BM1 Final Project

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Purpose

We will be analyzing data from the "County Demographic Information" (CDI) data set, which contains characteristics of 440 counties in the United States collected from 1990-1992. The primary objective of this investigation is to develop insight relevant to predicting the crime rate in counties.

Import the package we need

Data preprocessing

Transfer population variables to per capita variables

```
rm(list = ls())
cdi = read.csv("./data/cdi.csv") %>%
  mutate(crime_rate = crimes/pop,
         pcarea = area/pop,
         pcdocs = docs/pop,
         pcbeds = beds/pop,
         region = relevel(factor(region),ref = 3))
cdi_pc = cdi %>%
  dplyr::select(crime_rate, everything(), -id, -cty, -state, -area, -docs, -beds, -crimes, -totalinc)
summary(cdi_pc)
```

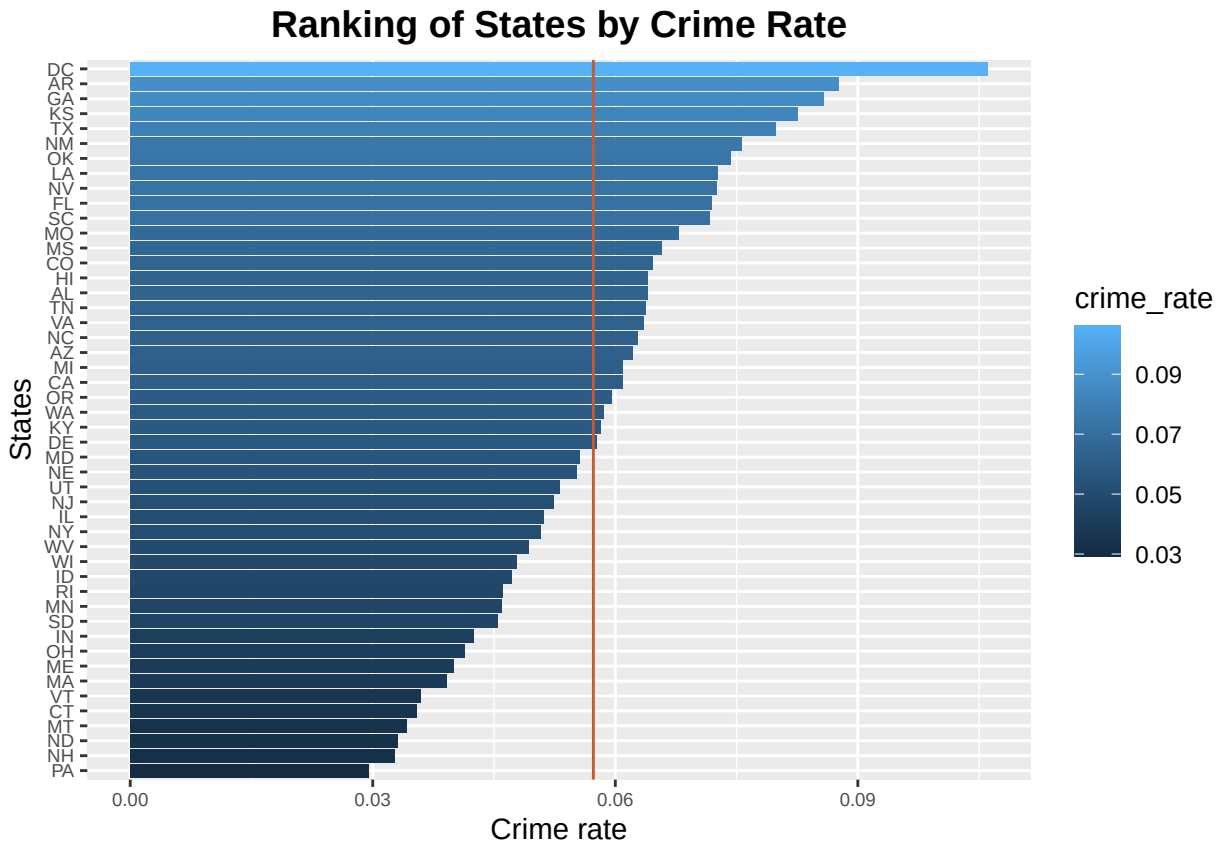
```
##    crime_rate            pop              pop18           pop65
##  Min.   :0.004601   Min.   : 100043   Min.   :16.40   Min.   : 3.000
##  1st Qu.:0.038102   1st Qu.: 139027   1st Qu.:26.20   1st Qu.: 9.875
##  Median :0.052429   Median : 217280   Median :28.10   Median :11.750
##  Mean   :0.057286   Mean   : 393011   Mean   :28.57   Mean   :12.170
##  3rd Qu.:0.072597   3rd Qu.: 436064   3rd Qu.:30.02   3rd Qu.:13.625
##  Max.   :0.295987   Max.   :8863164   Max.   :49.70   Max.   :33.800
##      hsgrad          bagrad         poverty          unemp
##  Min.   :46.60   Min.   : 8.10   Min.   : 1.400   Min.   : 2.200
##  1st Qu.:73.88   1st Qu.:15.28   1st Qu.: 5.300   1st Qu.: 5.100
##  Median :77.70   Median :19.70   Median : 7.900   Median : 6.200
##  Mean   :77.56   Mean   :21.08   Mean   : 8.721   Mean   : 6.597
##  3rd Qu.:82.40   3rd Qu.:25.32   3rd Qu.:10.900   3rd Qu.: 7.500
##  Max.   :92.90   Max.   :52.30   Max.   :36.300   Max.   :21.300
```

```
##     pcincome     region      pcarea             pcdocs
##  Min.   : 8899   3:152   Min.   :3.086e-05   Min.   :0.0003559
##  1st Qu.:16118   1:103   1st Qu.:1.323e-03   1st Qu.:0.0012127
##  Median :17759   2:108   Median :2.977e-03   Median :0.0017509
##  Mean   :18561   4: 77   Mean   :4.760e-03   Mean   :0.0021230
##  3rd Qu.:20270           3rd Qu.:5.199e-03   3rd Qu.:0.0024915
##  Max.   :37541           Max.   :7.542e-02   Max.   :0.0170377
##      pcbeds
##  Min.   :0.0001649
##  1st Qu.:0.0021972
##  Median :0.0033287
##  Mean   :0.0036493
##  3rd Qu.:0.0045649
##  Max.   :0.0196982
```

Exploratory Data Analysis

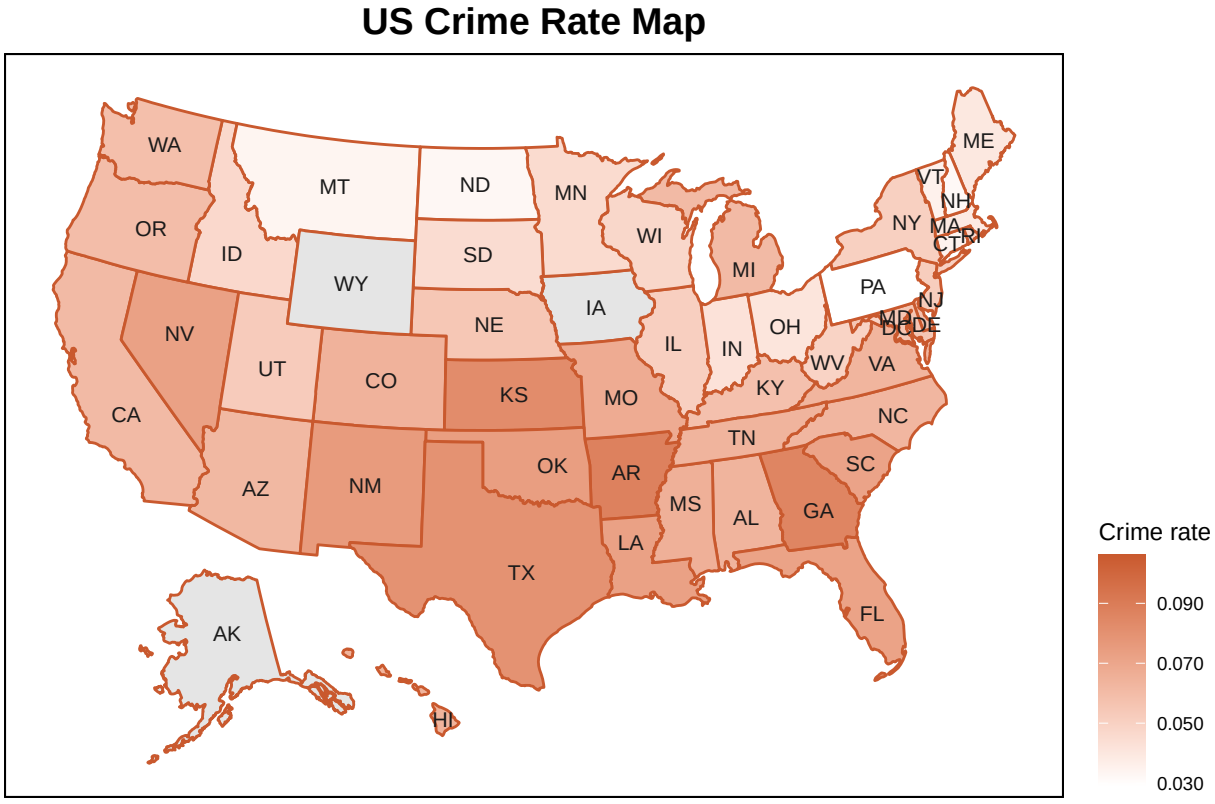
Rank of the crime rate by state

```
cdi_state <- cdi %>%
  group_by(state) %>%
  summarize(crime_rate = mean(crime_rate))
#cdi_state_rank <- cdi_state[order(-rank(cdi_state$crime_rate)),]

ggplot(cdi_state,aes(x=reorder(state,crime_rate),y=crime_rate,fill=crime_rate)) +
  geom_bar(stat ='identity')+
  coord_flip() +
  theme_grey() +
  labs(title = 'Ranking of States by Crime Rate',
       y='Crime rate',x='States') +
  geom_hline(yintercept = mean(cdi$crime_rate),color = "#C9592E")+
  theme(plot.title = element_text(hjust = 0.5,size = 14, face = "bold"),
        axis.text=element_text(size=6.5))
```



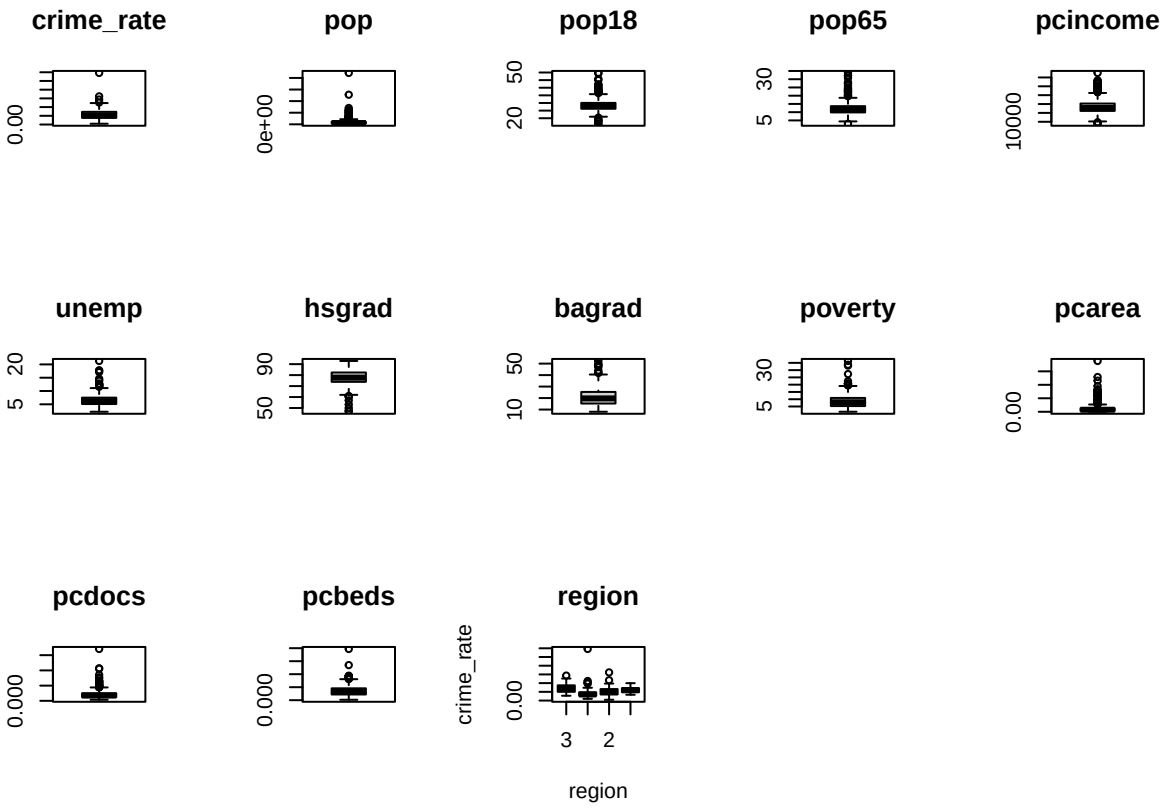
US crime rate map by state

```
p<-plot_usmap(data = cdi_state, values = "crime_rate", color = "#C9592E", size = 0.5,
              labels = TRUE, label_color = "grey10") +
   scale_fill_continuous(low = "white", high = "#C9592E", na.value = "grey90",
                         name = "Crime rate", label = scales::comma) +
   theme(legend.position = "right") +
   theme(panel.background = element_rect(colour = "black")) +
   labs(title = "US Crime Rate Map") +
   theme(plot.title = element_text(hjust = 0.5,size = 14, face = "bold"))
p$layers[[2]]$aes_params$size <- 2.8
print(p)
```



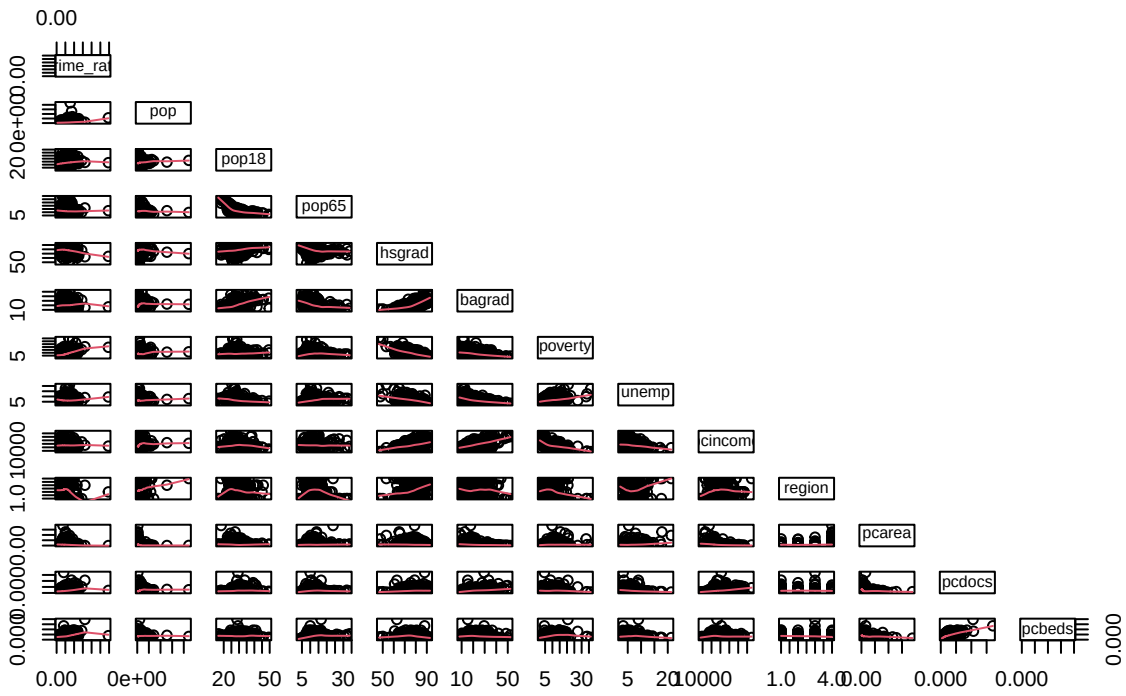
Boxplot for each variable

```
par(mfrow=c(3,5))
boxplot(cdi_pc$crime_rate,  main = "crime_rate")
boxplot(cdi_pc$pop, main = "pop")
boxplot(cdi_pc$pop18, main = "pop18")
boxplot(cdi_pc$pop65, main = "pop65")
boxplot(cdi_pc$pcincome, main = "pcincome")
boxplot(cdi_pc$unemp,main = "unemp")
boxplot(cdi_pc$hsgrad, main = "hsgrad")
boxplot(cdi_pc$bagrad, main = "bagrad")
boxplot(cdi_pc$poverty, main = "poverty")
boxplot(cdi_pc$pcarea, main = "pcarea")
boxplot(cdi_pc$pcdocs, main = "pcdocs")
boxplot(cdi_pc$pcbeds, main = "pcbeds")
boxplot(crime_rate ~ region, data = cdi_pc, main = "region")
```



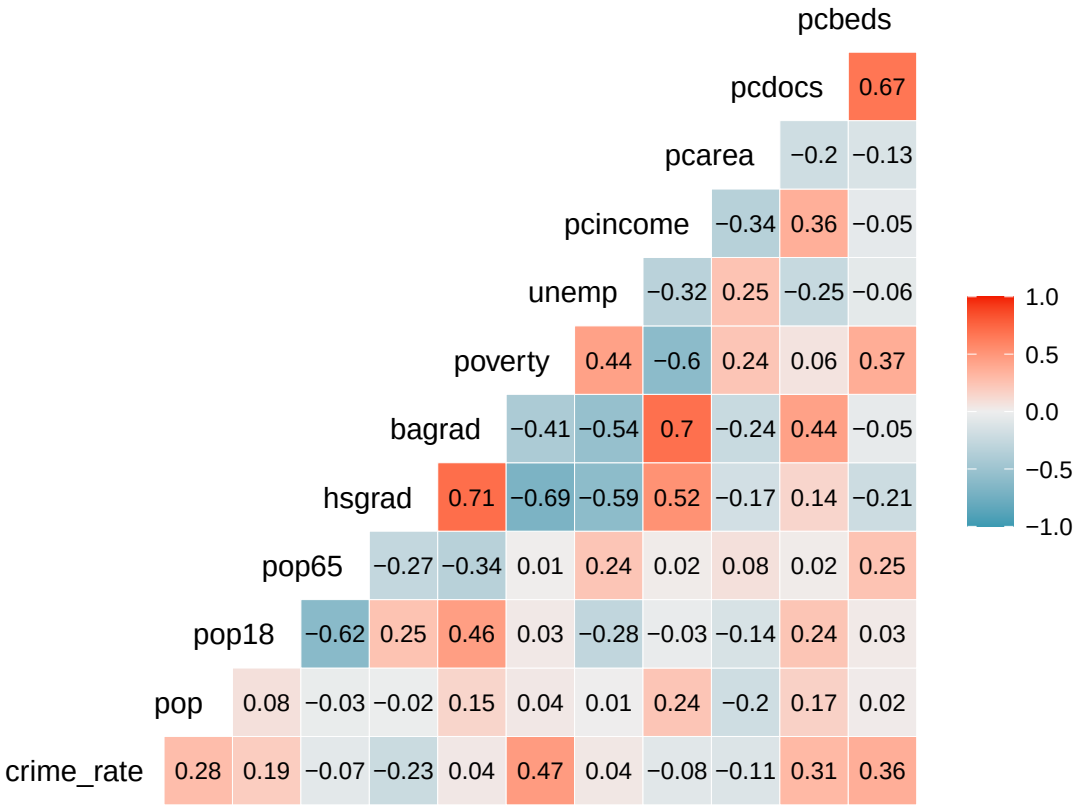
Scatterplot Matrix

```
pairs(~crime_rate +.,data=cdi_pc, panel = panel.smooth, upper.panel = NULL, main = "Scatterplot Matrix")
```



Correlation plot/ Heatmap

```
cdi_pc %>%
  dplyr::select(-region) %>%
  ggcorr(label = TRUE, hjust = 0.9, layout.exp = 2, label_size = 3, label_round = 2)
```



Modelling

Fit regression using all predictors

```
mult_fit = lm(crime_rate ~ ., data = cdi_pc)
summary(mult_fit)
```

```
##
## Call:
## lm(formula = crime_rate ~ ., data = cdi_pc)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.066728 -0.010908 -0.000201  0.009418  0.211437
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -4.781e-02  3.043e-02  -1.571  0.11690
## pop          7.796e-09  1.773e-09   4.397 1.39e-05 ***
## pop18        1.111e-03  3.674e-04   3.024  0.00264 **
## pop65        1.204e-04  3.423e-04   0.352  0.72518
## hsgrad       2.926e-04  3.003e-04   0.974  0.33045
## bagrad      -4.633e-04  3.350e-04  -1.383  0.16737
## poverty      2.539e-03  4.273e-04   5.942 5.86e-09 ***
```

```
## unemp        4.462e-04  5.944e-04   0.751  0.45326
## pcincome     1.746e-06  5.308e-07   3.289  0.00109 **
## region1     -2.383e-02  2.963e-03  -8.042 8.87e-15 ***
## region2     -1.601e-02  2.894e-03  -5.533 5.51e-08 ***
## region4     -2.401e-03  3.482e-03  -0.689  0.49090
## pcarea      -4.886e-01  1.701e-01  -2.873  0.00427 **
## pcdocs       4.313e-01  1.134e+00   0.380  0.70392
## pcbeds       2.671e+00  8.893e-01   3.003  0.00283 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01991 on 425 degrees of freedom
## Multiple R-squared:  0.4862, Adjusted R-squared:  0.4693
## F-statistic: 28.73 on 14 and 425 DF,  p-value: < 2.2e-16
```

Backwards Elimination

```
mult_fit_back <- step(mult_fit, direction='backward')
```

```
## Start:  AIC=-3431.87
## crime_rate ~ pop + pop18 + pop65 + hsgrad + bagrad + poverty +
##     unemp + pcincome + region + pcarea + pcdocs + pcbeds
##
##            Df Sum of Sq     RSS     AIC
## - pop65     1 0.0000490 0.16850 -3433.7
## - pcdocs    1 0.0000573 0.16851 -3433.7
## - unemp     1 0.0002234 0.16867 -3433.3
## - hsgrad    1 0.0003763 0.16883 -3432.9
## - bagrad    1 0.0007582 0.16921 -3431.9
## <none>                  0.16845 -3431.9
## - pcarea    1 0.0032712 0.17172 -3425.4
## - pcbeds    1 0.0035749 0.17203 -3424.6
## - pop18     1 0.0036248 0.17208 -3424.5
## - pcincome  1 0.0042869 0.17274 -3422.8
## - pop       1 0.0076647 0.17612 -3414.3
## - poverty   1 0.0139957 0.18245 -3398.8
## - region    3 0.0312633 0.19972 -3363.0
##
## Step:  AIC=-3433.74
## crime_rate ~ pop + pop18 + hsgrad + bagrad + poverty + unemp +
##     pcincome + region + pcarea + pcdocs + pcbeds
##
##            Df Sum of Sq     RSS     AIC
## - pcdocs    1 0.0000561 0.16856 -3435.6
## - unemp     1 0.0002518 0.16875 -3435.1
## - hsgrad    1 0.0003617 0.16886 -3434.8
## - bagrad    1 0.0007628 0.16926 -3433.8
## <none>                  0.16850 -3433.7
## - pcarea    1 0.0032245 0.17172 -3427.4
## - pcbeds    1 0.0041665 0.17267 -3425.0
## - pop18     1 0.0042054 0.17271 -3424.9
## - pcincome  1 0.0042628 0.17276 -3424.7
```

```
## - pop       1 0.0077852 0.17629 -3415.9
## - poverty   1 0.0142181 0.18272 -3400.1
## - region    3 0.0312244 0.19973 -3364.9
##
## Step:  AIC=-3435.59
## crime_rate ~ pop + pop18 + hsgrad + bagrad + poverty + unemp +
##     pcincome + region + pcarea + pcbeds
##
##            Df Sum of Sq     RSS     AIC
## - unemp     1 0.0002552 0.16881 -3436.9
## - hsgrad    1 0.0003389 0.16889 -3436.7
## - bagrad    1 0.0007073 0.16926 -3435.8
## <none>                  0.16856 -3435.6
## - pcarea    1 0.0032310 0.17179 -3429.2
## - pop18     1 0.0043858 0.17294 -3426.3
## - pcincome  1 0.0045074 0.17306 -3426.0
## - pop       1 0.0078624 0.17642 -3417.5
## - pcbeds    1 0.0103601 0.17892 -3411.3
## - poverty   1 0.0141806 0.18274 -3402.1
## - region    3 0.0314610 0.20002 -3366.3
##
## Step:  AIC=-3436.93
## crime_rate ~ pop + pop18 + hsgrad + bagrad + poverty + pcincome +
##     region + pcarea + pcbeds
##
##            Df Sum of Sq     RSS     AIC
## - hsgrad    1  0.000250 0.16906 -3438.3
## <none>                  0.16881 -3436.9
## - bagrad    1  0.000935 0.16975 -3436.5
## - pcarea    1  0.003127 0.17194 -3430.9
## - pop18     1  0.004390 0.17320 -3427.6
## - pcincome  1  0.005080 0.17389 -3425.9
## - pop       1  0.007769 0.17658 -3419.1
## - pcbeds    1  0.010289 0.17910 -3412.9
## - poverty   1  0.016870 0.18568 -3397.0
## - region    3  0.032233 0.20104 -3366.0
##
## Step:  AIC=-3438.28
## crime_rate ~ pop + pop18 + bagrad + poverty + pcincome + region +
##     pcarea + pcbeds
##
##            Df Sum of Sq     RSS     AIC
## - bagrad    1  0.000705 0.16977 -3438.4
## <none>                  0.16906 -3438.3
## - pcarea    1  0.003317 0.17238 -3431.7
## - pop18     1  0.004209 0.17327 -3429.5
## - pcincome  1  0.004897 0.17396 -3427.7
## - pop       1  0.007570 0.17663 -3421.0
## - pcbeds    1  0.010555 0.17962 -3413.6
## - poverty   1  0.024140 0.19320 -3381.6
## - region    3  0.032219 0.20128 -3367.5
##
## Step:  AIC=-3438.45
## crime_rate ~ pop + pop18 + poverty + pcincome + region + pcarea +
```

```
##     pcbeds
##
##            Df Sum of Sq     RSS     AIC
## <none>                  0.16977 -3438.4
## - pcarea    1  0.003619 0.17339 -3431.2
## - pop18     1  0.004100 0.17387 -3429.9
## - pcincome  1  0.005499 0.17527 -3426.4
## - pop       1  0.008260 0.17803 -3419.5
## - pcbeds    1  0.010408 0.18018 -3414.3
## - poverty   1  0.024541 0.19431 -3381.0
## - region    3  0.032233 0.20200 -3368.0
```

```
mult_fit_back
```

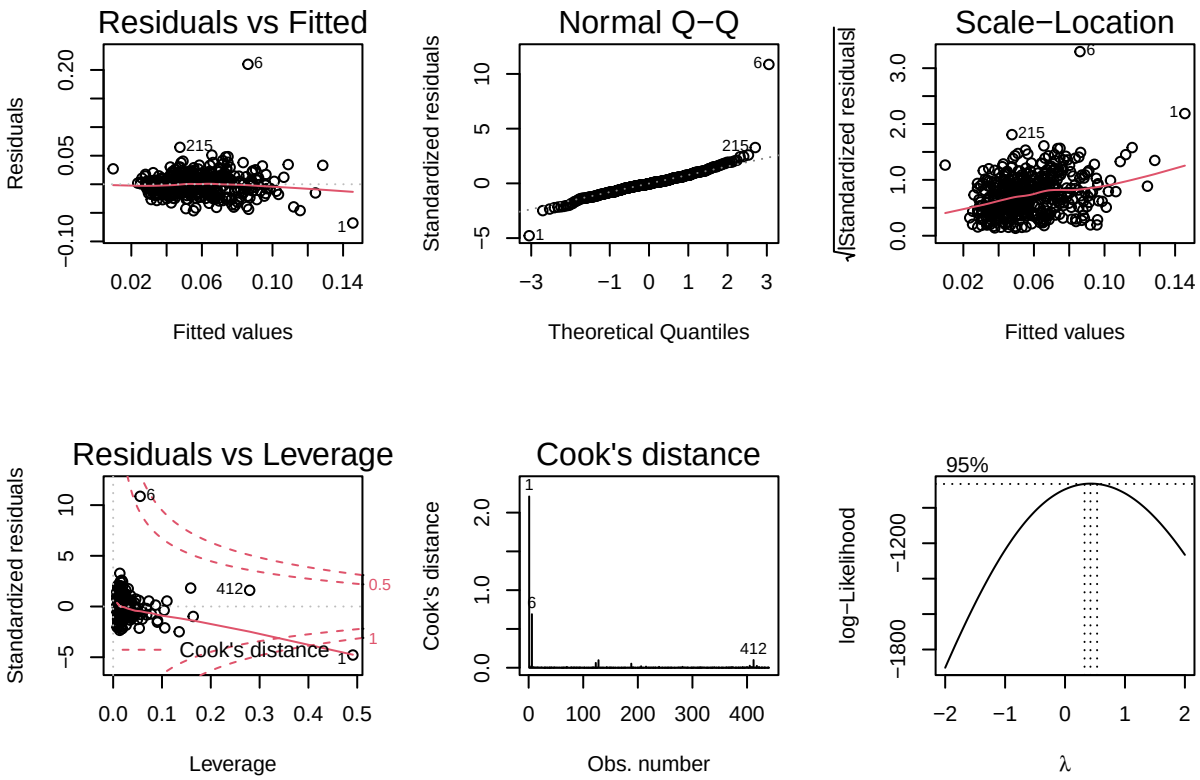
```
##
## Call:
## lm(formula = crime_rate ~ pop + pop18 + poverty + pcincome +
##     region + pcarea + pcbeds, data = cdi_pc)
##
## Coefficients:
## (Intercept)          pop        pop18      poverty     pcincome      region1
##  -1.034e-02    7.962e-09    7.451e-04    2.423e-03    1.236e-06   -2.209e-02
##     region2      region4       pcarea       pcbeds
##  -1.442e-02   -1.124e-03   -5.063e-01    2.868e+00
```

crime_rate ~ pop + pop18 + poverty + pcincome + region + pcarea + pcbeds

Model Diagnostics

Create Residuals vs Fitted plot & Normal Q-Q plot & Scale-Location plot & Residuals vs Leverage plot to detect the normality of residuals and outliers

```
par(mfrow=c(2,3))
plot(mult_fit_back)
plot(mult_fit_back, which = 4)
bc = boxcox(mult_fit_back)
```



Diagnose the model without outliers

```
# remove influential points
cdi_pc_out = cdi_pc[-c(1,6,412),]

# fit model with and without influential points
mult_fit_back_without = lm(crime_rate ~ pop + pop18 + poverty + pcincome + region + pcarea + pcbeds, da

summary(mult_fit_back)
```

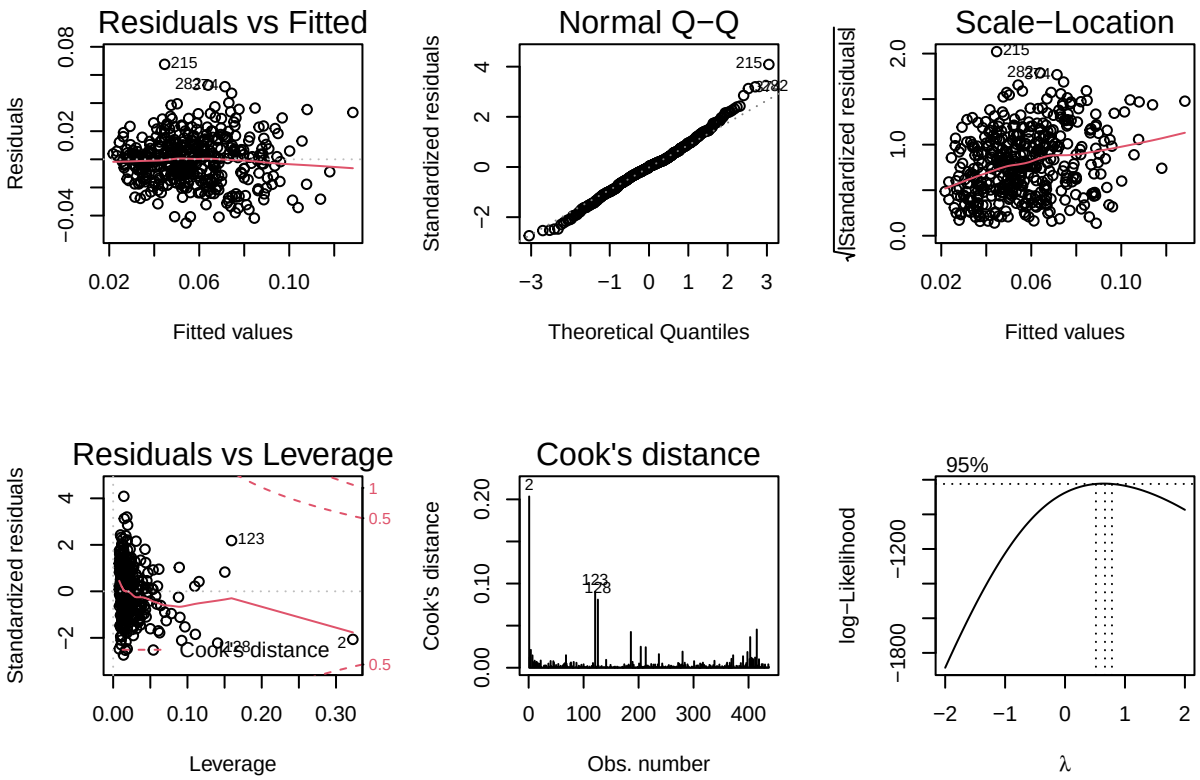
```
##
## Call:
## lm(formula = crime_rate ~ pop + pop18 + poverty + pcincome +
##     region + pcarea + pcbeds, data = cdi_pc)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.067811 -0.010690 -0.000725  0.010118  0.209881
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.034e-02  1.060e-02  -0.976 0.329595
## pop          7.962e-09  1.741e-09   4.574 6.26e-06 ***
## pop18        7.451e-04  2.312e-04   3.223 0.001367 **
## poverty      2.423e-03  3.073e-04   7.884 2.63e-14 ***
## pcincome     1.236e-06  3.312e-07   3.732 0.000216 ***
```

```
## region1     -2.209e-02  2.730e-03  -8.093 6.01e-15 ***
## region2     -1.442e-02  2.616e-03  -5.511 6.15e-08 ***
## region4     -1.124e-03  3.188e-03  -0.352 0.724665
## pcarea      -5.063e-01  1.672e-01  -3.027 0.002615 **
## pcbeds       2.868e+00  5.586e-01   5.134 4.30e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01987 on 430 degrees of freedom
## Multiple R-squared:  0.4822, Adjusted R-squared:  0.4713
## F-statistic: 44.49 on 9 and 430 DF,  p-value: < 2.2e-16
```

```
summary(mult_fit_back_without)
```

```
##
## Call:
## lm(formula = crime_rate ~ pop + pop18 + poverty + pcincome +
##     region + pcarea + pcbeds, data = cdi_pc_out)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.045291 -0.010145  0.000322  0.009630  0.067563
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -3.857e-03  8.932e-03  -0.432 0.666122
## pop          1.068e-08  2.077e-09   5.144 4.11e-07 ***
## pop18        7.779e-04  1.940e-04   4.009 7.20e-05 ***
## poverty      1.907e-03  2.635e-04   7.237 2.14e-12 ***
## pcincome     9.829e-07  2.839e-07   3.463 0.000589 ***
## region1     -2.542e-02  2.306e-03 -11.019  < 2e-16 ***
## region2     -1.569e-02  2.197e-03  -7.140 4.04e-12 ***
## region4     -9.152e-04  2.711e-03  -0.338 0.735789
## pcarea      -5.121e-01  1.642e-01  -3.119 0.001935 **
## pcbeds       3.262e+00  4.696e-01   6.946 1.41e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01665 on 427 degrees of freedom
## Multiple R-squared:  0.5614, Adjusted R-squared:  0.5521
## F-statistic: 60.73 on 9 and 427 DF,  p-value: < 2.2e-16
```

```
# diagnose the model without outliers
par(mfrow=c(2,3))
plot(mult_fit_back_without)
plot(mult_fit_back_without, which = 4)
bc_without = boxcox(mult_fit_back_without)
```



Box-cox transformation

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

```
## [1] 0.6666667
```

```
lambda
```

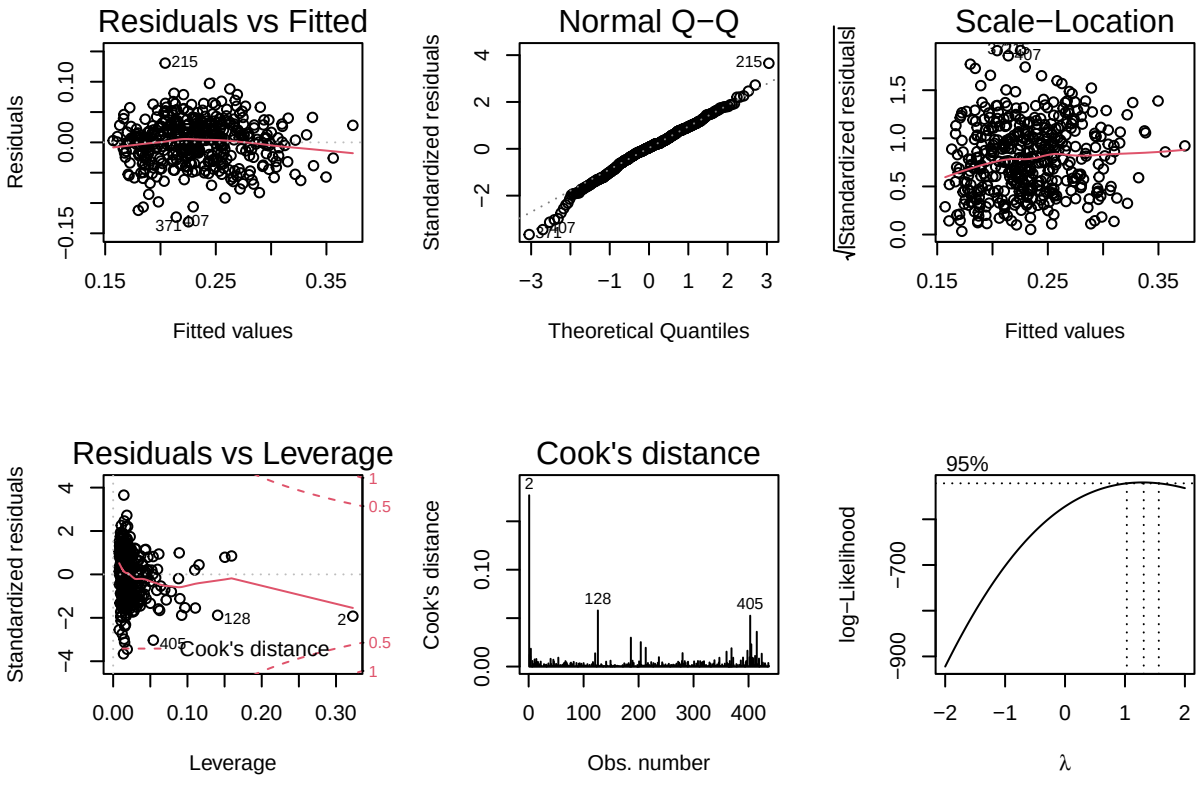
```
## [1] 0.6666667
```

```
mult_fit_back_without_trans = lm(crime_rate^0.5 ~ pop + pop18 + poverty + pcincome +
                                   region + pcarea + pcbeds, data = cdi_pc_out)

summary(mult_fit_back_without_trans)
```

```
##
## Call:
## lm(formula = crime_rate^0.5 ~ pop + pop18 + poverty + pcincome +
##     region + pcarea + pcbeds, data = cdi_pc_out)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.131052 -0.020616  0.001528  0.023104  0.130713
##
## Coefficients:
```

```
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.087e-01  1.934e-02   5.621 3.43e-08 ***
## pop          2.226e-08  4.496e-09   4.951 1.07e-06 ***
## pop18        1.608e-03  4.201e-04   3.827 0.000149 ***
## poverty      3.798e-03  5.705e-04   6.658 8.57e-11 ***
## pcincome     2.093e-06  6.146e-07   3.405 0.000724 ***
## region1     -5.709e-02  4.994e-03 -11.432  < 2e-16 ***
## region2     -3.463e-02  4.756e-03  -7.282 1.59e-12 ***
## region4      2.682e-04  5.868e-03   0.046 0.963566
## pcarea      -9.919e-01  3.554e-01  -2.791 0.005490 **
## pcbeds       6.543e+00  1.017e+00   6.435 3.31e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.03605 on 427 degrees of freedom
## Multiple R-squared:  0.547,  Adjusted R-squared:  0.5374
## F-statistic: 57.28 on 9 and 427 DF,  p-value: < 2.2e-16
```

```r
# Diagnose the model by square root transformation
par(mfrow = c(2,3))
plot(mult_fit_back_without_trans)
plot(mult_fit_back_without_trans, which = 4)
bc_without_trans = boxcox(mult_fit_back_without_trans)
```



Compare the Adjusted R^2

```
rbind(mult_fit_back %>% broom::glance() %>% mutate(model_type = "mult_fit_back"),
      mult_fit_back_without %>% broom::glance() %>% mutate(model_type = "mult_fit_back_without"),
      mult_fit_back_without_trans %>% broom::glance()%>% mutate(model_type = "mult_fit_back_without_tra
        dplyr::select(model_type, everything())
```

```
## # A tibble: 3 x 13
##   model_type      r.squared adj.r.squared  sigma statistic  p.value    df logLik
##   <chr>               <dbl>         <dbl>  <dbl>     <dbl>    <dbl> <dbl>  <dbl>
## 1 mult_fit_back       0.482         0.471 0.0199      44.5 3.64e-56     9  1105.
## 2 mult_fit_back_~     0.561         0.552 0.0167      60.7 6.54e-71     9  1175.
## 3 mult_fit_back_~     0.547         0.537 0.0360      57.3 6.01e-68     9   837.
## # ... with 5 more variables: AIC <dbl>, BIC <dbl>, deviance <dbl>,
## #   df.residual <int>, nobs <int>
```

Assessing Multicollinearity

```
# Calculate the variance inflation factor (VIF)
check_collinearity(mult_fit_back_without)
```

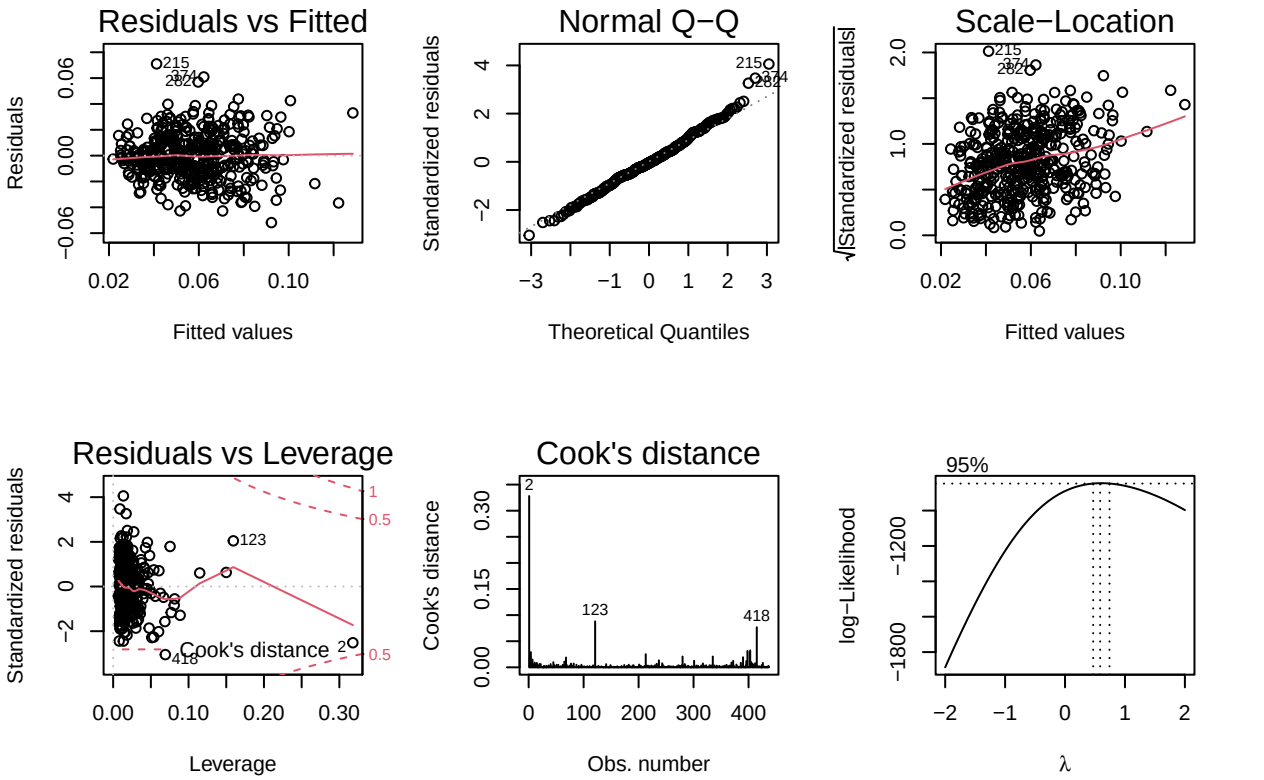
```
## # Check for Multicollinearity
##
## Low Correlation
##
##      Term  VIF Increased SE Tolerance
##       pop 1.00         1.00      1.00
##     pop18 4.82         2.20      0.21
##  pcincome 1.00         1.00      1.00
##    region 2.08         1.44      0.48
##    pcarea 1.96         1.40      0.51
##    pcbeds 3.92         1.98      0.26
##
## Moderate Correlation
##
##     Term  VIF Increased SE Tolerance
##  poverty 9.39         3.06      0.11
```

```
# Remove the variable with high VIF
mult_fit_back_without_vif = lm(crime_rate ~ pop + pop18 + pcincome + region + pcarea + pcbeds, data = c
summary(mult_fit_back_without_vif)
```

```
##
## Call:
## lm(formula = crime_rate ~ pop + pop18 + pcincome + region + pcarea +
##     pcbeds, data = cdi_pc_out)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
```

```
## -0.051836 -0.010389 -0.000806  0.010247  0.070996
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.984e-02  8.067e-03   3.699 0.000245 ***
## pop          1.470e-08  2.118e-09   6.943 1.44e-11 ***
## pop18        7.500e-04  2.053e-04   3.653 0.000291 ***
## pcincome    -2.241e-07  2.431e-07  -0.922 0.357136
## region1     -2.898e-02  2.385e-03 -12.154  < 2e-16 ***
## region2     -2.015e-02  2.231e-03  -9.030  < 2e-16 ***
## region4     -2.505e-03  2.859e-03  -0.876 0.381423
## pcarea      -2.990e-01  1.709e-01  -1.750 0.080901 .
## pcbeds       4.854e+00  4.390e-01  11.057  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01762 on 428 degrees of freedom
## Multiple R-squared:  0.5076, Adjusted R-squared:  0.4984
## F-statistic: 55.15 on 8 and 428 DF,  p-value: < 2.2e-16
```

```r
# Diagnose the model removing poverty term
par(mfrow = c(2,3))
plot(mult_fit_back_without_vif)
plot(mult_fit_back_without_vif, which = 4)
bc_without_trans = boxcox(mult_fit_back_without_vif)
```



Add the interaction terms

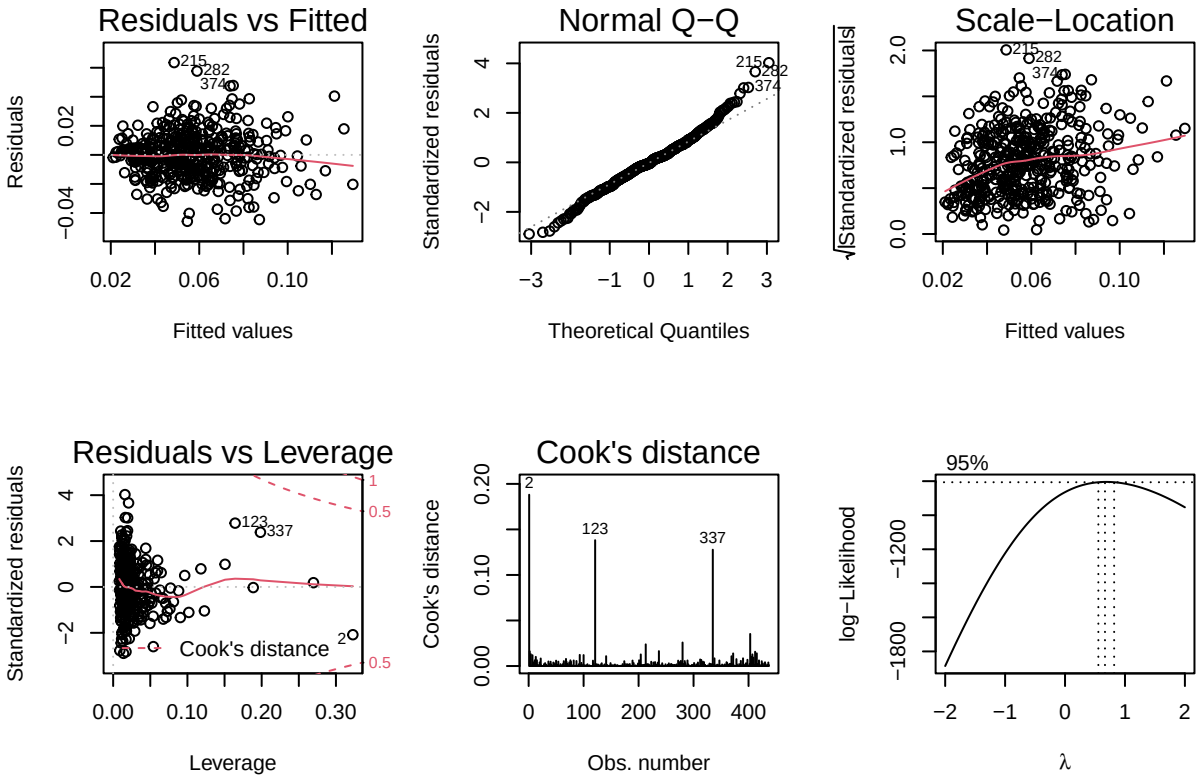
```
mult_fit_back_without_int = lm(crime_rate ~ pop + pop18 + pcincome + region + pcarea + pcbeds + poverty


summary(mult_fit_back_without_int)
```

```
##
## Call:
## lm(formula = crime_rate ~ pop + pop18 + pcincome + region + pcarea +
##     pcbeds + poverty + pcincome * poverty, data = cdi_pc_out)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.045731 -0.009495 -0.000758  0.008857  0.063537
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)       9.987e-03  8.802e-03   1.135  0.25717
## pop               7.785e-09  2.035e-09   3.825  0.00015 ***
## pop18             7.308e-04  1.856e-04   3.938 9.61e-05 ***
## pcincome          8.776e-08  3.048e-07   0.288  0.77353
## region1          -2.427e-02  2.211e-03 -10.977  < 2e-16 ***
## region2          -1.504e-02  2.102e-03  -7.157 3.63e-12 ***
## region4          -3.649e-03  2.625e-03  -1.390  0.16523
## pcarea           -3.749e-01  1.583e-01  -2.368  0.01834 *
## pcbeds            1.575e+00  5.196e-01   3.030  0.00259 **
## poverty          -1.525e-03  5.891e-04  -2.589  0.00997 **
## pcincome:poverty  2.707e-07  4.201e-08   6.444 3.16e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01591 on 426 degrees of freedom
## Multiple R-squared:  0.6003, Adjusted R-squared:  0.591
## F-statistic: 63.99 on 10 and 426 DF,  p-value: < 2.2e-16
```

```
anova(mult_fit_back_without,mult_fit_back_without_int)
```

```
## Analysis of Variance Table
##
## Model 1: crime_rate ~ pop + pop18 + poverty + pcincome + region + pcarea +
##     pcbeds
## Model 2: crime_rate ~ pop + pop18 + pcincome + region + pcarea + pcbeds +
##     poverty + pcincome * poverty
##   Res.Df     RSS Df Sum of Sq     F   Pr(>F)
## 1    427 0.11838
## 2    426 0.10787  1  0.010513 41.52 3.16e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Diagnose the model with interaction term
par(mfrow = c(2,3))
plot(mult_fit_back_without_int)
plot(mult_fit_back_without_int, which = 4)
bc_without_trans = boxcox(mult_fit_back_without_int)
```



Compare the Adjusted R^2 again

```
rbind(mult_fit_back %>% broom::glance() %>% mutate(model_type = "mult_fit_back"),
      mult_fit_back_without %>% broom::glance() %>% mutate(model_type = "mult_fit_back_without"),
      mult_fit_back_without_trans %>% broom::glance()%>% mutate(model_type = "mult_fit_back_without_tra
      mult_fit_back_without_vif %>% broom::glance() %>% mutate(model_type = "mult_fit_back_without_vif"
      mult_fit_back_without_int %>% broom::glance() %>% mutate(model_type = "mult_fit_back_without_int"
      dplyr::select(model_type, everything())
```

```
## # A tibble: 5 x 13
##   model_type      r.squared adj.r.squared  sigma statistic  p.value    df logLik
##   <chr>               <dbl>         <dbl>  <dbl>     <dbl>    <dbl> <dbl>  <dbl>
## 1 mult_fit_back       0.482         0.471 0.0199      44.5 3.64e-56     9  1105.
## 2 mult_fit_back_~     0.561         0.552 0.0167      60.7 6.54e-71     9  1175.
## 3 mult_fit_back_~     0.547         0.537 0.0360      57.3 6.01e-68     9   837.
## 4 mult_fit_back_~     0.508         0.498 0.0176      55.1 3.21e-61     8  1149.
## 5 mult_fit_back_~     0.600         0.591 0.0159      64.0 1.71e-78    10  1195.
## # ... with 5 more variables: AIC <dbl>, BIC <dbl>, deviance <dbl>,
## #   df.residual <int>, nobs <int>
```

Comparison between Cp

```
model2=mult_fit_back_without
cat("Mallow's CP for Model 2:", Cp(model2,S2=(summary(model2)$sigma)^2),"\n")
```

```
## Mallow's CP for Model 2: 10
```

```
model3=mult_fit_back_without_trans
cat("\nMallow's CP for Model 3:", Cp(model3,S2=(summary(model3)$sigma)^2),"\n")
```

```
##
## Mallow's CP for Model 3: 10
```

```
model4=mult_fit_back_without_vif
cat("\nMallow's CP for Model 4:", Cp(model4,S2=(summary(model4)$sigma)^2),"\n")
```

```
##
## Mallow's CP for Model 4: 9
```

```
model5=mult_fit_back_without_int
cat("\nMallow's CP for Model 5:", Cp(model5,S2=(summary(model5)$sigma)^2),"\n")
```

```
##
## Mallow's CP for Model 5: 11
```

Model Validation

Compute RMSE, adjusted R^2, AIC and BIC by cross-validation

```
set.seed(1234)
cv_df =
  crossv_kfold(cdi_pc_out, k = 10) %>%
  mutate(
    train = map(train, as_tibble),
    test = map(test, as_tibble)) %>%
  mutate(
    mult_fit_back_without = map(train, ~lm(crime_rate ~ pop + pop18 + poverty +
                                pcincome + region + pcarea + pcbeds, data = .x)),
    mult_fit_back_without_trans = map(train, ~lm(sqrt(crime_rate) ~ pop + pop18 + poverty +
                                   pcincome + region + pcarea + pcbeds, data = .x)),
    mult_fit_back_without_vif = map(train, ~lm(crime_rate ~ pop + pop18 +
                                  pcincome + region + pcarea + pcbeds, data = .x)),
    mult_fit_back_without_int = map(train, ~lm(crime_rate ~ pop + pop18 + pcincome + region + pcarea + p
  mutate(
    rmse_model2 = map2_dbl(mult_fit_back_without, test, ~rmse(model = .x, data = .y)),
    rmse_model3 = map2_dbl(mult_fit_back_without_trans, test, ~rmse(model = .x, data = .y)),
    rmse_model4 = map2_dbl(mult_fit_back_without_vif, test, ~rmse(model = .x, data = .y)),
```

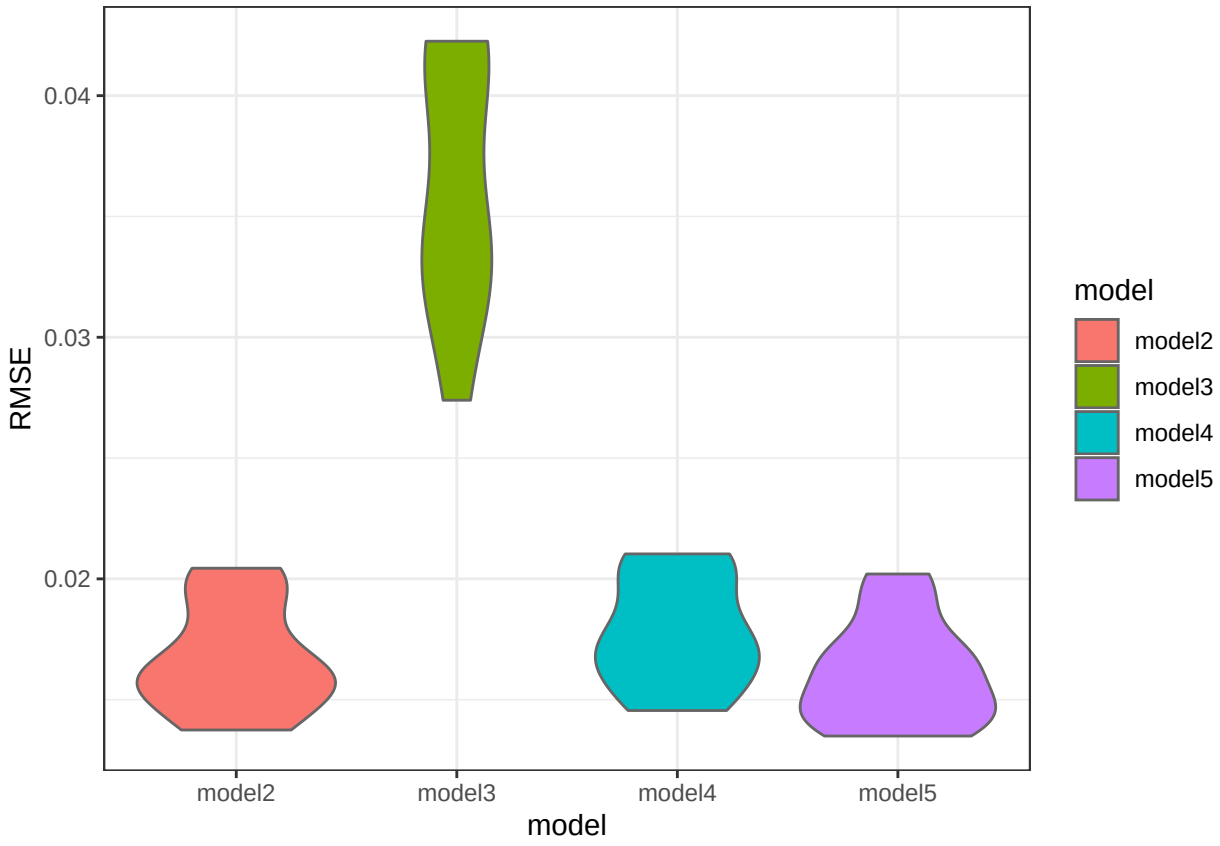
```
    rmse_model5 = map2_dbl(mult_fit_back_without_int, test, ~rmse(model = .x, data = .y))) %>%
  mutate(
    res_model2 = map(mult_fit_back_without, broom::glance %>% as.data.frame),
    res_model3 = map(mult_fit_back_without_trans, broom::glance %>% as.data.frame),
    res_model4 = map(mult_fit_back_without_vif, broom::glance %>% as.data.frame),
    res_model5 = map(mult_fit_back_without_int, broom::glance %>% as.data.frame))%>%
  unnest(res_model2, res_model3, res_model4, res_model5) %>%
  dplyr::select(rmse_model2,rmse_model3,rmse_model4,rmse_model5,
                value.adj.r.squared,value.adj.r.squared1,value.adj.r.squared2,value.adj.r.squared3,
                value.AIC, value.AIC1, value.AIC2, value.AIC3,
                value.BIC, value.BIC1, value.BIC2, value.BIC3) %>%
  rename(adjR_model2 = value.adj.r.squared,
         adjR_model3 = value.adj.r.squared1,
         adjR_model4 = value.adj.r.squared2,
         adjR_model5 = value.adj.r.squared3,
         aic_model2 = value.AIC,
         aic_model3 = value.AIC1,
         aic_model4 = value.AIC2,
         aic_model5 = value.AIC3,
         bic_model2 = value.BIC,
         bic_model3 = value.BIC1,
         bic_model4 = value.BIC2,
         bic_model5 = value.BIC3,)


cv_df %>%
  summarise_each(funs(mean( .,na.rm = TRUE))) %>%
  t()
```

```
##                       [,1]
## rmse_model2  1.673048e-02
## rmse_model3  3.621843e-02
## rmse_model4  1.777271e-02
## rmse_model5  1.608495e-02
## adjR_model2  5.520743e-01
## adjR_model3  5.374572e-01
## adjR_model4  4.985934e-01
## adjR_model5  5.911387e-01
## aic_model2  -2.093559e+03
## aic_model3  -1.486017e+03
## aic_model4  -2.050102e+03
## aic_model5  -2.128419e+03
## bic_model2  -2.049839e+03
## bic_model3  -1.442297e+03
## bic_model4  -2.010356e+03
## bic_model5  -2.080724e+03
```

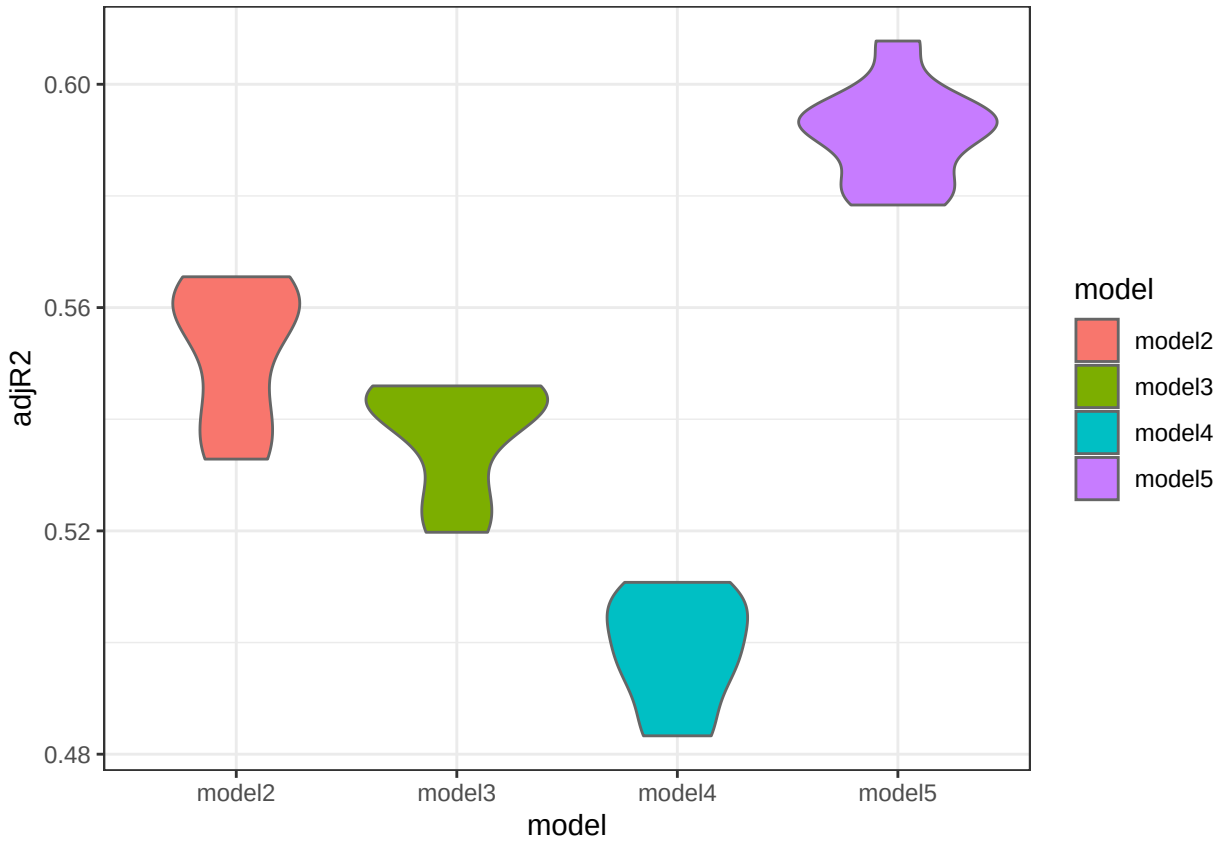
Plot the violin plot

```
unnest_cd_df = cv_df %>%
  pivot_longer(rmse_model2:bic_model5,
```

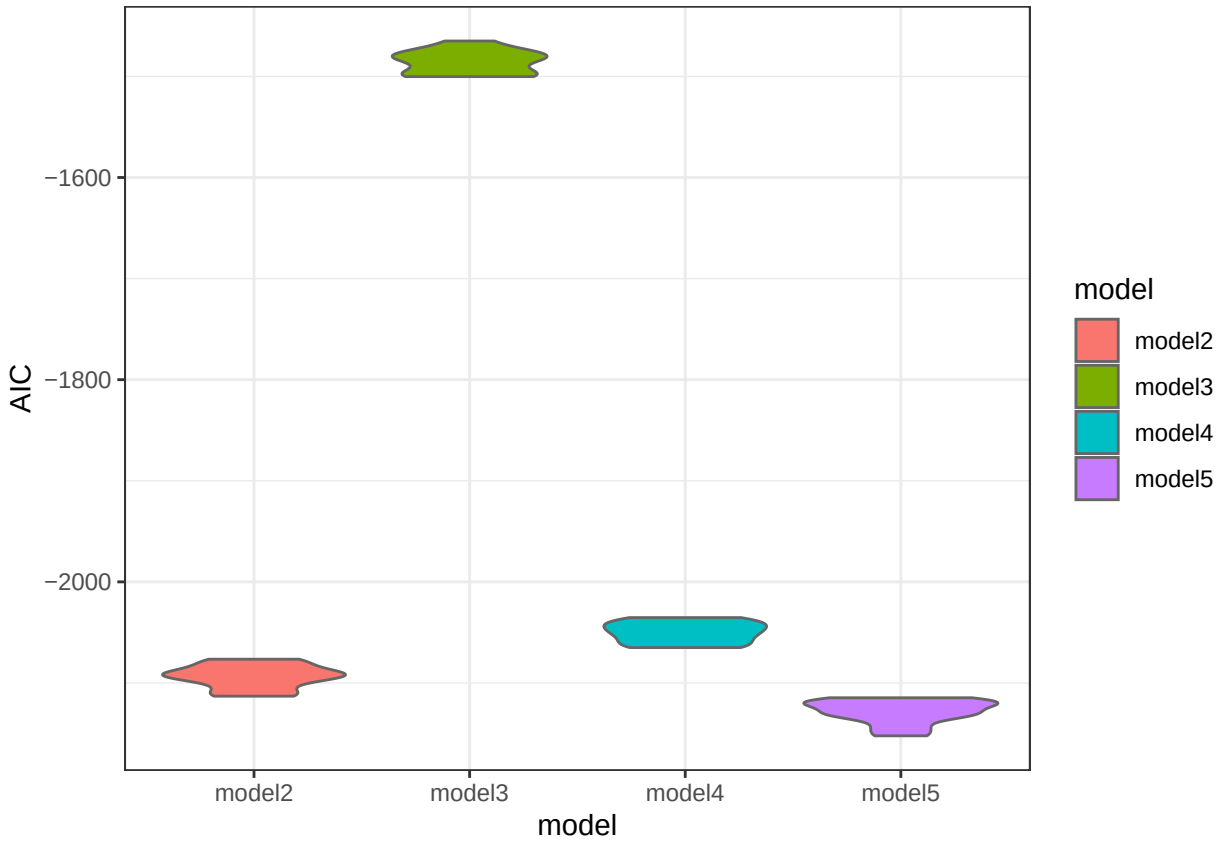
```
               names_pattern = "(.*)(......)$",
               names_to = c("limit", "model")) %>%
  mutate(limit=ifelse(limit=="", "value", limit)) %>%
  pivot_wider(id_cols = model,
              names_from = limit,
              values_from = value,
              names_repair = "check_unique") %>%
  unnest(c(rmse_, adjR_, aic_, bic_)) %>%
  rename(RMSE = rmse_,
         adjR2 = adjR_,
         AIC = aic_,
         BIC = bic_)

unnest_cd_df %>% ggplot(aes(x = model, y = RMSE)) + geom_violin(aes(fill=model),color="grey40") + theme_
```



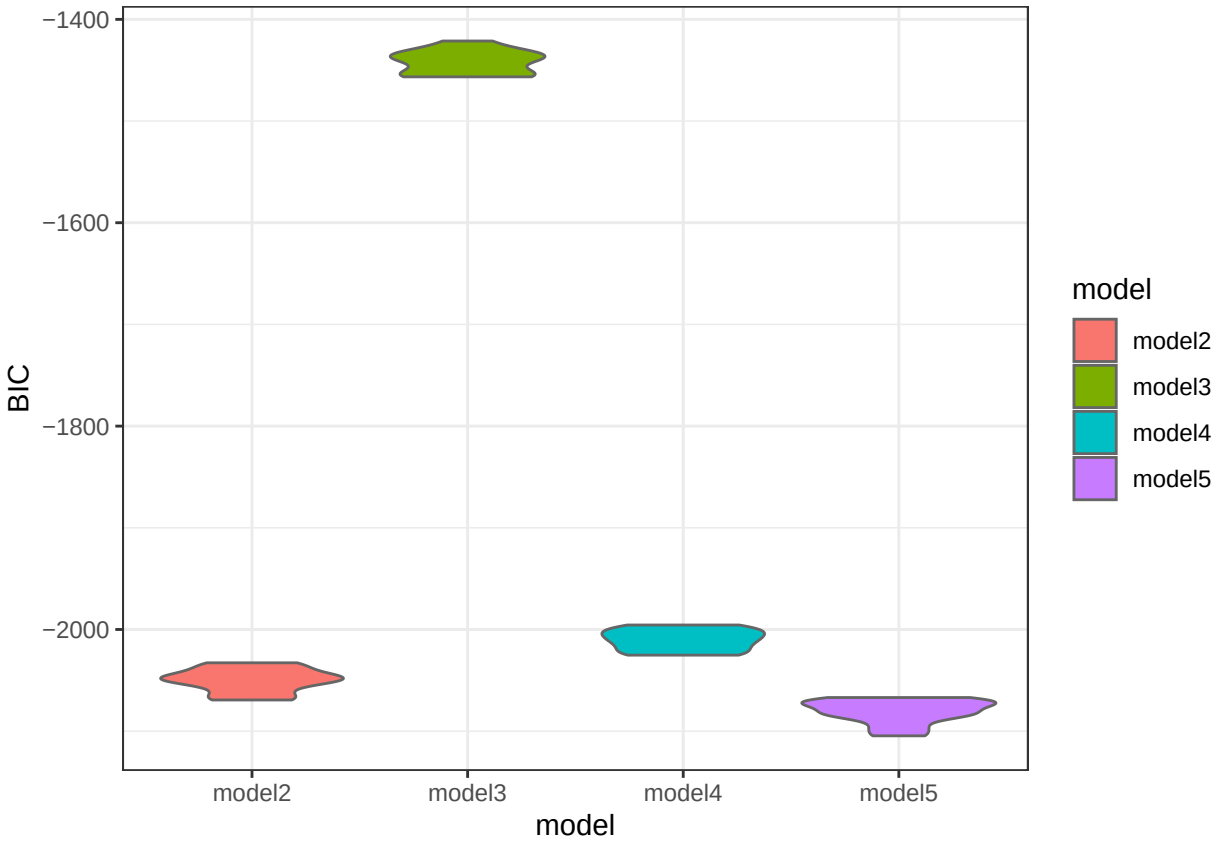

```
unnest_cd_df %>% ggplot(aes(x = model, y = adjR2)) + geom_violin(aes(fill=model),color="grey40") + theme
```




```
unnest_cd_df %>% ggplot(aes(x = model, y = AIC)) + geom_violin(aes(fill=model),color="grey40") + theme_
```




```
unnest_cd_df %>% ggplot(aes(x = model, y = BIC)) + geom_violin(aes(fill=model),color="grey40") + theme_
```



Thanks for reading!