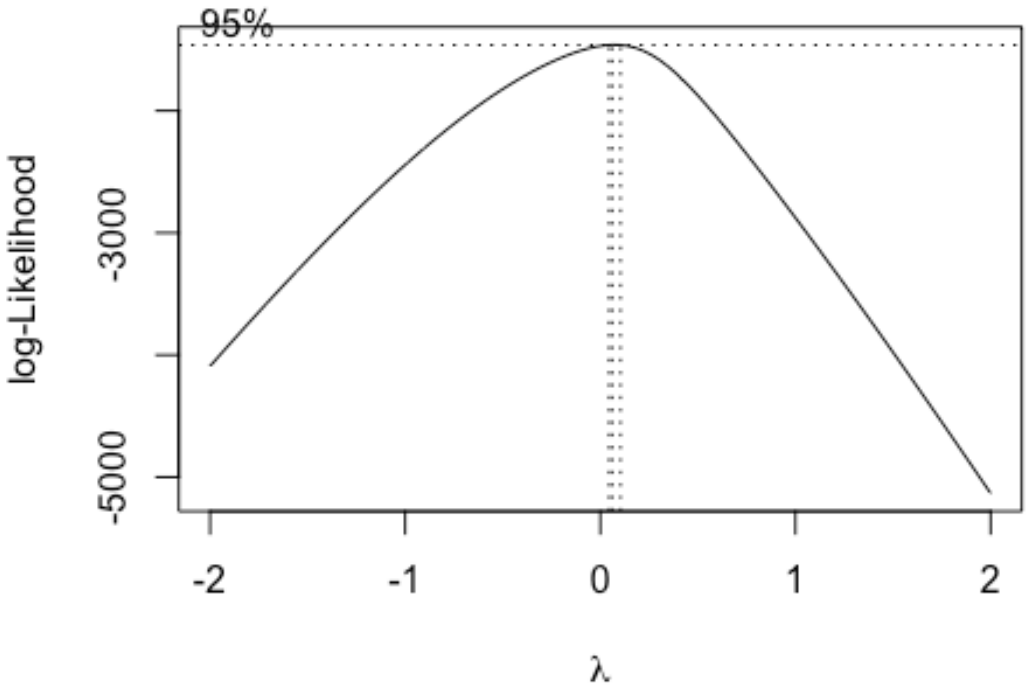
Power Transformation

```
mlr4 = lm(crim~ 0 +   rad*dis + ptratio + black+medv+rad*nox , data = df)
summary(mlr4)
```

```
##
##                                                                  Call:
##  lm(formula  =  crim  ~  0  +  rad  *  dis  +  ptratio  +  black  +  medv  +
##                               rad      *      nox,      data      =      df)
##
##                                                               Residuals:
##            Min               1Q     Median               3Q            Max
##     -11.810         -1.238         -0.291              0.707         71.213
##
##                                                            Coefficients:
##                             Estimate   Std.   Error   t   value   Pr(>|t|)
##   rad                 2.352948        0.323698        7.269   1.41e-12   ***
##   dis                 1.414262        0.227568        6.215   1.09e-09   ***
##     ptratio     -0.176981              0.117935         -1.501     0.134077
##    black           -0.005616          0.003354       -1.674    0.094688    .
##    medv             -0.161579         0.033120      -4.879    1.44e-06    ***
##   nox                  6.526916        3.313172         1.970   0.049393    *
##    rad:dis    -0.349350          0.036138       -9.667       <    2e-16    ***
##    rad:nox     -1.597729           0.425654        -3.754    0.000195    ***
##                                                                           ---
```

```
##  Signif.  codes:    0  '***'  0.001  '**'  0.01  '*'  0.05  '.'  0.1  ' '  1
##
##   Residual   standard   error:   6.047   on   498   degrees   of   freedom
##   Multiple   R-squared:      0.5859,   Adjusted   R-squared:      0.5792
## F-statistic: 88.06 on 8 and 498 DF,  p-value: < 2.2e-16
```

```
bc = boxcox(mlr4, data = df)
```




```
lambda                          =                          bc$x[which.max(bc$y)]
lambda
```

```
## [1] 0.06060606
```

```
dfnew                                  =                                  df
dfnew$crim = df$crim^lambda
```

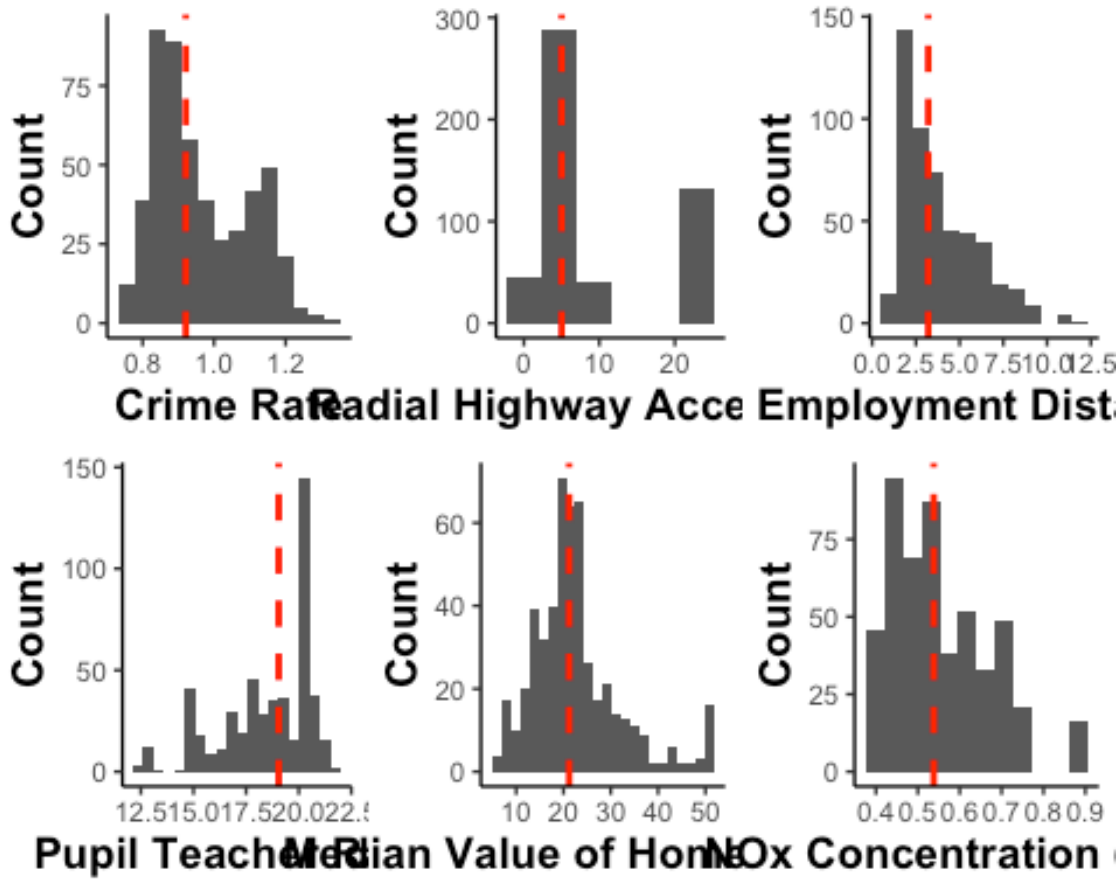
```
mlr5  =  lm(crim~     0  +rad*dis  +  ptratio  +  medv  +  nox,  data  =  dfnew)
summary(mlr5)
```

```
##
##                                                                    Call:
## lm(formula = crim ~ 0 + rad * dis + ptratio + medv + nox, data = dfnew)
##
##                                                                 Residuals:
```

```
##             Min               1Q       Median               3Q              Max
##    -0.158766    -0.037238         0.002491         0.043698         0.177525
##
##                                                                    Coefficients:
##                                Estimate   Std.   Error   t   value   Pr(>|t|)
##   rad                 0.0098229      0.0008806      11.154      <   2e-16   ***
##   dis                  0.0169361      0.0022508         7.525   2.48e-13   ***
##    ptratio       0.0183480       0.0009885       18.561       <    2e-16    ***
##   medv              0.0024981      0.0002924         8.543      <   2e-16   ***
##   nox                 0.8045297      0.0277055      29.039      <   2e-16   ***
##    rad:dis     -0.0014372         0.0003429         -4.191     3.28e-05     ***
##                                                                              ---
##  Signif.  codes:    0  '***'  0.001  '**'  0.01  '*'  0.05  '.'  0.1  ' '  1
##
##   Residual   standard   error:   0.06163   on   500   degrees   of   freedom
##    Multiple    R-squared:       0.996,       Adjusted    R-squared:       0.996
## F-statistic: 2.084e+04 on 6 and 500 DF,  p-value: < 2.2e-16
```

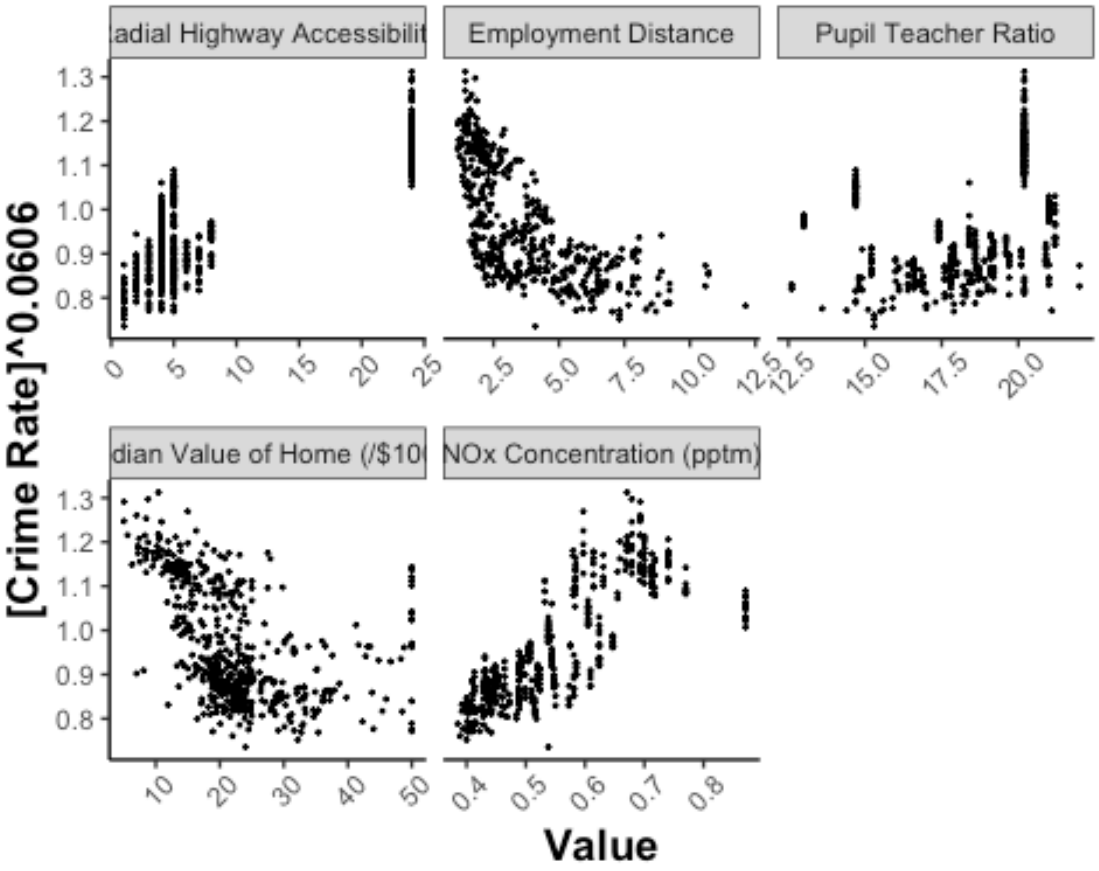
Distribution of Variables

```
dfnew2    =    dfnew[,c('crim','rad','dis',    'ptratio',    'medv',    'nox')]
colnames(dfnew2) = c('Crime Rate', 'Radial Highway Accessibility', 'Employmen
t Distance', 'Pupil Teacher Ratio',"Median Value of Home (/$1000)", 'NOx Conc
entration                                                          (pptm)')

mlr6 = lm(`Crime Rate` ~ 0 +`Radial Highway Accessibility`+`Employment Distan
ce` + `Pupil Teacher Ratio` + `Median Value of Home (/$1000)`  +`NOx Concentr
ation             (pptm)`,             data             =             dfnew2)


outp         =         "/Users/nickwawee/Desktop/BGSU/MSA         6701/plots/"
distplot       =       plotdists(dfnew2,outp,       brtype       =       'FD')
distplot
```



Scatter Plot of All Variables

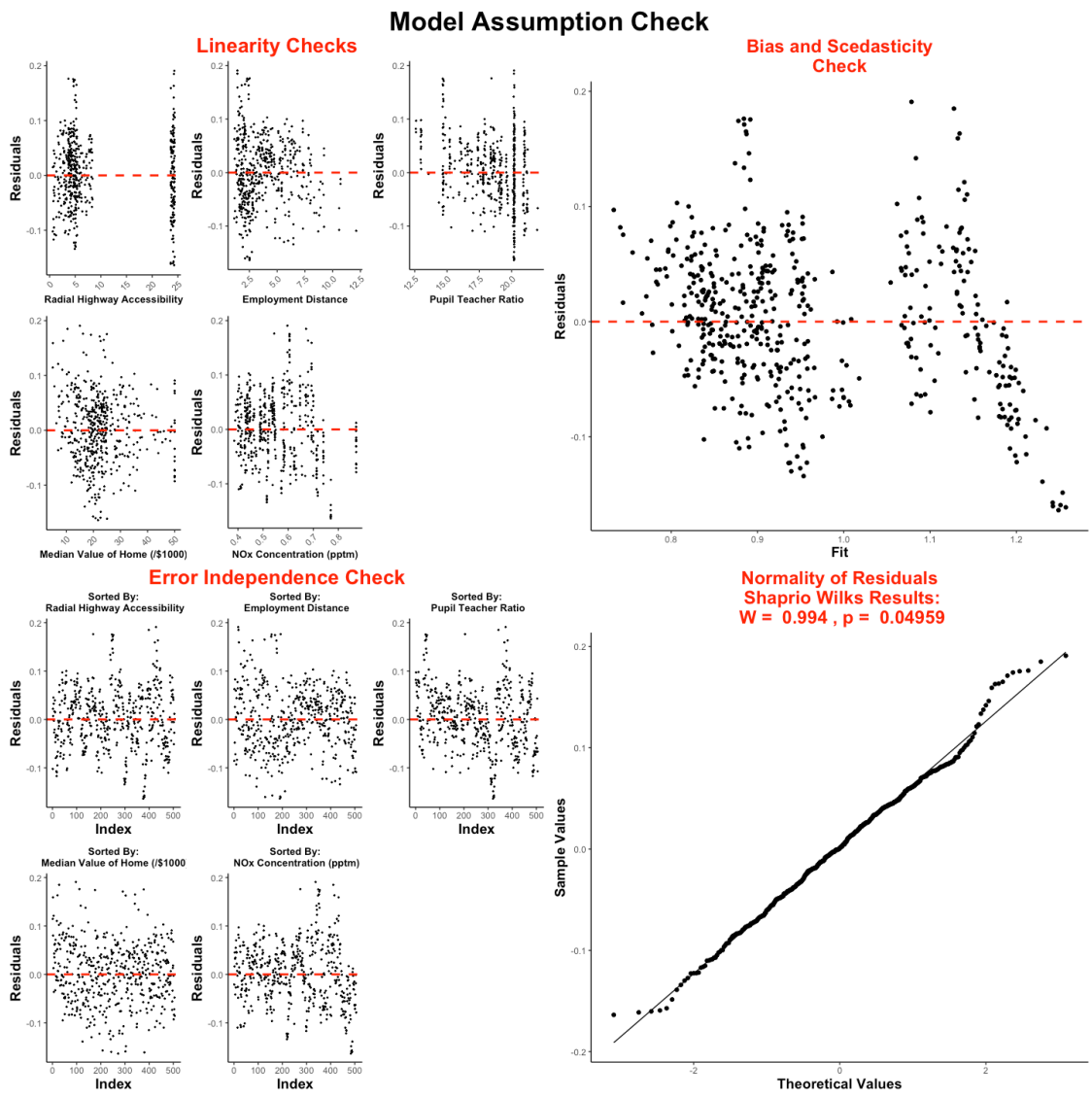
```
df.m = melt(dfnew2,id.vars = 'Crime Rate')
colnames(df.m) = c('Crime Rate', 'Variable', 'Value')
#df.m$Variable = apply(strsplit2(df.m$Variable, split = "_")[,1:5], 1, paste,
collapse = " ")
ggplot(data=df.m, aes(x=Value, y = `Crime Rate`))+
  geom_point(size = 0.25)+plot_opts+facet_wrap(~Variable, scales = 'free_x')+
  ylab(paste('[Crime Rate]^', as.character(round(lambda,4)), sep = ""))+theme
(axis.text.x=element_text(angle =45, vjust = 0.7))
```




```
ggsave(filename = paste(outp,'scatter.png',sep=""), dpi = 600, width = 1.5*5,
height = 5, units = 'in')
```

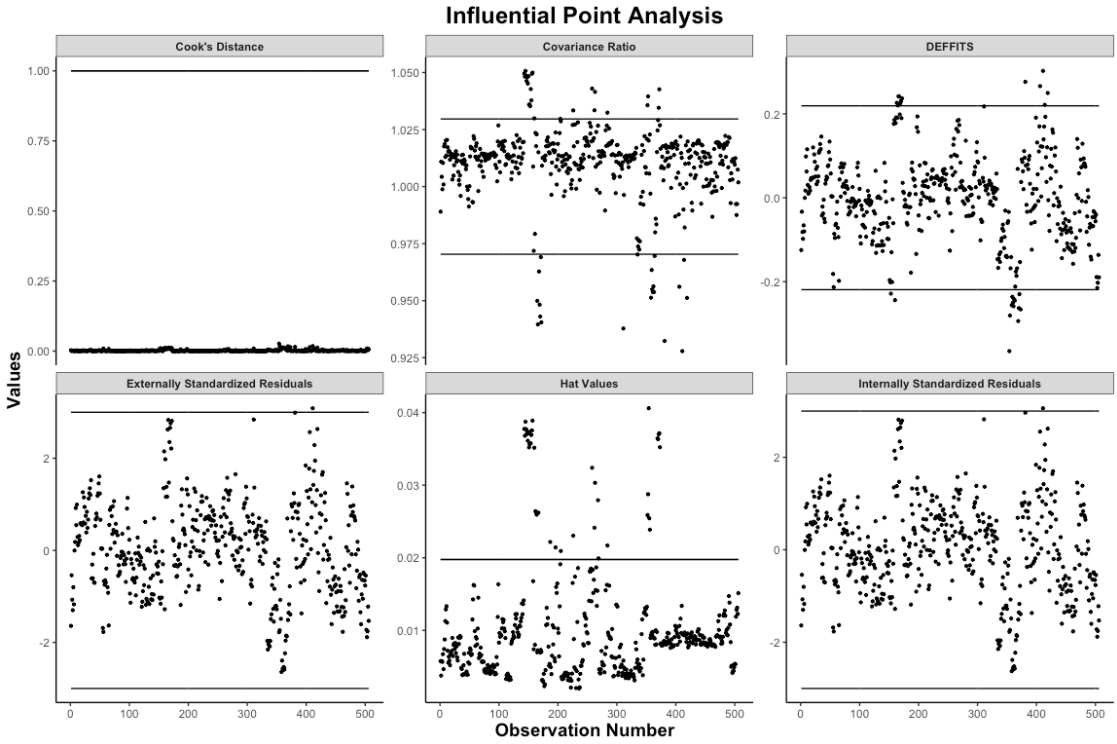
Assumption Check

```
pf                =                Assumption_Check(mlr6,                outp)
pf
```

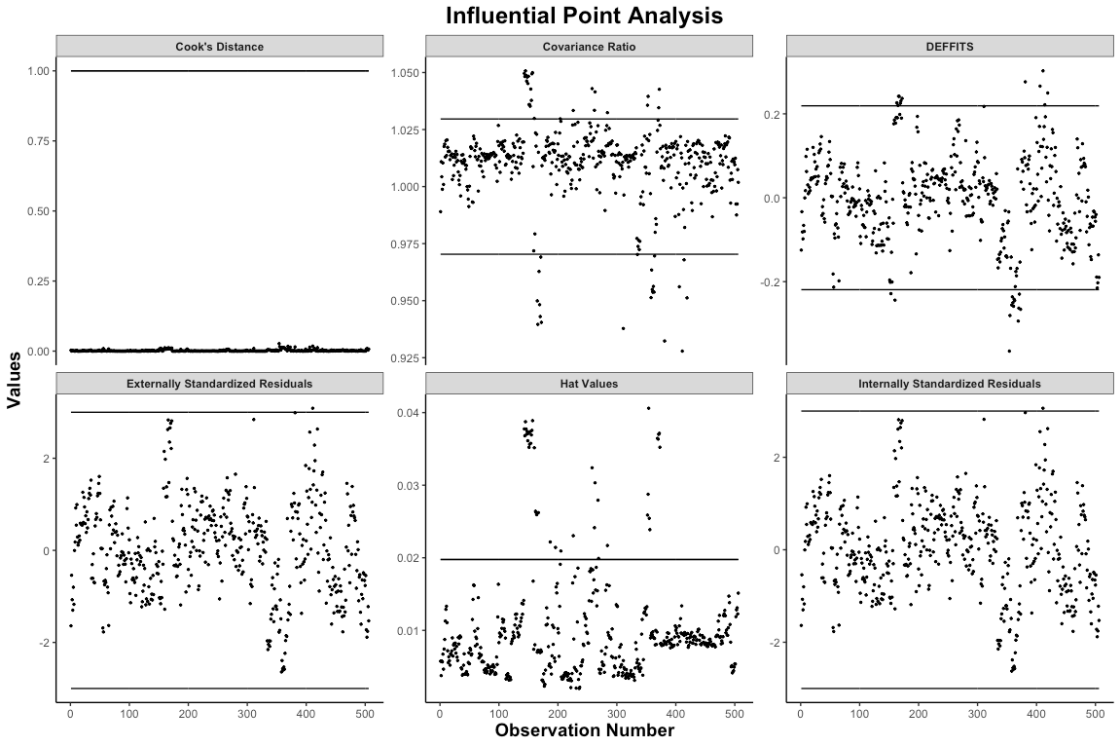


Influential Analysis

```
ret_df                    =                    infl_analysis(mlr6)
ret_df          =          cbind(ret_df,          dfnew2)
p    =    ggplot(data=    ret_df,    aes(x=    Row_Num,    y    =    Values))+
  geom_point(size                    =                    .8)+
  facet_wrap(~Type, scales = "free_y")+plot_opts+geom_line(aes(y=Bound1))+geo
m_line(aes(y=Bound2))+
  #geom_label_repel(aes(label=Label),          size          =          4)+
  labs(title = 'Influential Point Analysis', x = 'Observation Number')+ theme
(strip.text          =          element_text(face          =          'bold'))
p
```




```
ggsave(filename = '/Users/nickwawee/Desktop/BGSU/MSA 6701/plots/infl.png', pl
ot = p, width = 1.5*10, height = 10, units = 'in', limitsize = F)

p    =    ggplot(data=    ret_df,    aes(x=    Row_Num,    y    =    Values))+
  geom_point(size                                =                          .5)+
  facet_wrap(~Type, scales = "free_y")+plot_opts+geom_line(aes(y=Bound1))+geo
m_line(aes(y=Bound2))+
  #geom_label_repel(aes(label=Label),          size          =          4)+
  labs(title = 'Influential Point Analysis', x = 'Observation Number')+ theme
(strip.text          =          element_text(face          =          'bold'))
p
```




```
ggsave(filename = '/Users/nickwawee/Desktop/BGSU/MSA 6701/plots/infl.png', pl
ot = p, width = 1.5*6, height = 6, units = 'in', limitsize = F)
```

Hypothesis Testing

Test for significance of regression: H0: All regression coefficients are equal to zero. H1: At least one regression coefficient is not equal to 0.

```
linearHypothesis(mlr5, c('rad = 0', 'dis = 0', 'ptratio = 0', 'medv = 0', 'no
x = 0'))
```

```
##                   Linear                   hypothesis                    test
##
##                                                                  Hypothesis:
##                        rad                          =                      0
##                        dis                          =                      0
##                    ptratio                            =                    0
##                       medv                           =                     0
##                        nox                          =                      0
##
##             Model             1:             restricted             model
##   Model   2:   crim   ~   0   +   rad   *   dis   +   ptratio   +   medv   +   nox
##
##       Res.Df           RSS   Df   Sum   of   Sq              F          Pr(>F)
##            1                                              505           127.341
##   2          500       1.899     5          125.44   6604.9   <   2.2e-16   ***
##                                                                             ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Confidence Intervals

```
rmse                          =                          sqrt(mean(mlr6$residuals^2))
knitr::kable(confint(mlr6))
```

	2.5 %	97.5 %
Radial Highway Accessibility	0.0057384	0.0073894
Employment Distance	0.0071787	0.0136930
Pupil Teacher Ratio	0.0167573	0.0206891
Median Value of Home (/$1000)	0.0019411	0.0031086
NOx Concentration (pptm)	0.7661554	0.8756984

Other Metrics

```
rmse                          =                          sqrt(mean(mlr6$residuals^2))
rmse

## [1] 0.0623321

AIC(mlr6)

## [1] -1360.616

BIC(mlr6)

## [1] -1335.257
```