BIST8130 - Final Proejct Codings

11/22/2021

```
library(tidyverse)
library(corrplot)
library(leaps)
library(performance)
library(MASS)
library(caret)

knitr::opts_chunk$set(
  fig.width = 8,
  fig.asp = .6,
  out.width = "90%",
  echo = TRUE, warning = FALSE, dpi=300

)
```

Step 1: Data Preprocessing

After importing the csv file containing the County Demographic Information (CDI) data, we notice that crimes, physicians, and hospital beds are given as numbers, while other info are given as proportions. We therefore compute the number of crimes, physicians, and hospital beds per 1000 people.

```
cdi_data = read_csv("./data/cdi.csv") %>%
  janitor::clean_names() %>%
  mutate(
    cty_state = str_c(cty,",",state),
    docs_rate_1000 = 1000 * docs/pop,
    # Compute number of doctors/hospital beds per 1000 people.
    beds_rate_1000 = 1000 * beds/pop,
    density = as.numeric(pop)/as.numeric(area),
    crime_rate_1000 = 1000 * crimes/pop) %>%
  # Compute number of crimes per 1000 people.
  dplyr::select(-docs,-beds,-crimes) %>%
  relocate(id,cty_state,cty)

#knitr::kable(head(cdi_data))
```

Step 2 - Exploratory Analysis

We then take a closer look of each variables, calculate the pairwise correlations between variables, and list all the correlations between the crime rate (our interest) and all other variables.

```
cdi_data_exp = cdi_data %>%
  dplyr::select(-id,-cty,-state, -cty_state)
```

```
par(mfrow=c(4,3))
boxplot(cdi_data_exp$area,main="Area")
boxplot(cdi_data_exp$pop,main="Population")
boxplot(cdi_data_exp$pop18,main="Population 18-34")
boxplot(cdi_data_exp$pop65,main="Population 65+")
boxplot(cdi_data_exp$hsgrad,main="Highschool grads")
boxplot(cdi_data_exp$bagrad,main="Bachelor's grads")

#par(mfrow=c(2,3))
boxplot(cdi_data_exp$poverty,main="Poverty Rate")
boxplot(cdi_data_exp$unemp,main="Unemployment Rate")
boxplot(cdi_data_exp$pcincome,main="Income Per Capita")
boxplot(cdi_data_exp$totalinc,main="Income Total")
boxplot(cdi_data_exp$docs_rate_1000,main="Active Physicians")
boxplot(cdi_data_exp$beds_rate_1000,main="Hospital Beds")
```

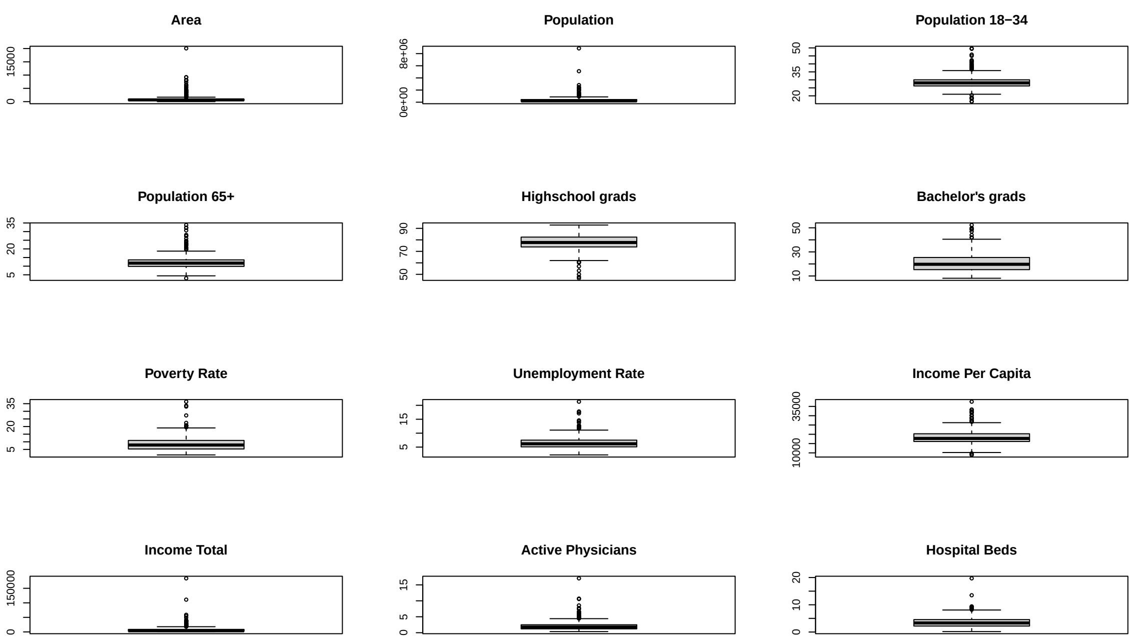

Figure 1: boxplot of continuous variables distribution

```
par(mfrow=c(1,1))

ggplot(cdi_data,aes(region)) +
  geom_histogram(binwidth = 0.5) +
  theme_classic() +
```

```r
  xlab("Region")+
  ylab("Count") +
  labs(title = "Histogram: Counts of four regions")
```

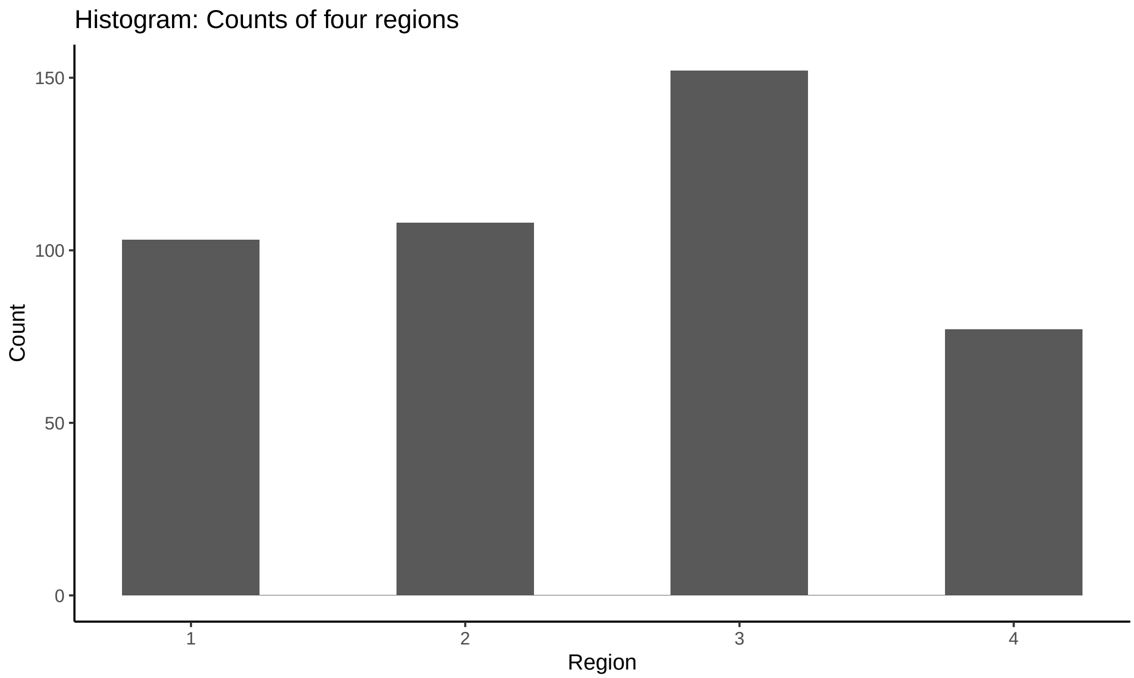

Figure 2: Histogram of catagorical variable:region distribution

```r
boxplot(cdi_data_exp$crime_rate_1000,main="Boxplot of Crime Rate",horizontal = TRUE)
```

```r
# data exploratory
# pairs(cdi_data_exp)
```

```r
# correlation plot
cdi_data_cor = cor(cdi_data_exp)
corrplot(cdi_data_cor, type = "upper", diag = FALSE, title = "Correlation heatmap")
```

```r
crime_1000_cor = data.frame(cdi_data_cor) %>%
  dplyr::select("Crime Rate (Per 1000)" = crime_rate_1000) %>%
  t()

#knitr::kable(crime_1000_cor,digits = 2)
```

Remove outliers and high leverage point

```r
# Remove high leverage points

cdi_data_clean = cdi_data[cdi_data$area >= quantile(cdi_data$area,0.002) & cdi_data$area <= qua
cdi_data_clean = cdi_data_clean[cdi_data_clean$pop >= quantile(cdi_data_clean$pop,0.002) & cdi_
cdi_data_clean = cdi_data_clean[cdi_data_clean$pop18 >= quantile(cdi_data_clean$pop18,0.002) &
cdi_data_clean = cdi_data_clean[cdi_data_clean$pop65 >= quantile(cdi_data_clean$pop65,0.002) &
```

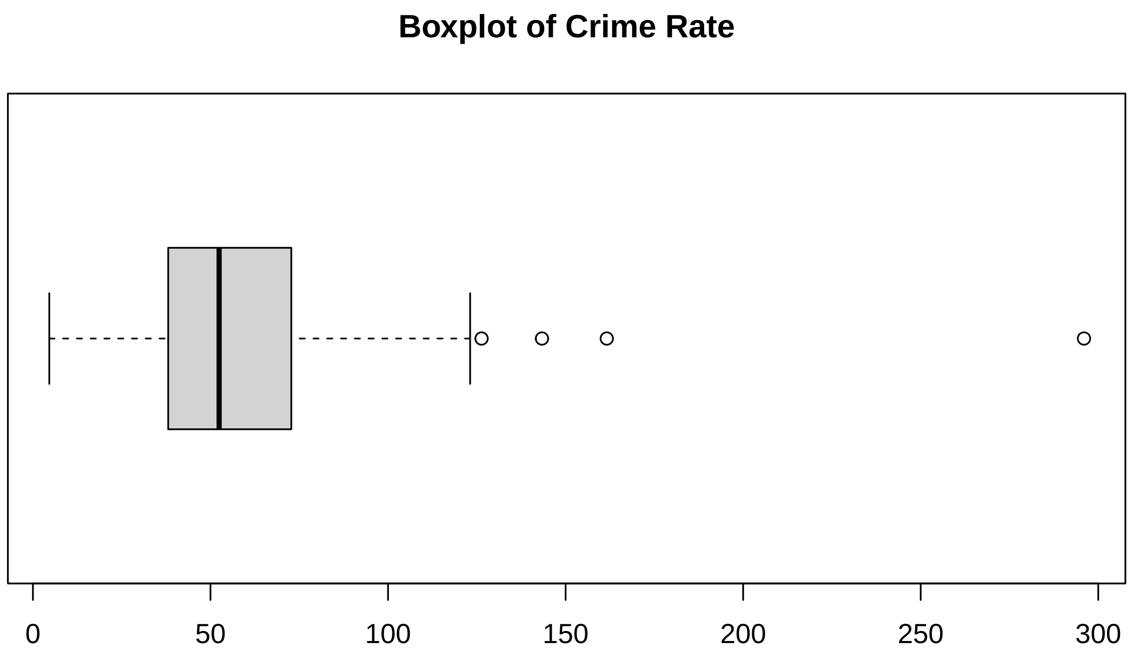

Figure 3: boxplot of dependent variable: crime rate

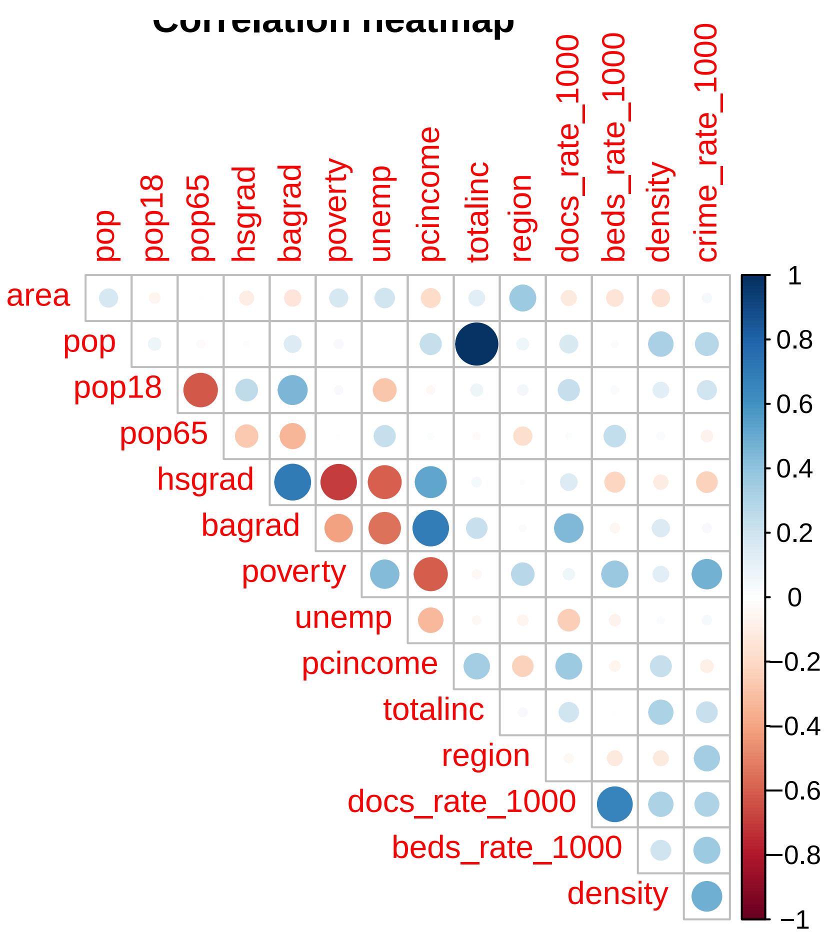

Figure 4: Correlation heatmap

```
cdi_data_clean = cdi_data_clean[cdi_data_clean$hsgrad >= quantile(cdi_data_clean$hsgrad,0.002)
cdi_data_clean = cdi_data_clean[cdi_data_clean$bagrad >= quantile(cdi_data_clean$bagrad,0.002)

cdi_data_clean = cdi_data_clean[cdi_data_clean$poverty >= quantile(cdi_data_clean$poverty,0.00
cdi_data_clean = cdi_data_clean[cdi_data_clean$unemp >= quantile(cdi_data_clean$unemp,0.002) &
cdi_data_clean = cdi_data_clean[cdi_data_clean$pcincome >= quantile(cdi_data_clean$pcincome,0.
cdi_data_clean = cdi_data_clean[cdi_data_clean$totalinc >= quantile(cdi_data_clean$totalinc,0.
cdi_data_clean = cdi_data_clean[cdi_data_clean$docs_rate_1000 >= quantile(cdi_data_clean$docs_
cdi_data_clean = cdi_data_clean[cdi_data_clean$beds_rate_1000 >= quantile(cdi_data_clean$beds_
cdi_data_clean = cdi_data_clean[cdi_data_clean$beds_rate_1000 >= quantile(cdi_data_clean$beds_
cdi_data_clean = cdi_data_clean[cdi_data_clean$density >= quantile(cdi_data_clean$density,0.00

cdi_data_clean = cdi_data_clean[cdi_data_clean$crime_rate_1000 >= quantile(cdi_data_clean$crime
```

```
par(mfrow=c(4,3))
boxplot(cdi_data_clean$area,main="Area")
boxplot(cdi_data_clean$pop,main="Population")
boxplot(cdi_data_clean$pop18,main="Population 18-34")
boxplot(cdi_data_clean$pop65,main="Population 65+")
boxplot(cdi_data_clean$hsgrad,main="Highschool grads")
boxplot(cdi_data_clean$bagrad,main="Bachelor's grads")

boxplot(cdi_data_clean$poverty,main="Poverty Rate")
boxplot(cdi_data_clean$unemp,main="Unemployment Rate")
boxplot(cdi_data_clean$pcincome,main="Income Per Capita")
boxplot(cdi_data_clean$totalinc,main="Income Total")
boxplot(cdi_data_clean$docs_rate_1000,main="Active Physicians")
boxplot(cdi_data_clean$beds_rate_1000,main="Hospital Beds")
```

Training/Test set split

```
cdi_data_clean = cdi_data_clean %>%
  dplyr::select(-id,-cty_state, -cty,-state) %>%
  mutate(region = factor(region))

set.seed(1)
dt = sort(sample(nrow(cdi_data_clean), nrow(cdi_data_clean)*.9))
train_data = cdi_data_clean[dt,]
test_data = cdi_data_clean[-dt,]
```

Model construction

Data used for building model:

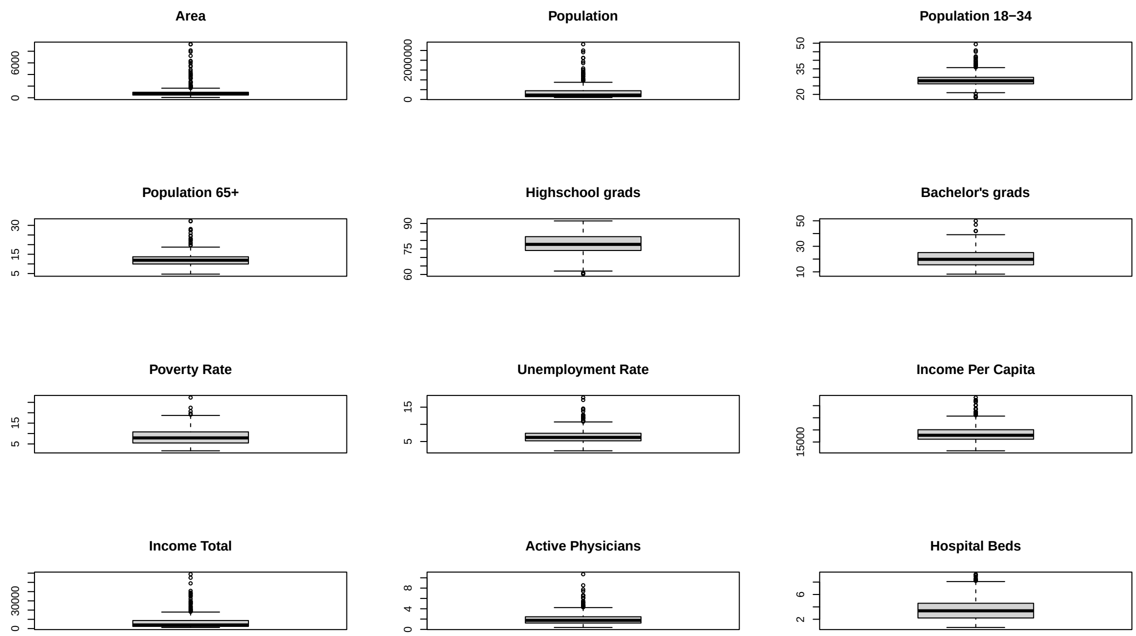

Figure 5: Boxplot of each continuous variables aftern cleaning outliers

```
cdi_model = train_data
```

Stepwise regression

```
full.fit = lm(crime_rate_1000 ~ ., data = cdi_model)
summary(full.fit) %>%
  broom::tidy() %>%
  mutate(p_rank = rank(p.value))
```

```
## # A tibble: 17 x 6
##    term            estimate  std.error statistic  p.value p_rank
##    <chr>              <dbl>      <dbl>     <dbl>    <dbl>  <dbl>
##  1 (Intercept)    -107.        29.0          -3.71  2.42e- 4      8
##  2 area             -0.000471  0.000881      -0.535 5.93e- 1     16
##  3 pop               0.0000788 0.0000130      6.08  3.10e- 9      3
##  4 pop18             1.25      0.358          3.50  5.26e- 4      9
##  5 pop65             0.0779    0.318          0.245 8.07e- 1     17
##  6 hsgrad            0.354     0.276          1.28  2.00e- 1     13
##  7 bagrad           -0.687     0.320         -2.15  3.23e- 2     10
##  8 poverty           2.18      0.428          5.09  5.95e- 7      6
##  9 unemp             0.628     0.532          1.18  2.39e- 1     14
## 10 pcincome          0.00325   0.000608       5.35  1.62e- 7      4
## 11 totalinc         -0.00333   0.000638      -5.23  2.92e- 7      5
## 12 region2          10.6       2.61           4.08  5.63e- 5      7
## 13 region3          29.5       2.60          11.4   1.04e-25      1
## 14 region4          22.1       3.34           6.62  1.34e-10      2
```

```
## 15 docs_rate_1000    1.81       1.20           1.51  1.31e- 1     12
## 16 beds_rate_1000    1.75       0.834          2.10  3.67e- 2     11
## 17 density           0.000743   0.000691       1.07  2.83e- 1     15
```

```
backward = step(full.fit, direction='backward') %>%  broom::tidy() %>%  rename(backward = "term
```

```
## Start:  AIC=2059.35
## crime_rate_1000 ~ area + pop + pop18 + pop65 + hsgrad + bagrad +
##     poverty + unemp + pcincome + totalinc + region + docs_rate_1000 +
##     beds_rate_1000 + density
##
##                  Df Sum of Sq    RSS    AIC
## - pop65           1        15  89297 2057.4
## - area            1        73  89354 2057.7
## - density         1       293  89574 2058.6
## - unemp           1       353  89635 2058.8
## - hsgrad          1       418  89699 2059.1
## <none>                         89281 2059.3
## - docs_rate_1000  1       581  89863 2059.7
## - beds_rate_1000  1      1116  90397 2061.9
## - bagrad          1      1171  90452 2062.2
## - pop18           1      3107  92388 2070.0
## - poverty         1      6562  95844 2083.5
## - totalinc        1      6938  96219 2085.0
## - pcincome        1      7248  96529 2086.2
## - pop             1      9382  98663 2094.2
## - region          3     34907 124189 2175.1
##
## Step:  AIC=2057.41
## crime_rate_1000 ~ area + pop + pop18 + hsgrad + bagrad + poverty +
##     unemp + pcincome + totalinc + region + docs_rate_1000 + beds_rate_1000 +
##     density
##
##                  Df Sum of Sq    RSS    AIC
## - area            1        67  89364 2055.7
## - density         1       304  89601 2056.7
## - unemp           1       383  89680 2057.0
## - hsgrad          1       408  89705 2057.1
## <none>                         89297 2057.4
## - docs_rate_1000  1       592  89889 2057.8
## - bagrad          1      1169  90466 2060.2
## - beds_rate_1000  1      1277  90574 2060.7
## - pop18           1      3748  93044 2070.6
## - poverty         1      6706  96002 2082.1
## - totalinc        1      6926  96222 2083.0
## - pcincome        1      7255  96552 2084.2
## - pop             1      9371  98668 2092.2
## - region          3     34901 124197 2173.2
```

```
##
## Step:  AIC=2055.69
## crime_rate_1000 ~ pop + pop18 + hsgrad + bagrad + poverty + unemp +
##     pcincome + totalinc + region + docs_rate_1000 + beds_rate_1000 +
##     density
##
##                  Df Sum of Sq    RSS    AIC
## - unemp           1       356  89720 2055.2
## - density         1       429  89793 2055.5
## - hsgrad          1       431  89795 2055.5
## <none>                         89364 2055.7
## - docs_rate_1000  1       588  89952 2056.1
## - bagrad          1      1171  90535 2058.5
## - beds_rate_1000  1      1280  90644 2058.9
## - pop18           1      3723  93087 2068.8
## - poverty         1      6662  96027 2080.2
## - totalinc        1      6868  96232 2081.0
## - pcincome        1      7226  96590 2082.4
## - pop             1      9406  98770 2090.6
## - region          3     34833 124198 2171.2
##
## Step:  AIC=2055.16
## crime_rate_1000 ~ pop + pop18 + hsgrad + bagrad + poverty + pcincome +
##     totalinc + region + docs_rate_1000 + beds_rate_1000 + density
##
##                  Df Sum of Sq    RSS    AIC
## - hsgrad          1       328  90049 2054.5
## - density         1       408  90129 2054.8
## <none>                         89720 2055.2
## - docs_rate_1000  1       590  90310 2055.6
## - beds_rate_1000  1      1043  90764 2057.4
## - bagrad          1      1505  91225 2059.3
## - pop18           1      3735  93455 2068.2
## - totalinc        1      7018  96738 2080.9
## - pcincome        1      7957  97677 2084.5
## - poverty         1      8464  98184 2086.4
## - pop             1      9555  99275 2090.5
## - region          3     36161 125881 2174.1
##
## Step:  AIC=2054.51
## crime_rate_1000 ~ pop + pop18 + bagrad + poverty + pcincome +
##     totalinc + region + docs_rate_1000 + beds_rate_1000 + density
##
##                  Df Sum of Sq    RSS    AIC
## - density         1       336  90385 2053.9
## <none>                         90049 2054.5
## - docs_rate_1000  1       500  90549 2054.6
## - beds_rate_1000  1      1207  91255 2057.4
```

```
## - bagrad          1      1244  91292 2057.6
## - pop18           1      3512  93560 2066.6
## - totalinc        1      7116  97164 2080.6
## - pcincome        1      7638  97686 2082.6
## - poverty         1      8900  98948 2087.3
## - pop             1      9648  99697 2090.1
## - region          3     35889 125937 2172.3
##
## Step:  AIC=2053.88
## crime_rate_1000 ~ pop + pop18 + bagrad + poverty + pcincome +
##     totalinc + region + docs_rate_1000 + beds_rate_1000
##
##                   Df Sum of Sq    RSS    AIC
## <none>                          90385 2053.9
## - docs_rate_1000  1       791  91175 2055.1
## - beds_rate_1000  1      1114  91498 2056.4
## - bagrad          1      1662  92046 2058.6
## - pop18           1      4171  94556 2068.5
## - totalinc        1      7177  97562 2080.1
## - pcincome        1      8992  99377 2086.9
## - pop             1      9887 100271 2090.2
## - poverty         1      9966 100351 2090.5
## - region          3     35598 125982 2170.4
```

```r
both = step(full.fit, direction = "both") %>% broom::tidy() %>% rename(stepwise = "term")
```

```
## Start:  AIC=2059.35
## crime_rate_1000 ~ area + pop + pop18 + pop65 + hsgrad + bagrad +
##     poverty + unemp + pcincome + totalinc + region + docs_rate_1000 +
##     beds_rate_1000 + density
##
##                   Df Sum of Sq    RSS    AIC
## - pop65           1        15  89297 2057.4
## - area            1        73  89354 2057.7
## - density         1       293  89574 2058.6
## - unemp           1       353  89635 2058.8
## - hsgrad          1       418  89699 2059.1
## <none>                          89281 2059.3
## - docs_rate_1000  1       581  89863 2059.7
## - beds_rate_1000  1      1116  90397 2061.9
## - bagrad          1      1171  90452 2062.2
## - pop18           1      3107  92388 2070.0
## - poverty         1      6562  95844 2083.5
## - totalinc        1      6938  96219 2085.0
## - pcincome        1      7248  96529 2086.2
## - pop             1      9382  98663 2094.2
## - region          3     34907 124189 2175.1
##
```

```
## Step:  AIC=2057.41
## crime_rate_1000 ~ area + pop + pop18 + hsgrad + bagrad + poverty +
##     unemp + pcincome + totalinc + region + docs_rate_1000 + beds_rate_1000 +
##     density
##
##                  Df Sum of Sq    RSS    AIC
## - area            1        67  89364 2055.7
## - density         1       304  89601 2056.7
## - unemp           1       383  89680 2057.0
## - hsgrad          1       408  89705 2057.1
## <none>                         89297 2057.4
## - docs_rate_1000  1       592  89889 2057.8
## + pop65           1        15  89281 2059.3
## - bagrad          1      1169  90466 2060.2
## - beds_rate_1000  1      1277  90574 2060.7
## - pop18           1      3748  93044 2070.6
## - poverty         1      6706  96002 2082.1
## - totalinc        1      6926  96222 2083.0
## - pcincome        1      7255  96552 2084.2
## - pop             1      9371  98668 2092.2
## - region          3     34901 124197 2173.2
##
## Step:  AIC=2055.69
## crime_rate_1000 ~ pop + pop18 + hsgrad + bagrad + poverty + unemp +
##     pcincome + totalinc + region + docs_rate_1000 + beds_rate_1000 +
##     density
##
##                  Df Sum of Sq    RSS    AIC
## - unemp           1       356  89720 2055.2
## - density         1       429  89793 2055.5
## - hsgrad          1       431  89795 2055.5
## <none>                         89364 2055.7
## - docs_rate_1000  1       588  89952 2056.1
## + area            1        67  89297 2057.4
## + pop65           1        10  89354 2057.7
## - bagrad          1      1171  90535 2058.5
## - beds_rate_1000  1      1280  90644 2058.9
## - pop18           1      3723  93087 2068.8
## - poverty         1      6662  96027 2080.2
## - totalinc        1      6868  96232 2081.0
## - pcincome        1      7226  96590 2082.4
## - pop             1      9406  98770 2090.6
## - region          3     34833 124198 2171.2
##
## Step:  AIC=2055.16
## crime_rate_1000 ~ pop + pop18 + hsgrad + bagrad + poverty + pcincome +
##     totalinc + region + docs_rate_1000 + beds_rate_1000 + density
##
```

```
##                  Df Sum of Sq    RSS    AIC
## - hsgrad          1       328  90049 2054.5
## - density         1       408  90129 2054.8
## <none>                         89720 2055.2
## - docs_rate_1000  1       590  90310 2055.6
## + unemp           1       356  89364 2055.7
## + area            1        40  89680 2057.0
## + pop65           1        37  89683 2057.0
## - beds_rate_1000  1      1043  90764 2057.4
## - bagrad          1      1505  91225 2059.3
## - pop18           1      3735  93455 2068.2
## - totalinc        1      7018  96738 2080.9
## - pcincome        1      7957  97677 2084.5
## - poverty         1      8464  98184 2086.4
## - pop             1      9555  99275 2090.5
## - region          3     36161 125881 2174.1
##
## Step:  AIC=2054.51
## crime_rate_1000 ~ pop + pop18 + bagrad + poverty + pcincome +
##     totalinc + region + docs_rate_1000 + beds_rate_1000 + density
##
##                  Df Sum of Sq    RSS    AIC
## - density         1       336  90385 2053.9
## <none>                         90049 2054.5
## - docs_rate_1000  1       500  90549 2054.6
## + hsgrad          1       328  89720 2055.2
## + unemp           1       253  89795 2055.5
## + area            1        60  89989 2056.3
## + pop65           1        18  90030 2056.4
## - beds_rate_1000  1      1207  91255 2057.4
## - bagrad          1      1244  91292 2057.6
## - pop18           1      3512  93560 2066.6
## - totalinc        1      7116  97164 2080.6
## - pcincome        1      7638  97686 2082.6
## - poverty         1      8900  98948 2087.3
## - pop             1      9648  99697 2090.1
## - region          3     35889 125937 2172.3
##
## Step:  AIC=2053.88
## crime_rate_1000 ~ pop + pop18 + bagrad + poverty + pcincome +
##     totalinc + region + docs_rate_1000 + beds_rate_1000
##
##                  Df Sum of Sq    RSS    AIC
## <none>                         90385 2053.9
## + density         1       336  90049 2054.5
## + hsgrad          1       256  90129 2054.8
## + unemp           1       247  90138 2054.9
## - docs_rate_1000  1       791  91175 2055.1
```

```
## + area            1       159  90225 2055.2
## + pop65           1        28  90356 2055.8
## - beds_rate_1000  1      1114  91498 2056.4
## - bagrad          1      1662  92046 2058.6
## - pop18           1      4171  94556 2068.5
## - totalinc        1      7177  97562 2080.1
## - pcincome        1      8992  99377 2086.9
## - pop             1      9887 100271 2090.2
## - poverty         1      9966 100351 2090.5
## - region          3     35598 125982 2170.4
```

Variables chosen from stepwise regression:

```
bind_cols(backward[-1,1],both[-1,1]) %>% knitr::kable(caption = "Vairable selected from stepwis
```

Table 1: Vairable selected from stepwise regression

backward	stepwise
pop	pop
pop18	pop18
bagrad	bagrad
poverty	poverty
pcincome	pcincome
totalinc	totalinc
region2	region2
region3	region3
region4	region4
docs_rate_1000	docs_rate_1000
beds_rate_1000	beds_rate_1000

Criteria based selection

```
sb = regsubsets(crime_rate_1000 ~ ., data = cdi_model, nvmax = 14)
sumsb = summary(sb) # pop pop18 hsgrad bagrad poverty pcincome totalinc region beds_rate_1000
```

```
coef(sb, id = 12)
```

```
##    (Intercept)            pop          pop18         bagrad        poverty
##  -7.368622e+01   7.827941e-05   1.162002e+00  -5.380707e-01   2.089757e+00
##       pcincome       totalinc        region2        region3        region4
##   3.228481e-03  -3.333453e-03   1.092941e+01   2.844105e+01   2.185595e+01
## docs_rate_1000 beds_rate_1000        density
##   1.666795e+00   1.692793e+00   7.548111e-04
```

```
par(mfrow=c(1,2))
plot(2:15, sumsb$cp, xlab="No. of parameters", ylab="Cp Statistic")
abline(0,1)

plot(2:15, sumsb$adjr2, xlab="No of parameters", ylab="Adj R2")
```

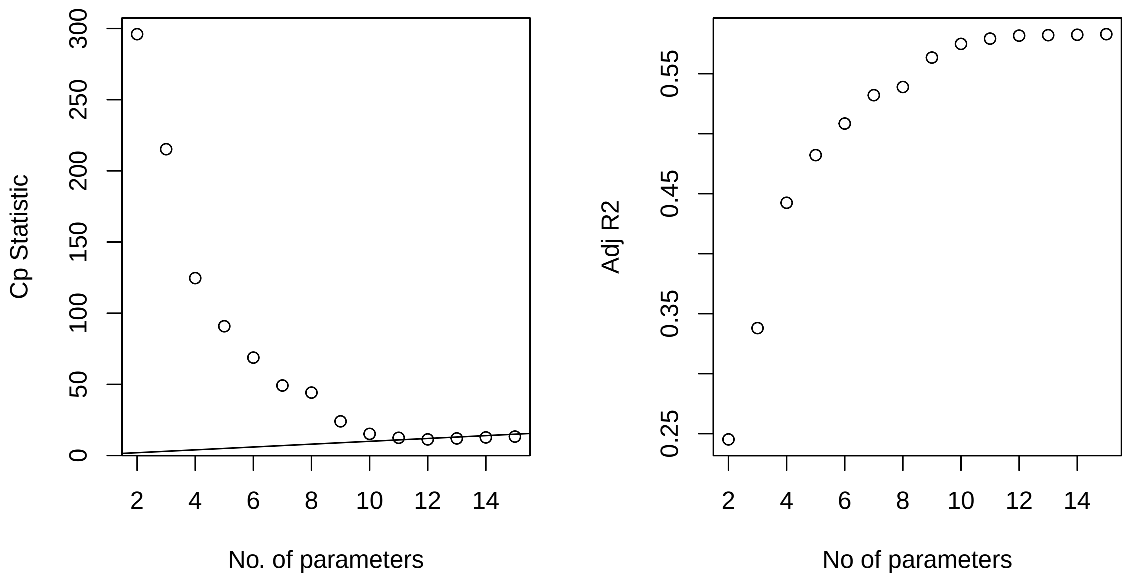

Figure 6: Subset selection for best parameter numbers

According to the output, we determine that the number of variables should be above 12 because $C_p \leq p$. Based on this analysis, we find that `unemp` could also be selected.

Discussion

We need to remove totalinc, because it can be replaced. totalinc = pcincome * pop.

Model building from the vairables we selected

```
fit_nest = lm(crime_rate_1000 ~
                  pop + pop18 + bagrad +
                  poverty + unemp + pcincome + pcincome*pop + region +
                  beds_rate_1000 + density, data = cdi_model)
summary(fit_nest)
```

```
##
## Call:
## lm(formula = crime_rate_1000 ~ pop + pop18 + bagrad + poverty +
##     unemp + pcincome + pcincome * pop + region + beds_rate_1000 +
##     density, data = cdi_model)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -42.553  -9.838  -0.756   8.236  58.758
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -8.155e+01  1.504e+01  -5.424 1.08e-07 ***
```

```
## pop              7.754e-05  1.270e-05   6.107 2.65e-09 ***
## pop18            1.197e+00  3.109e-01   3.849  0.00014 ***
## bagrad          -3.414e-01  2.493e-01  -1.369  0.17184
## poverty          1.976e+00  3.846e-01   5.139 4.56e-07 ***
## unemp            5.316e-01  5.176e-01   1.027  0.30509
## pcincome         3.219e-03  5.942e-04   5.417 1.12e-07 ***
## region2          1.108e+01  2.470e+00   4.485 9.86e-06 ***
## region3          2.923e+01  2.581e+00  11.326  < 2e-16 ***
## region4          2.260e+01  2.923e+00   7.731 1.10e-13 ***
## beds_rate_1000  2.580e+00  6.268e-01   4.116 4.80e-05 ***
## density          9.984e-04  6.331e-04   1.577  0.11565
## pop:pcincome    -3.288e-09  6.296e-10  -5.222 3.02e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 15.92 on 356 degrees of freedom
## Multiple R-squared:  0.5947, Adjusted R-squared:  0.581
## F-statistic: 43.52 on 12 and 356 DF,  p-value: < 2.2e-16
```

```r
par(mfrow = c(2,2))
plot(fit_nest)
```

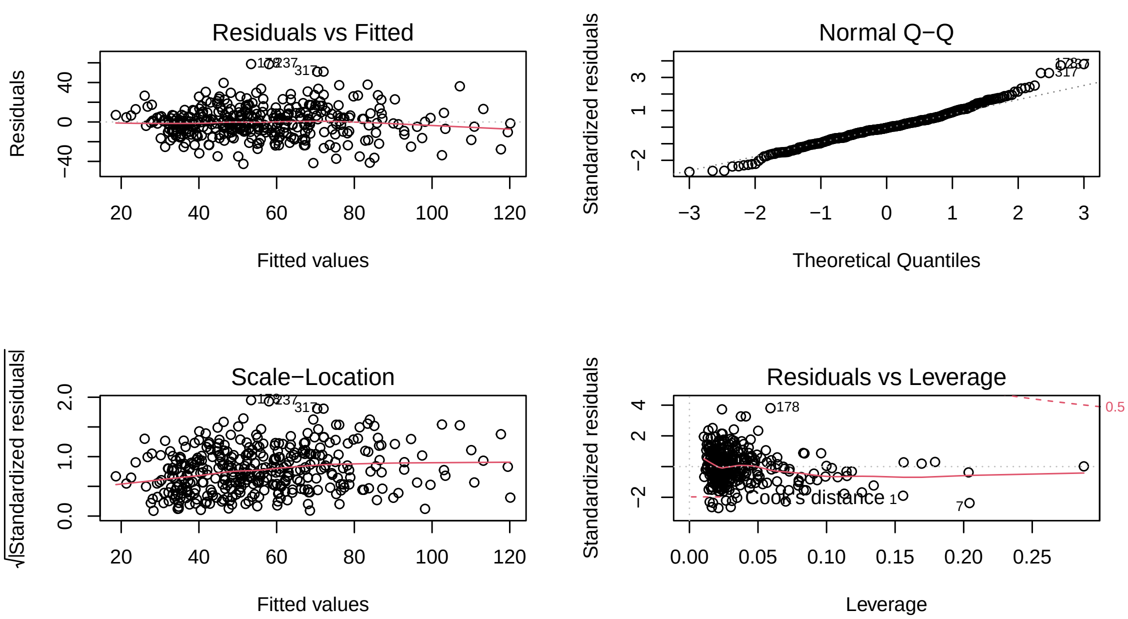

Figure 7: Diagnose plots of model without interaction terms

```r
boxcox(fit_nest)
```

The peak of boxcox plot is close to around 0.5~1. Try $\sqrt{y}$ transformation

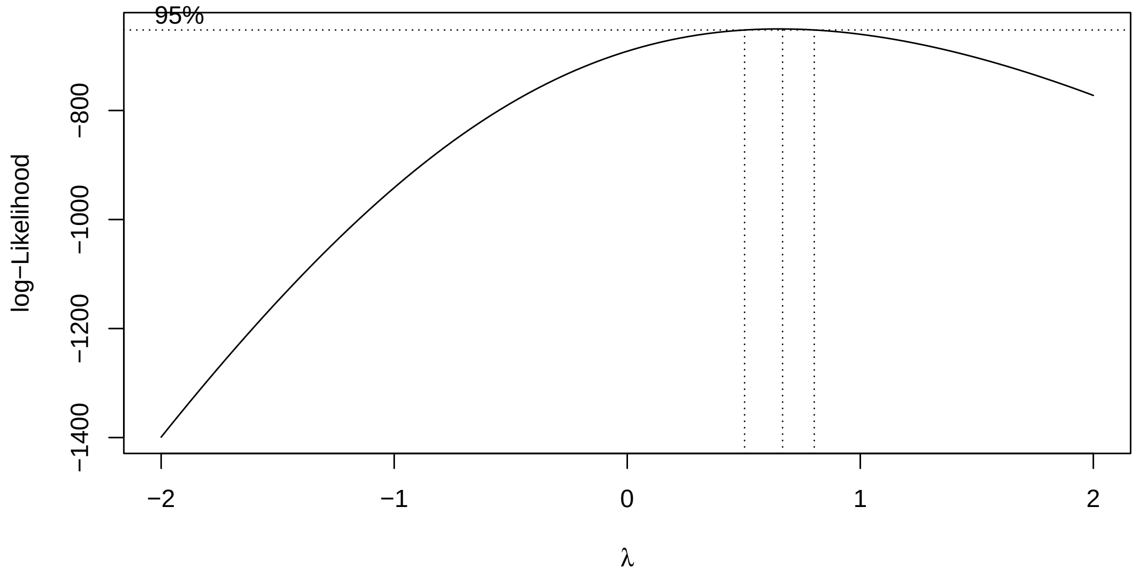

Figure 8: Boxcox plot of model without interaction terms

transformation

```
cdi_model_trans = cdi_model %>%
  mutate(
    y_sqrt = sqrt(crime_rate_1000)
  )

fit_nest_trans = lm(y_sqrt ~
                   pop + pop18 + bagrad +
                  poverty + unemp + pcincome + pcincome*pop + region +
                  beds_rate_1000 + density, data = cdi_model_trans)
summary(fit_nest_trans)
```

```
##
## Call:
## lm(formula = y_sqrt ~ pop + pop18 + bagrad + poverty + unemp +
##     pcincome + pcincome * pop + region + beds_rate_1000 + density,
##     data = cdi_model_trans)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.9877 -0.6110  0.0241  0.6136  3.5331
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -1.680e+00  1.039e+00  -1.617 0.106787
## pop             4.793e-06  8.772e-07   5.464 8.77e-08 ***
## pop18           7.959e-02  2.148e-02   3.706 0.000244 ***
## bagrad         -2.516e-02  1.723e-02  -1.460 0.145065
```

```
## poverty          1.136e-01  2.657e-02   4.277 2.44e-05 ***
## unemp            4.156e-02  3.576e-02   1.162 0.245947
## pcincome         2.050e-04  4.106e-05   4.994 9.28e-07 ***
## region2          8.173e-01  1.707e-01   4.788 2.47e-06 ***
## region3          2.074e+00  1.783e-01  11.633  < 2e-16 ***
## region4          1.747e+00  2.020e-01   8.648  < 2e-16 ***
## beds_rate_1000   1.865e-01  4.331e-02   4.306 2.15e-05 ***
## density          6.461e-05  4.374e-05   1.477 0.140538
## pop:pcincome    -2.005e-10  4.350e-11  -4.609 5.64e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.1 on 356 degrees of freedom
## Multiple R-squared:  0.5763, Adjusted R-squared:  0.562
## F-statistic: 40.35 on 12 and 356 DF,  p-value: < 2.2e-16
```

```
par(mfrow = c(2,2))
plot(fit_nest_trans)
```

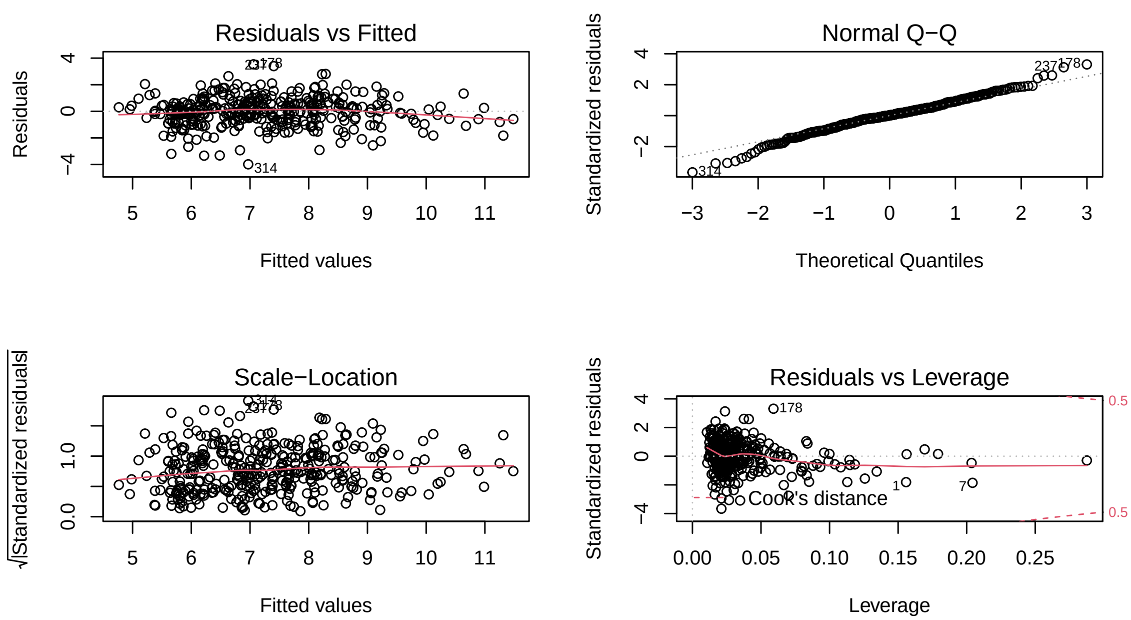

Figure 9: Diagnose plots of model without interaction terms

Compare to the diagnose plots of untransformed model, we found that the residuals are more unevenly distributed. Therefore, transformed model is worse. We select the untransformed model.

Our first model:

$$crime\_rate\_1000 = pop+pop18+bagrad+poverty+unemp+pcincome+pcincome*pop+regionbeds\_rate\_1000+c$$

Add Interaction term: poverty+income

According to Census Bureau, the number of persons below the official government poverty level was 33.6 million in 1990, representing 13.5 percent of the Nation's population. Thus, we can use this criteria to divide `poverty` into two category: higher than national poverty rate and lower than national poverty rate.

```
poverty_status = cdi_model %>%
  mutate(national_poverty = if_else(poverty > 13.5, "higher", "lower"))

ggplot(poverty_status, aes(x = pcincome, y = crime_rate_1000, color = national_poverty)) +
  geom_point(alpha = .5) +
  geom_smooth(method = "lm", se = F, aes(group = national_poverty, color = national_poverty)) +
  labs(
    title = "Crime Rate and Per Capita Income by Poverty Status",
    x = "Per Capita Income",
    y = "Crime Rate ",
    color = "Comparison with national avergae"
  )
```

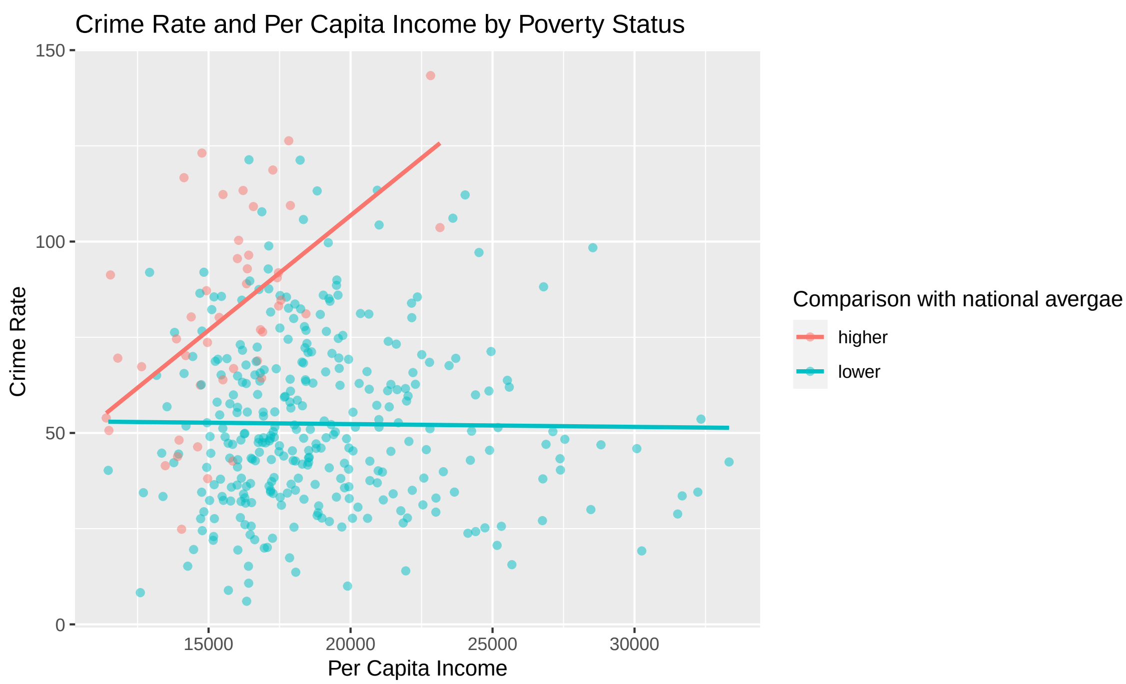

Figure 10: Interaction plot of Income Per Capita and Poverty

```
fit_int1 = lm(crime_rate_1000 ~
                  pop + pop18 + bagrad +
                 poverty + unemp + pcincome + pcincome*pop + region +
                 beds_rate_1000 + density +
                 poverty*pcincome, data = cdi_model)
summary(fit_int1) %>% broom::tidy()
```

```
## # A tibble: 14 x 5
##    term              estimate std.error statistic  p.value
##    <chr>                <dbl>     <dbl>     <dbl>    <dbl>
##  1 (Intercept)       -4.53e+1  1.65e+ 1     -2.74  6.42e- 3
```

```
##  2 pop               6.08e-5  1.28e- 5     4.74  3.13e- 6
##  3 pop18             1.05e+0  3.04e- 1     3.45  6.36e- 4
##  4 bagrad           -2.18e-1  2.44e- 1    -0.895 3.71e- 1
##  5 poverty          -2.71e+0  1.07e+ 0    -2.54  1.16e- 2
##  6 unemp             5.86e-1  5.03e- 1     1.17  2.45e- 1
##  7 pcincome          1.33e-3  7.05e- 4     1.88  6.08e- 2
##  8 region2           1.01e+1  2.41e+ 0     4.21  3.25e- 5
##  9 region3           2.79e+1  2.52e+ 0    11.0   1.47e-24
## 10 region4           1.98e+1  2.90e+ 0     6.83  3.71e-11
## 11 beds_rate_1000    1.46e+0  6.54e- 1     2.24  2.57e- 2
## 12 density           1.04e-4  6.44e- 4     0.161 8.72e- 1
## 13 pop:pcincome     -2.51e-9  6.34e-10    -3.96  9.21e- 5
## 14 poverty:pcincome  3.12e-4  6.65e- 5     4.68  4.00e- 6
```

```
check_collinearity(fit_int1)
```

```
## # Check for Multicollinearity
##
## Low Correlation
##
##              Term  VIF Increased SE Tolerance
##               pop 1.00         1.00      1.00
##             pop18 2.24         1.50      0.45
##            bagrad 2.77         1.66      0.36
##           poverty 1.17         1.08      0.85
##             unemp 1.68         1.30      0.59
##          pcincome 1.12         1.06      0.89
##            region 1.53         1.24      0.65
##    beds_rate_1000 1.34         1.16      0.75
##           density 1.02         1.01      0.98
##      pop:pcincome 1.00         1.00      1.00
##  poverty:pcincome 1.00         1.00      1.00
```

We notice that `density`, `bagrad` are not significant

```
# remove density
fit_int1 = lm(crime_rate_1000 ~
                   pop + pop18 + bagrad +
                  poverty + unemp + pcincome + pcincome*pop + region +
                  beds_rate_1000  +
                  poverty*pcincome, data = cdi_model)
summary(fit_int1)
```

```
##
## Call:
## lm(formula = crime_rate_1000 ~ pop + pop18 + bagrad + poverty +
##     unemp + pcincome + pcincome * pop + region + beds_rate_1000 +
##     poverty * pcincome, data = cdi_model)
##
## Residuals:
```

```
##     Min      1Q  Median      3Q     Max
## -45.232  -7.999  -0.618   8.174  65.416
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -4.571e+01  1.634e+01  -2.797 0.005434 **
## pop               6.078e-05  1.282e-05   4.742 3.07e-06 ***
## pop18             1.057e+00  2.971e-01   3.558 0.000424 ***
## bagrad           -2.230e-01  2.416e-01  -0.923 0.356551
## poverty          -2.744e+00  1.043e+00  -2.631 0.008882 **
## unemp             5.863e-01  5.024e-01   1.167 0.244043
## pcincome          1.332e-03  7.028e-04   1.895 0.058862 .
## region2           1.011e+01  2.397e+00   4.216 3.16e-05 ***
## region3           2.783e+01  2.510e+00  11.089  < 2e-16 ***
## region4           1.977e+01  2.884e+00   6.857 3.12e-11 ***
## beds_rate_1000    1.464e+00  6.531e-01   2.241 0.025630 *
## pop:pcincome     -2.501e-09  6.318e-10  -3.959 9.09e-05 ***
## poverty:pcincome  3.149e-04  6.346e-05   4.962 1.08e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 15.45 on 356 degrees of freedom
## Multiple R-squared:  0.6182, Adjusted R-squared:  0.6054
## F-statistic: 48.04 on 12 and 356 DF,  p-value: < 2.2e-16
```

```
check_collinearity(fit_int1)
```

```
## # Check for Multicollinearity
##
## Low Correlation
##
##              Term  VIF Increased SE Tolerance
##               pop 1.00         1.00      1.00
##             pop18 2.20         1.48      0.45
##            bagrad 2.73         1.65      0.37
##           poverty 1.18         1.09      0.85
##             unemp 1.68         1.30      0.59
##          pcincome 1.13         1.06      0.89
##            region 1.54         1.24      0.65
##    beds_rate_1000 1.34         1.16      0.74
##      pop:pcincome 1.00         1.00      1.00
##  poverty:pcincome 1.00         1.00      1.00
```

```
# remove bagrad
fit_int1 = lm(crime_rate_1000 ~
                  pop + pop18 +
                 poverty + unemp + pcincome + pcincome*pop + region +
                 beds_rate_1000  +
                 poverty*pcincome, data = cdi_model)
```

```r
summary(fit_int1)
```

```
##
## Call:
## lm(formula = crime_rate_1000 ~ pop + pop18 + poverty + unemp +
##     pcincome + pcincome * pop + region + beds_rate_1000 + poverty *
##     pcincome, data = cdi_model)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -46.347  -8.473  -0.664   8.474  66.131
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -3.891e+01  1.458e+01  -2.668 0.007976 **
## pop               5.931e-05  1.272e-05   4.664 4.38e-06 ***
## pop18             8.676e-01  2.149e-01   4.037 6.62e-05 ***
## poverty          -2.902e+00  1.029e+00  -2.822 0.005041 **
## unemp             7.587e-01  4.663e-01   1.627 0.104593
## pcincome          9.555e-04  5.722e-04   1.670 0.095839 .
## region2           1.019e+01  2.395e+00   4.252 2.71e-05 ***
## region3           2.761e+01  2.497e+00  11.054  < 2e-16 ***
## region4           1.911e+01  2.791e+00   6.846 3.33e-11 ***
## beds_rate_1000    1.437e+00  6.523e-01   2.204 0.028193 *
## pop:pcincome     -2.416e-09  6.249e-10  -3.866 0.000131 ***
## poverty:pcincome  3.238e-04  6.271e-05   5.163 4.04e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 15.45 on 357 degrees of freedom
## Multiple R-squared:  0.6173, Adjusted R-squared:  0.6055
## F-statistic: 52.36 on 11 and 357 DF,  p-value: < 2.2e-16
```

```r
check_collinearity(fit_int1)
```

```
## # Check for Multicollinearity
##
## Low Correlation
##
##             Term  VIF Increased SE Tolerance
##              pop 1.00         1.00      1.00
##            pop18 1.15         1.07      0.87
##          poverty 1.16         1.08      0.86
##            unemp 1.45         1.20      0.69
##         pcincome 1.08         1.04      0.92
##           region 1.41         1.19      0.71
##   beds_rate_1000 1.34         1.16      0.75
##     pop:pcincome 1.00         1.00      1.00
```

```
## poverty:pcincome 1.00         1.00      1.00
```

diagnose

```r
par(mfrow = c(2,2))
plot(fit_int1)
```

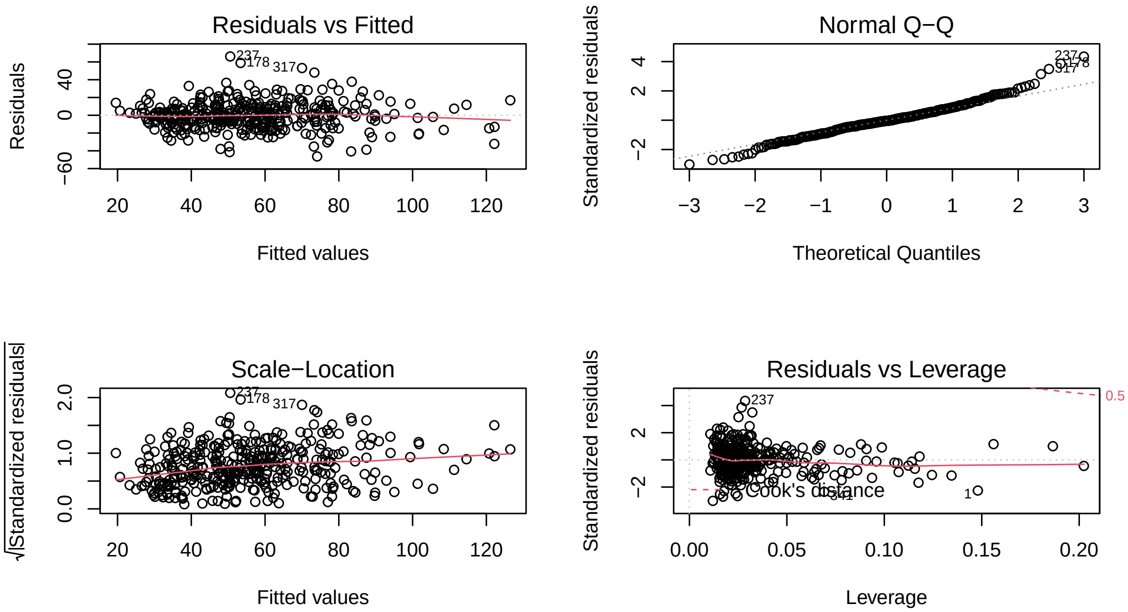

Figure 11: Diagnose plots with interaction terms:poverty*pcincome

```r
boxcox(fit_int1)
```

The peak of boxcox plot is close to around 0.5~1. Try $\sqrt{y}$ transformation

transformation

```r
cdi_model_trans = cdi_model %>%
  mutate(
    y_sqrt = sqrt(crime_rate_1000)
  )

fit_int1_trans = lm(y_sqrt ~
                  pop + pop18 +
                 poverty + unemp + pcincome + pcincome*pop + region +
                 beds_rate_1000  +
                 poverty*pcincome, data = cdi_model_trans)
summary(fit_int1_trans)
```

```
##
## Call:
## lm(formula = y_sqrt ~ pop + pop18 + poverty + unemp + pcincome +
```

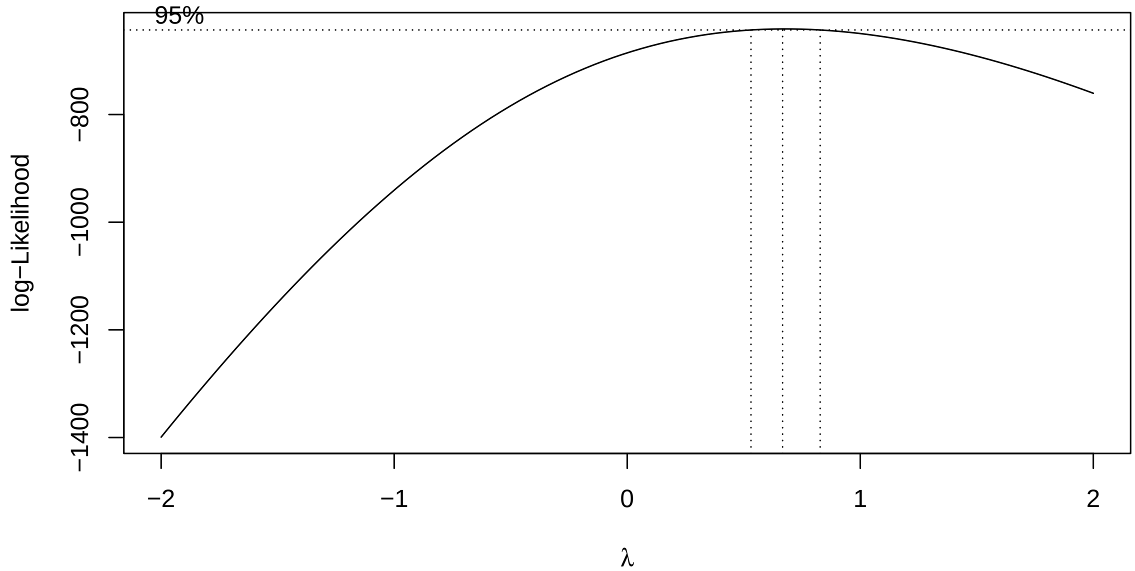

Figure 12: Boxcox plot with interaction terms:poverty*pcincome

```
##     pcincome * pop + region + beds_rate_1000 + poverty * pcincome,
##     data = cdi_model_trans)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.9081 -0.5460  0.0236  0.6370  3.8835
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)       1.119e+00  1.013e+00   1.105 0.270025
## pop               3.617e-06  8.834e-07   4.094 5.24e-05 ***
## pop18             5.584e-02  1.493e-02   3.741 0.000214 ***
## poverty          -1.976e-01  7.145e-02  -2.765 0.005987 **
## unemp             5.875e-02  3.239e-02   1.814 0.070592 .
## pcincome          5.599e-05  3.975e-05   1.409 0.159836
## region2           7.617e-01  1.664e-01   4.577 6.51e-06 ***
## region3           1.967e+00  1.735e-01  11.340  < 2e-16 ***
## region4           1.514e+00  1.939e-01   7.811 6.40e-14 ***
## beds_rate_1000    1.139e-01  4.532e-02   2.513 0.012407 *
## pop:pcincome     -1.439e-10  4.341e-11  -3.316 0.001007 **
## poverty:pcincome  2.064e-05  4.356e-06   4.738 3.12e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.073 on 357 degrees of freedom
## Multiple R-squared:  0.5956, Adjusted R-squared:  0.5832
## F-statistic:  47.8 on 11 and 357 DF,  p-value: < 2.2e-16
```

```r
par(mfrow = c(2,2))
plot(fit_int1_trans)
```

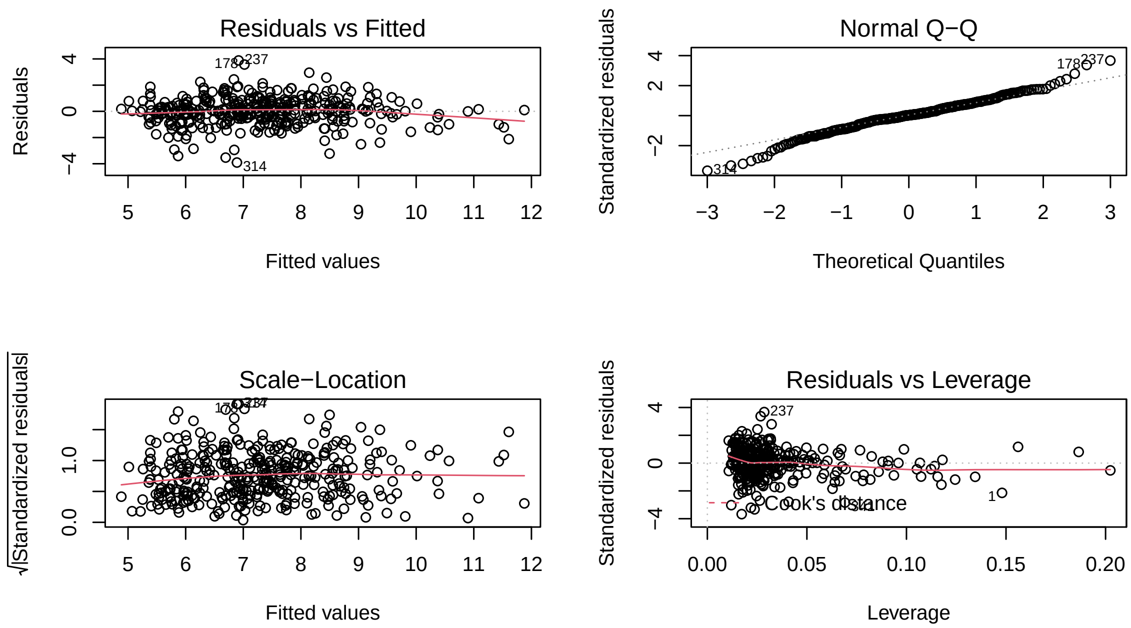

Figure 13: Diagnose plots with interaction terms:poverty*pcincome

Compare to the diagnose plots of untransformed model, we found that the residuals are more unevenly distributed. Therefore, transformed model is worse. We select the untransformed model.

Our second model:

$$crime\_rate\_1000 = pop + pop18 + poverty + unemp + pcincome + pcincome * pop + region + beds\_rate\_1000 + poverty$$

Add interaction term: pcincome + bagrad

According to Census Bureau, national percent of persons 25 years old or older with bachelor's degrees is 20.8%. Thus, we can use this criteria to divide `bagrad` into two category: higher than national `bagrad` and lower than national `bargrad`.

```r
bagrad_status = cdi_model %>%
  mutate(national_bagrad = if_else(bagrad > 20.8, "higher", "lower"))

ggplot(bagrad_status, aes(x = pcincome, y = crime_rate_1000, color = national_bagrad)) +
  geom_point(alpha = .5) +
  geom_smooth(method = "lm", se = F, aes(group = national_bagrad, color = national_bagrad)) +
  ylim(0,150) +
  labs(
    title = "Crime Rate and Per Capita Income by Percent Bachelor's Degrees Status",
    x = "Per Capita Income",
    y = "Crime Rate",
    color = "Comparison with national avergae"
  )
```

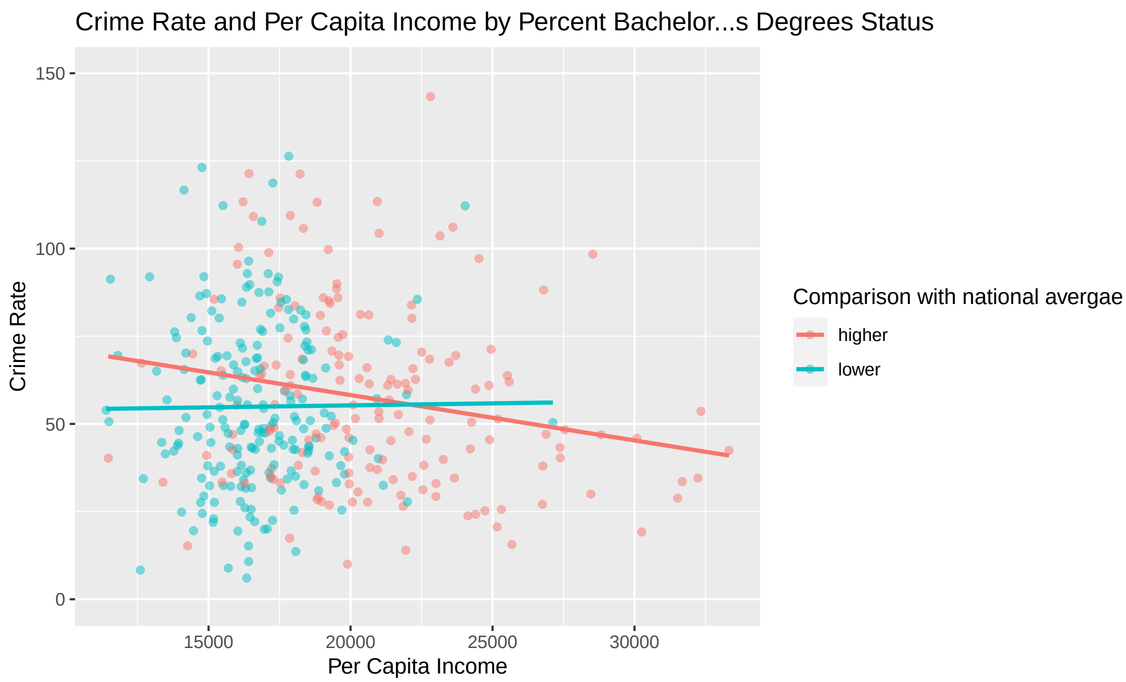

Figure 14: Interaction plot of Income Per Capita and Bachelor's Degree Status

```
fit_int2 = lm(crime_rate_1000 ~
                  pop + pop18 + bagrad +
                  poverty + unemp + pcincome + pcincome*pop + region +
                  beds_rate_1000 + density +
                  pcincome*bagrad, data = cdi_model)
summary(fit_int2)
```

```
##
## Call:
## lm(formula = crime_rate_1000 ~ pop + pop18 + bagrad + poverty +
##     unemp + pcincome + pcincome * pop + region + beds_rate_1000 +
##     density + pcincome * bagrad, data = cdi_model)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -43.172  -9.081  -0.720   7.774  62.901
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)        -1.155e+02  1.878e+01  -6.149 2.11e-09 ***
## pop                 6.096e-05  1.375e-05   4.433 1.24e-05 ***
## pop18               9.339e-01  3.201e-01   2.918 0.003750 **
## bagrad              1.519e+00  6.755e-01   2.249 0.025141 *
## poverty             2.295e+00  3.954e-01   5.804 1.43e-08 ***
## unemp               6.891e-01  5.148e-01   1.339 0.181565
```

```
## pcincome         5.249e-03  9.036e-04   5.809 1.40e-08 ***
## region2          1.141e+01  2.446e+00   4.662 4.44e-06 ***
## region3          2.910e+01  2.553e+00  11.396  < 2e-16 ***
## region4          2.184e+01  2.904e+00   7.520 4.52e-13 ***
## beds_rate_1000   2.116e+00  6.397e-01   3.307 0.001039 **
## density          1.139e-03  6.281e-04   1.813 0.070695 .
## pop:pcincome    -2.501e-09  6.773e-10  -3.692 0.000257 ***
## bagrad:pcincome -9.115e-05  3.081e-05  -2.958 0.003299 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 15.75 on 355 degrees of freedom
## Multiple R-squared:  0.6044, Adjusted R-squared:  0.5899
## F-statistic: 41.72 on 13 and 355 DF,  p-value: < 2.2e-16
```

```
check_collinearity(fit_int2)
```

```
## # Check for Multicollinearity
##
## Low Correlation
##
##             Term  VIF Increased SE Tolerance
##              pop 1.00         1.00      1.00
##            pop18 1.47         1.21      0.68
##           bagrad 1.74         1.32      0.58
##          poverty 2.02         1.42      0.49
##            unemp 1.44         1.20      0.70
##         pcincome 1.15         1.07      0.87
##           region 1.51         1.23      0.66
##   beds_rate_1000 1.80         1.34      0.55
##          density 1.02         1.01      0.98
##     pop:pcincome 1.00         1.00      1.00
##  bagrad:pcincome 1.00         1.00      1.00
```

diagnose

```
par(mfrow = c(2,2))
plot(fit_int2)
```

```
boxcox(fit_int2)
```

The peak of boxcox plot is close to around 0.5~1. Try $\sqrt{y}$ transformation

transformation

```
fit_int2_trans = lm(y_sqrt ~
                  pop + pop18 + bagrad +
                  poverty + unemp + pcincome + pcincome*pop + region +
                  beds_rate_1000 + density +
```

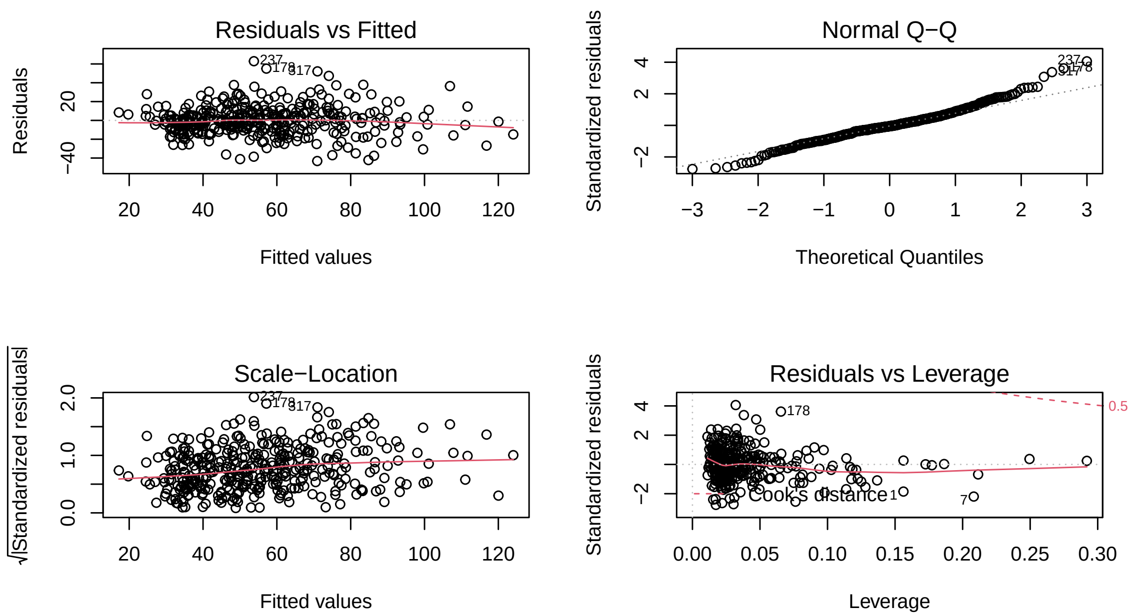

Figure 15: Diagnose plots with interaction terms:pcincome*bagrad

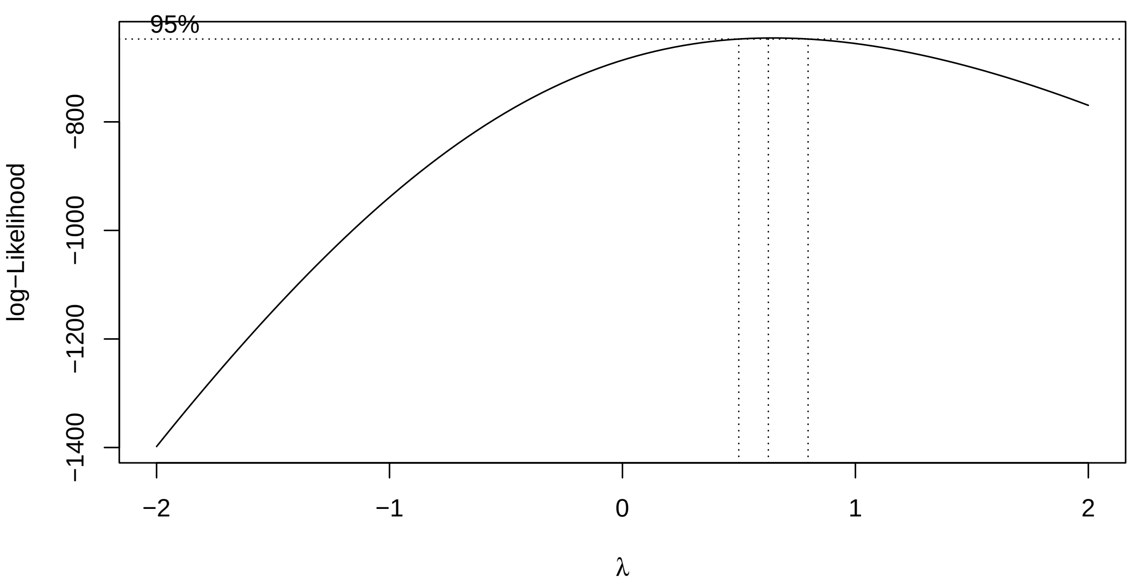

Figure 16: Boxcox plot with interaction terms:pcincome*bagrad

```
                  pcincome*bagrad, data = cdi_model_trans)
summary(fit_int2_trans)
```

```
##
## Call:
## lm(formula = y_sqrt ~ pop + pop18 + bagrad + poverty + unemp +
##     pcincome + pcincome * pop + region + beds_rate_1000 + density +
##     pcincome * bagrad, data = cdi_model_trans)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.8851 -0.5999  0.0186  0.5943  3.7092
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)     -4.162e+00  1.295e+00  -3.213 0.001435 **
## pop              3.579e-06  9.487e-07   3.773 0.000189 ***
## pop18            6.036e-02  2.208e-02   2.734 0.006580 **
## bagrad           1.110e-01  4.660e-02   2.383 0.017712 *
## poverty          1.370e-01  2.728e-02   5.022 8.13e-07 ***
## unemp            5.309e-02  3.551e-02   1.495 0.135827
## pcincome         3.537e-04  6.233e-05   5.673 2.91e-08 ***
## region2          8.412e-01  1.688e-01   4.984 9.75e-07 ***
## region3          2.065e+00  1.761e-01  11.721  < 2e-16 ***
## region4          1.691e+00  2.003e-01   8.441 8.13e-16 ***
## beds_rate_1000   1.525e-01  4.413e-02   3.455 0.000616 ***
## density          7.487e-05  4.333e-05   1.728 0.084871 .
## pop:pcincome    -1.429e-10  4.672e-11  -3.058 0.002399 **
## bagrad:pcincome -6.673e-06  2.126e-06  -3.139 0.001835 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.087 on 355 degrees of freedom
## Multiple R-squared:  0.5878, Adjusted R-squared:  0.5727
## F-statistic: 38.94 on 13 and 355 DF,  p-value: < 2.2e-16
```

```
par(mfrow = c(2,2))
plot(fit_int2_trans)
```

Compare to the diagnose plots of untransformed model, we found that the residuals are more unevenly distributed. Therefore, transformed model is worse. We select the untransformed model.

The third model: crime_rate_1000 ~
pop + pop18 + bagrad + poverty + unemp + pcincome + pcincome*pop + region + beds_rate_1000 + density + pcincome*bagrad*

Our third model:

$$crime\_rate\_1000 = pop+pop18+bagrad+poverty+unemp+pcincome+pcincome*pop+region+beds\_rate\_1000-$$

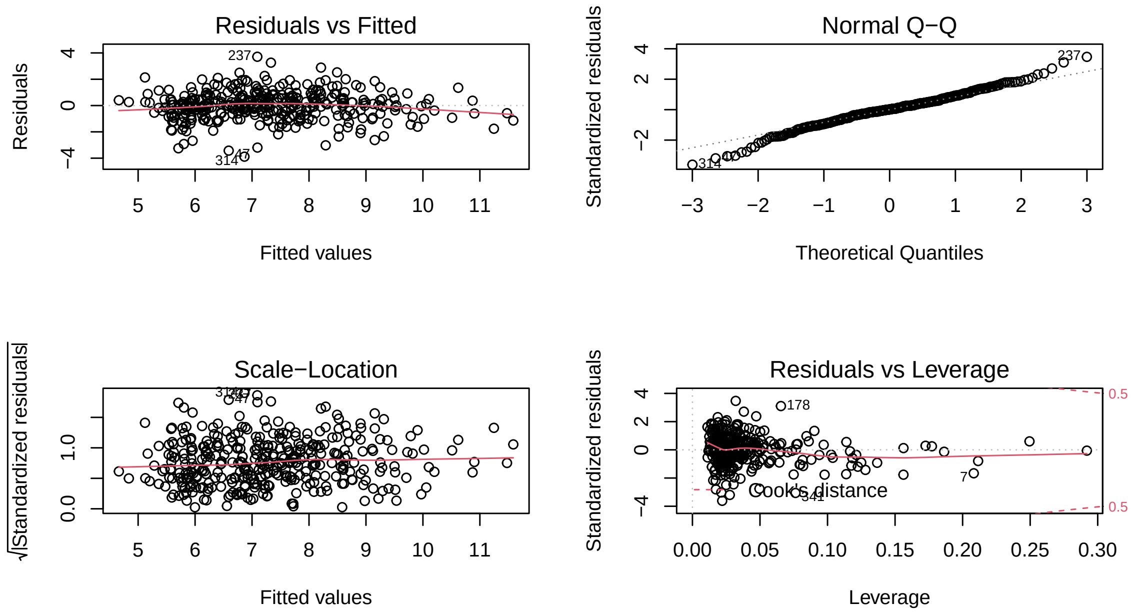

Figure 17: Diagnose plots with interaction terms:pcincome*bagrad

Cross validation

model 1

```
set.seed(1)
train = trainControl(method = "cv", number = 5)

model_train1 = train(crime_rate_1000 ~
                  pop + pop18 + bagrad +
                  poverty + unemp + pcincome + pcincome*pop + region +
                  beds_rate_1000 + density,data = cdi_model,
                   trControl = train,
                   method = 'lm',
                   na.action = na.pass)
print(model_train1)
```

```
## Linear Regression
##
## 369 samples
##   9 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 295, 296, 296, 295, 294
## Resampling results:
##
##   RMSE     Rsquared   MAE
```

```
##   16.0146  0.5760938  11.95215
##
## Tuning parameter 'intercept' was held constant at a value of TRUE
```

model 2

```
set.seed(1)
train = trainControl(method = "cv", number = 5)

model_train2 = train(crime_rate_1000 ~
                      pop + pop18 +
                     poverty + unemp + pcincome + pcincome*pop + region +
                     beds_rate_1000  +
                     poverty*pcincome, data = cdi_model,
                      trControl = train,
                      method = 'lm',
                      na.action = na.pass)

summary(model_train2)
```

```
##
## Call:
## lm(formula = .outcome ~ ., data = dat)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -46.347  -8.473  -0.664   8.474  66.131
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)           -3.891e+01  1.458e+01  -2.668 0.007976 **
## pop                    5.931e-05  1.272e-05   4.664 4.38e-06 ***
## pop18                  8.676e-01  2.149e-01   4.037 6.62e-05 ***
## poverty               -2.902e+00  1.029e+00  -2.822 0.005041 **
## unemp                  7.587e-01  4.663e-01   1.627 0.104593
## pcincome               9.555e-04  5.722e-04   1.670 0.095839 .
## region2                1.019e+01  2.395e+00   4.252 2.71e-05 ***
## region3                2.761e+01  2.497e+00  11.054  < 2e-16 ***
## region4                1.911e+01  2.791e+00   6.846 3.33e-11 ***
## beds_rate_1000         1.437e+00  6.523e-01   2.204 0.028193 *
## `pop:pcincome`        -2.416e-09  6.249e-10  -3.866 0.000131 ***
## `poverty:pcincome`     3.238e-04  6.271e-05   5.163 4.04e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 15.45 on 357 degrees of freedom
## Multiple R-squared:  0.6173, Adjusted R-squared:  0.6055
## F-statistic: 52.36 on 11 and 357 DF,  p-value: < 2.2e-16
```

model 3

```
set.seed(1)
train = trainControl(method = "cv", number = 5)

model_train3 = train(crime_rate_1000 ~
                    pop + pop18 + bagrad +
                    poverty + unemp + pcincome + pcincome*pop + region +
                    beds_rate_1000 + density +
                    pcincome*bagrad,  data = cdi_model,
                     trControl = train,
                     method = 'lm',
                     na.action = na.pass)
summary(model_train3)
```

```
##
## Call:
## lm(formula = .outcome ~ ., data = dat)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -43.172  -9.081  -0.720   7.774  62.901
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)        -1.155e+02  1.878e+01  -6.149 2.11e-09 ***
## pop                 6.096e-05  1.375e-05   4.433 1.24e-05 ***
## pop18               9.339e-01  3.201e-01   2.918 0.003750 **
## bagrad              1.519e+00  6.755e-01   2.249 0.025141 *
## poverty             2.295e+00  3.954e-01   5.804 1.43e-08 ***
## unemp               6.891e-01  5.148e-01   1.339 0.181565
## pcincome            5.249e-03  9.036e-04   5.809 1.40e-08 ***
## region2             1.141e+01  2.446e+00   4.662 4.44e-06 ***
## region3             2.910e+01  2.553e+00  11.396  < 2e-16 ***
## region4             2.184e+01  2.904e+00   7.520 4.52e-13 ***
## beds_rate_1000      2.116e+00  6.397e-01   3.307 0.001039 **
## density             1.139e-03  6.281e-04   1.813 0.070695 .
## `pop:pcincome`     -2.501e-09  6.773e-10  -3.692 0.000257 ***
## `bagrad:pcincome` -9.115e-05  3.081e-05  -2.958 0.003299 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 15.75 on 355 degrees of freedom
## Multiple R-squared:  0.6044, Adjusted R-squared:  0.5899
## F-statistic: 41.72 on 13 and 355 DF,  p-value: < 2.2e-16
```

Compare RMSE

```r
model <- c("1", "2", "3")

RMSE <- c(round(model_train1$results$RMSE, 2),  round(model_train2$results$RMSE,2),
          round(model_train3$results$RMSE, 2))

R_sq <- c(round(model_train1$results$Rsquared, 3),
          round(model_train2$results$Rsquared, 3),
          round(model_train3$results$Rsquared, 3))

RMSE_table <- data.frame(model, RMSE, R_sq)

coefs_1 = model_train1$finalModel$coefficients
names_1 = model_train1$finalModel$xNames

knitr::kable(RMSE_table, caption = "RMSE table for three models")
```

Table 2: RMSE table for three models

model	RMSE	R_sq
1	16.01	0.576
2	15.48	0.603
3	15.92	0.582

The second model has the lowest RMSE.

Model Assessment on testing set

```r
test_data = test_data %>%
  mutate(
    y = crime_rate_1000,
    y_model_1 = predict(model_train1,test_data),
    y_model_2 = predict(model_train2,test_data),
    y_model_3 = predict(model_train3,test_data))

RMSPE_1 = sqrt(mean((test_data$y-test_data$y_model_1)^2))
RMSPE_2 = sqrt(mean((test_data$y-test_data$y_model_2)^2))
RMSPE_3 = sqrt(mean((test_data$y-test_data$y_model_3)^2))



model_assessment =
  tibble(
    RMSPE_1 = round(RMSPE_1,2),
    RMSPE_2 = round(RMSPE_2,2),
```

```
    RMSPE_3 = round(RMSPE_3,2)) %>%
  pivot_longer(RMSPE_1:RMSPE_3,
               names_to = "model",
               names_prefix = "RMSPE_",
               values_to = "RMSPE") %>%
  left_join(RMSE_table,by="model") %>%
  dplyr::select(Model=model,R_square = R_sq,RMSE,RMSPE)

knitr::kable(model_assessment, caption = "Model assessment table", booktabs = TRUE)
```

Table 3: Model assessment table

Model	R_square	RMSE	RMSPE
1	0.576	16.01	14.79
2	0.603	15.48	15.04
3	0.582	15.92	14.94