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Q1:

$$Y_{1} = \beta_{0} + \beta_{1} X_{1} + \beta_{2} X_{2} + \beta_{3} X_{1} X_{2} + \mathcal{E}$$

$$Y_{2} = \alpha_{0} + \alpha_{1} X_{1} + \alpha_{2} X_{2} + \alpha_{3} X_{1} X_{2} + \mathcal{E}$$

$$\text{When } X_{1} = 1$$

$$\begin{cases}
Y_{1} = \beta_{0} + \beta_{1} + (\beta_{2} + \beta_{3}) X_{2} + \mathcal{E} \\
Y_{2} = \alpha_{0} + \alpha_{1} + (\alpha_{2} + \alpha_{3}) X_{2} + \mathcal{E} \\
Y_{2} = \alpha_{0} + \alpha_{1} + (\alpha_{2} + \alpha_{3}) X_{2} + \mathcal{E}
\end{cases}$$

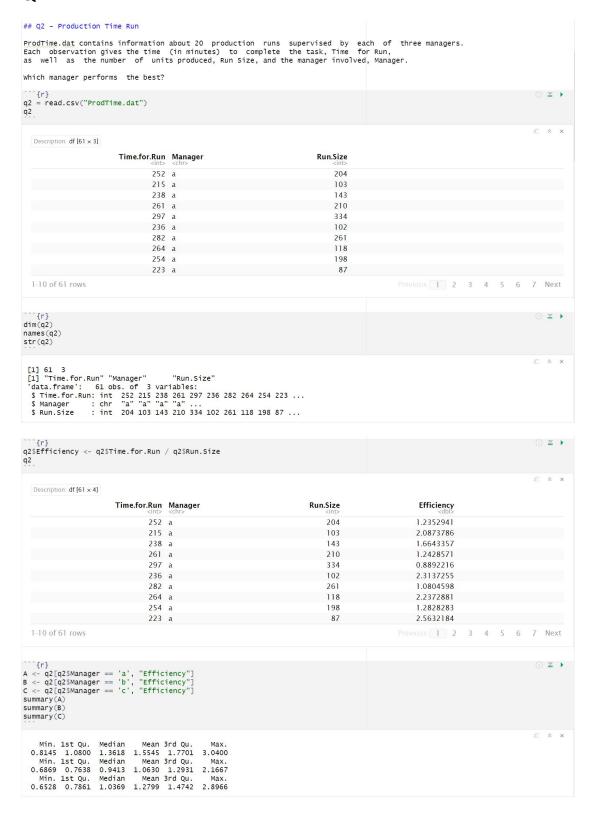
$$\begin{cases}
Y_{1} = \beta_{0} + \beta_{2} X_{2} + \mathcal{E} \\
Y_{2} = \alpha_{0} - \alpha_{1} + (\alpha_{2} - \alpha_{3}) X_{2} + \mathcal{E}
\end{cases}$$

$$\begin{cases}
Y_{1} = \beta_{0} + \beta_{2} X_{2} + \mathcal{E} \\
Y_{2} = \alpha_{0} - \alpha_{1} + (\alpha_{2} - \alpha_{3}) X_{2} + \mathcal{E}
\end{cases}$$

$$\begin{cases}
\beta_{0} = \alpha_{0} - \alpha_{1} \\
\beta_{1} = 2\alpha_{1} \\
\beta_{2} = \alpha_{2} - \alpha_{3}
\end{cases}$$

$$\begin{cases}
\beta_{1} = 2\alpha_{1} \\
\beta_{2} = \alpha_{2} - \alpha_{3} \\
\beta_{3} = 2\alpha_{3}
\end{cases}$$

# Q2:

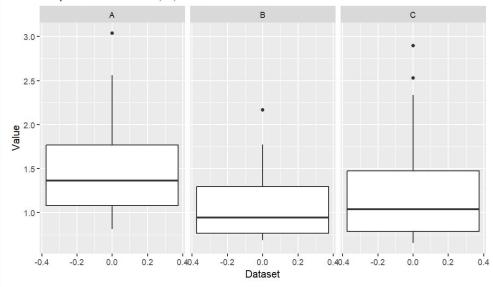


```
fr}
df_A <- data.frame(Value = A)
df_B <- data.frame(Value = B)
df_C <- data.frame(Value = C)

combined_df <- rbind(df_A, df_B, df_C)
combined_df$Dataset <- rep(c("A", "B", "C"), each = nrow(df_A))|

ggplot(combined_df, aes(y = Value)) +
  geom_boxplot() +
  facet_wrap(~ Dataset, nrow = 1) +
  xlab("Dataset") + ylab("Value") +
  ggtitle("Boxplots of Datasets A, B, and C")</pre>
```

#### Boxplots of Datasets A, B, and C



```
t.test(B, A , alternative = "less")
t.test(B, C , alternative = "less")
```

#### Welch Two Sample t-test

```
data: B and A
t = -3.0511, df = 32.651, p-value = 0.002252
alternative hypothesis: true difference in means is less than 0
95 percent confidence interval:
        -Inf -0.218792
sample estimates:
mean of x mean of y
1.062995 1.554498
```

#### Welch Two Sample t-test

#### As a result:

According to the above figure and t-test, B Manager performs better than A Manger. But B Manager and C Manager do not have significant difference.

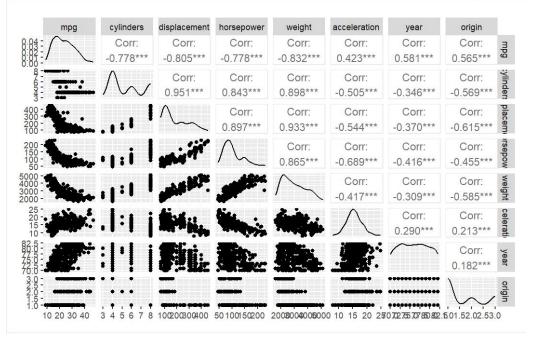
# Q3:

## Q3.1:

```
```{r, eval = F}
# check if you have ISLR package, if not, instal
if(!requireNamespace('ISLR')) install.packages('ISLR')
  auto_data <- ISLR::Auto
Explore the data, with particular focus on pairwise plots and summary statistics. Briefly summarize your findings and any peculiarities in the data.
dim(auto_data)
names(auto_data)
str(auto_data)
sum(is.na(auto_data))
summary(auto_data)
  [1] 392 9
[1] "mpg"
[8] "origin"
'data.frame':
   "cylinders"
  "displacement" "horsepower"
  "weight"
   "acceleration" "year'
                                 "cylinders" "displacement" "horsepower" "weight" "acceleration" "year"
"name"

392 obs. of 9 variables:
: num 18 15 18 16 17 15 14 14 14 15 ...
: num 8 8 8 8 8 8 8 8 8 ...
t: num 307 350 318 304 302 429 454 440 455 390 ...
: num 130 165 150 150 140 198 220 215 225 190 ...
: num 3504 3693 3436 3433 3449 ...
in: num 12 11.5 11 12 10.5 10 9 8.5 10 8.5 ...
: num 70 70 70 70 70 70 70 70 70 70 ...
: num 1 1 1 1 1 1 1 1 1 1 ...
: Factor w/ 304 levels "amc ambassador brougham",..: 49 36 231 14 161 141 54 223 241 2 ...
    $ mpg :
$ cylinders :
$ displacement:
$ horsepower :
    $ weight
    $ acceleration:
$ year :
$ origin :
    $ name
  [1] 0
                                      cylinders
Min. :3.000
1st Qu.:4.000
Median :4.000
Mean :5.472
   displacement
Min. : 68.0
1st Qu.:105.0
Median :151.0
Mean :194.4
   year
Min. :70.00
1st Qu.:73.00
Median :76.00
Mean :75.98
    mpg
Min. : 9.00
   horsepower
  weight
  acceleration
  horsepower
Min. : 46.0
1st Qu.: 75.0
Median : 93.5
Mean :104.5
  Min.
   :1613
   Min.
  : 8.00
    1st Qu.:17.00
Median :22.75
Mean :23.45
  1st Qu.:2225
Median :2804
Mean :2978
  1st Qu.:13.78
Median :15.50
Mean :15.54
    3rd Qu.:29.00
                                       3rd Qu.:8.000
  3rd Ou.: 275.8
   3rd Qu.:126.0
  3rd Qu.: 3615
   3rd Ou.:17.02
  3rd Qu.: 79.00
                  :46.60
  :8.000
   :455.0
            origin
  name
    Min. :1.000
1st Qu.:1.000
Median :1.000
                                       amc matador
                                       ford pinto
toyota corolla
                                       amc gremlin :
amc hornet :
chevrolet chevette:
    Mean
                   :1.577
    3rd Qu.:2.000
Max. :3.000
                                       (Other)
```

```
auto_data %>%
select_if(is.numeric) %>%
ggpairs(progress =FALSE)
```



```
```{r}
auto_data %>%
  select_if(is.numeric) %>%
  cor()
                   mpg cylinders displacement horsepower weight acceleration year origin 1.0000000 -0.7776175 -0.8051269 -0.7784268 -0.8322442 0.4233285 0.5805410 0.5652088 -0.7776175 1.0000000 0.9508233 0.8429834 0.8975273 -0.5046834 -0.3456474 -0.5689316
 mpg
 cylinders
                  -0.7776175 1.0000000
                                                                                               -0.5438005 -0.3698552 -0.6145351
-0.6891955 -0.4163615 -0.4551715
 displacement -0.8051269 0.9508233
                                                  1.0000000 0.8972570 0.9329944
 0.8972570 1.0000000 0.8645377
                                                                                               -0.4168392 -0.3091199 -0.5850054
1.0000000 0.2903161 0.2127458
                                                 0.9329944 0.8645377 1.0000000
                                                 -0.5438005 -0.6891955 -0.4168392
 year
                   0.5805410 -0.3456474
                                                 -0.3698552 -0.4163615 -0.3091199
                                                                                                 0.2903161 1.0000000 0.1815277
                                                                                                 0.2127458 0.1815277 1.0000000
 origin
                   0.5652088 -0.5689316
                                                 -0.6145351 -0.4551715 -0.5850054
```{r}
ggplot(data = auto_data %>% select_if(is.numeric) %>% cor() %>% reshape2::melt(),
aes(x = Var1 ,y = Var2, fill = value)) +
geom_tile(color="white", size=0.1) +
xlab("") +
ylab("") +
guides(fill = guide_legend(data.crdle = "Correlation")) +
scale_fill_gradient( low = "#56B1F7", high = "#132B43") +
theme(axis.text.x = element_text(angle = 25, hjust = 1))
              origin -
              year-
       acceleration -
   value
   -0.5
             weight-
   0.0
       horsepower -
   0.5
   1.0
      displacement -
          cylinders -
               mpa
                               cylinders
                                      displacement
  weight
  acceleration
  horsepower
   origin
  Veal
```

#### Q3.2:

```
```{r}
Q3_2_1 <- lm(mpg~year,auto_data)
summary(Q3_2_1)
 Call:
 lm(formula = mpg ~ year, data = auto_data)
 Residuals:
     Min
               1Q Median
                                 3Q
                                        Max
 -12.0212 -5.4411 -0.4412 4.9739 18.2088
 Coefficients:
             Estimate Std. Error t value Pr(>|t|)
 (Intercept) -70.01167
                        6.64516 -10.54 <2e-16 ***
                         0.08736 14.08 <2e-16 ***
              1.23004
 year
 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
 Residual standard error: 6.363 on 390 degrees of freedom
 Multiple R-squared: 0.337, Adjusted R-squared: 0.3353
 F-statistic: 198.3 on 1 and 390 DF, p-value: < 2.2e-16
p-value < 0.05, year is a significant variable at the .05 level.
When year increases 1 unit, mpg will increase 1.230 units.
ii:
```{r}
Q3_2_2 <- lm(mpg~year+horsepower,auto_data)
summary(Q3_2_2)
 Ca11:
 lm(formula = mpg ~ year + horsepower, data = auto_data)
 Residuals:
                                   3Q
     Min
                1Q
                    Median
   Max
 -12.0768 -3.0783 -0.4308 2.5884 15.3153
 Coefficients:
               Estimate Std. Error t value Pr(>|t|)
 (Intercept) -12.739166 5.349027 -2.382 0.0177 * year 0.657268 0.066262 9.919 <2e-16 **
  <2e-16 ***
                         0.006341 -20.761
            -0.131654
   <2e-16 ***
 horsepower
 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
 Residual standard error: 4.388 on 389 degrees of freedom
 Multiple R-squared: 0.6855, Adjusted R-squared: 0.6839
 F-statistic: 423.9 on 2 and 389 DF, p-value: < 2.2e-16
p-value < 0.05, year is a significant variable at the .05 level.
When year increases 1 unit, mpg will increase 0.657 units.
```

### iii:

When adding another parameter to the original model, it will affect the significance of the other original parameters on the results.

#### iv:

```
```{r}
Q3_2_4 <- lm(mpg~year*horsepower,auto_data)
summary(Q3_2_4)
 lm(formula = mpg ~ year * horsepower, data = auto_data)
Residuals:
      Min
                10 Median
                                     3Q
                                              Max
 -12.3492 -2.4509 -0.4557 2.4056 14.4437
 Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
 (Intercept)
                  -1.266e+02 1.212e+01 -10.449 <2e-16 ***
year 2.192e+00 1.613e-01 13.585 <2e-16 ***
horsepower 1.046e+00 1.154e-01 9.063 <2e-16 ***
year:horsepower -1.596e-02 1.562e-03 -10.217 <2e-16 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '1
Residual standard error: 3.901 on 388 degrees of freedom
Multiple R-squared: 0.7522,
                                  Adjusted R-squared: 0.7503
 F-statistic: 392.5 on 3 and 388 DF, p-value: < 2.2e-16
p-value < 0.05, the interaction effect is a significant variable at the .05 level.
```

### Q3.3:

```
Q3_3_1 <- lm(mpg ~ horsepower + cylinders, ISLR::Auto)
summary(Q3_3_1)
 Call:
 lm(formula = mpg ~ horsepower + cylinders, data = ISLR::Auto)
 Residuals:
 Min 1Q Median 3Q Max
-11.4378 -3.2422 -0.3721 2.3532 16.9289
 Coefficients:
 horsepower -0.08612
cylinders -1.91982
 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
 Residual standard error: 4.584 on 389 degrees of freedom
 Multiple R-squared: 0.6569, Adjusted R-squared: 0.6
F-statistic: 372.4 on 2 and 389 DF, p-value: < 2.2e-16
                                     Adjusted R-squared: 0.6551
p-value < 0.01, the cylinders is a significant variable at the 0.01 level.
When cylinders increases 1 unit, mpg will decrease 1.920 units.
But we know that cylinders and mpg are positively related, so the model has some problems.
ii:
Q3_3_2 <-lm(mpg ~ horsepower + as.factor(cylinders), ISLR::Auto)
summary(Q3_3_2)
 lm(formula = mpg ~ horsepower + as.factor(cylinders), data = ISLR::Auto)
 Residuals:
 Min 1Q Median 3Q Max
-9.5917 -2.7067 -0.6102 1.9001 16.3258
 Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
                          30.77614 2.41283 12.755 < 2e-16 ***
-0.10303 0.01133 -9.095 < 2e-16 ***
 (Intercept)
 horsepower
                                       2.16921 3.030 0.00261 **
3.26661 1.553 0.12120
 as.factor(cylinders)4 6.57344
as.factor(cylinders)5 5.07367
 as.factor(cylinders)6 -0.34406
                                       2.18580 -0.157 0.87501
 as.factor(cylinders)8 0.49738
                                        2.27639
                                                  0.218 0.82716
 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
 Residual standard error: 4.27 on 386 degrees of freedom
 Multiple R-squared: 0.7046, Adjusted R-squared: 0.7
F-statistic: 184.1 on 5 and 386 DF, p-value: < 2.2e-16
                                   Adjusted R-squared: 0.7008
Only for category 4, p-value < 0.01, the cylinders is a significant variable at the 0.01 level. For category 5, 6, 8, the cylinders is not a significant variable at the 0.01 level.
Cylinder 4 cars have average 6.573 units higher mpg than cylinder 3 cars do.
```

```
{r}
anova(Q3_3_1, Q3_3_2)
                                                                                                                                                                                                            ⊕ ∡ ▶
 Analysis of Variance Table
Model 1: mpg ~ horsepower + cylinders
Model 2: mpg ~ horsepower + as.factor(cylinders)
Res.Df RSS Df Sum of Sq F Pr(>F)
1 389 8172.5
2 386 7036.7 3 1135.8 20.769 1.705e-12 ***
 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Based on this ANOVA table, it seems that treating cylinders as a factor variable provides a significantly better model fit compared to treating it as a numeric variable.

The fundamental difference between treating "cylinders" as a numeric or a factor representation of the variable.

The choice between treating "cylinders" as numeric or factor depends on the nature of the variable and the specific requirements

of your analysis.

If the number of cylinders has inherent numerical meaning, treating it as numeric is appropriate.

However, if the cylinder counts represent distinct categories without an ordering pattern, treating it as a factor variable is more appropriate.

# Q4:

```
```{r} crime <- read.csv("CrimeData_sub.csv", stringsAsFactors = F, na.strings = c("?")) crime <- na.omit(crime) crime
  Description: df [368 x 103]
         state
                              population
  household.size
   race.pctblack
  race.pctwhite
   race.pctasian
  race.pcthisp
                              10.132971
         CA
   2.89
  21.34
  49.42
  17.21
  26.78
         CA
                               12.100929
   2.62
  1.30
   14.14
  74.02
  20.96
         CA
                               10.182520
   3 34
   18 97
  53.60
  20.84
  10.73
                               9.681843
  1.42
   13.79
  83.94
   2.40
         FL
   2.63
         CA
                               11.392948
   2.70
  2 92
  87 36
  2.82
  13 97
                               9.389490
   2.71
  88.57
         CA
  0.24
  1.11
  17.04
         CA
                               10.056337
   4.17
  7 95
  82 42
  1 36
  19.55
   2.37
  0.94
         CA
                               10.172293
  91.30
  6.07
   6.46
         CA
                               10.050657
   2.09
  0.70
  95 77
  1.74
   6.86
   10
                              10.372616
  91.28
  5.46
   5.40
        CA
   2.20
  1.70
  1-10 of 368 rows | 1-9 of 103 columns
  3 4
  37 Next
```

```
| The property of the property
```

```
```{r}
crime[crime==0] <- NA
sapply(crime, function(x) sum(is.na(x)))
                                                                                               population
                   household, size
                                                        race.pctblack
                                                                                           race.pctwhite
                                                         race.pcthisp
                    race.pctasian
                                                                                            age.pct12to21
                    age.pct12to29
                                                        age.pct16to24
                                                                                              age.pct65up
                         num.urban
                                                            pct.urban
                                                                                               med.income
                                 51
                                                                    51
                     pct.wage.inc
                                                     pct.farmself.inc
                                                                                              pct.inv.inc
                   pct.socsec.inc
                                                      pct.pubasst.inc
                                                                                               pct.retire
                   med.family.inc
                                                           percap.inc
                                                                                             white.percap
                                                        indian.percap
                     black.percap
                                                                                             asian.percap
```

```
med.owncost.as.pct.hhinc.womort
                                                     num.in.shelters
                                                                                           num.homeless
                                                                                       pct.samehouse1985
                                                  pct.born.samestate
                  pct.foreignborn
                                                   pct.samestate1985
                                                                                       land.area
                 pct.samecity1985
                                               0
pct.use.publictransit
                       pop.density
                                                                                     pct.police.drugunits
             violentcrimes.perpop
crime$pct.police.drugunits <- NULL
crime$num.homeless <- NULL
crime$num.in.shelters <- NULL
crime$pct.urban <- NULL
crime$num.urban <- NULL</pre>
crime[is.na(crime)] <- 0</pre>
```

#### Q4.1:

```
```{r}
set.seed(123)
split \leftarrow sample(c(rep(0, 0.8 * nrow(crime)), rep(1, 0.2 * nrow(crime))))
train_data <- crime[split == 0, ]
test_data <- crime[split == 1, ]</pre>
```{r}
model_train_q4_1 <- lm(train_data$violentcrimes.perpop~., data= train_data)
summary(model_train_q4_1)
fitrain <- summary(model_train_q4_1)
 Call:
 lm(formula = train_data$violentcrimes.perpop ~ ., data = train_data)
 Residuals:
     Min
               1Q Median
                                 3Q
                                          Max
 -892.66 -156.81 -11.97 146.13 1023.96
 Coefficients:
                                       Estimate Std. Error t value Pr(>|t|)
                                      6.685e+03 1.515e+04 0.441 0.65945
2.123e+02 2.552e+02 0.832 0.40638
 (Intercept)
 stateFL
                                     -7.305e+00 8.056e+00 -0.907 0.36561
 fold
                                     -5.805e+02 3.487e+02 -1.665 0.09760
 population
 household.size
                                     -2.354e+02 4.531e+02 -0.519 0.60404
                                     2.960e+01 9.642e+00 3.070 0.00244 **
 race.pctblack
 race.pctwhite
                                     3.052e+00 7.453e+00 0.409 0.68266
 race.pctasian
                                     -6.340e+00 1.253e+01 -0.506 0.61344
                                    -1.133e+01 9.620e+00 -1.178 0.24033

5.403e+01 5.209e+01 1.037 0.30090

-3.943e+01 3.910e+01 -1.008 0.31451

3.681e+00 6.153e+01 0.060 0.95236

5.933e+01 2.881e+01 2.059 0.04078 *
 race.pcthisp
 age.pct12to21
 age.pct12to29
 age.pct16to24
 age.pct65up
med.income
                                     -1.480e-02 2.012e-02 -0.736 0.46290
                                     1.943e+01 2.000e+01 0.972 0.33235
 pct.wage.inc
```

```
```{r}
model_test_q4_1 = predict(model_train_q4_1, test_data)
summary(model_test_q4_1)
   Min. 1st Qu. Median
                           Mean 3rd Qu.
   Max.
                         888.7 1128.4 2843.8
 -424.9
         441.1 824.6
···{r}
cat("Training RMSE:", mean(fitrain$residuals^2), "\n")
cat("Training R-squared:", mean(fitrain$residuals^2), "\n")
cat("Testing RMSE:", RMSE(model_test_q4_1, test_data$violentcrimes.perpop), "\n")
cat("Testing R-squared:", R2(model_test_q4_1, test_data$violentcrimes.perpop), "\n")
Training RMSE: 70752.12
Training R-squared: 70752.12
Testing RMSE: 463.0018
Testing R-squared: 0.6056186
```

#### 04.2:

```
i:
X.train <- model.matrix(violentcrimes.perpop~., data=train_data)
Y.train <- train_data$violentcrimes.perpop</pre>
[r]
matrix.crimes <- data.frame(CRIMES = Y.train, X.train)</pre>
 fit.lasso.cv <- cv.glmnet(X.train, Y.train, alpha=1, nfolds=5, lambda = 10^seq(-3,0,length=100))
 names(fit.lasso.cv)
  [1] "lambda" "cvm" "cvsd" [10] "lambda.min" "lambda.1se" "index"
   "glmnet.fit"
   "cvup"
  "cvlo"
   "nzero"
  "ca11"
  "name"
coef.min <- coef(fit.lasso.cv, s="lambda.min")
coef.min <- coef.min[which(coef.min !=0),]</pre>
 var.min <- rownames(as.matrix(coef.min))</pre>
 var.min[2]='state'
 lm.input <- as.formula(paste("violentcrimes.perpop", "~", paste(var.min[-1], collapse = "+")))</pre>
 lm.input
  violentcrimes.perpop ~ state + fold + population + household.size +
          race.pctblack + race.pctwhite + race.pcthisp + age.pct12to21 + age.pct12to29 + age.pct6Sup + med.income + pct.wage.inc + pct.inv.inc + pct.pubasst.inc + pct.retire + white.percap + black.percap + indian.percap + asian.percap + other.percap +
          hisp.percap + pct.pop.underpov + pct.less9thgrade + pct.not.hsgrad +
          pct.bs.ormore + pct.unemployed + pct.employed + pct.employed.manuf +
pct.occup.manuf + male.pct.divorce + male.pct.nvrmarried +
female.pct.divorce + ave.people.per.fam + pct.fam2parents +
          pct.kids2parents + pct.teens2parents + pct.worknom + pct.kids.nvrmarried + num.immig + pct.immig.recent + pct.immig.recent8 + pct.pop.immig8 + pct.english.only + pct.no.english.well + ave.people.per.rented.hh + pct.people.ownoccup.hh + pct.people.dense.hh + pct.hh.less3br +
          med.num.br + num.vacant.house + pct.house.occup + pct.house.vacant +
pct.house.vacant.6moplus + med.yr.house.built + pct.house.nophone +
pct.house.no.plumb + value.ownoccup.house.lowquart + value.ownoccup.med +
          value.ownoccup.highquart + rent.lowquart + rent.highquart +
med.rent + med.rent.aspct.hhinc + med.owncost.aspct.hhinc.wmort +
med.owncost.as.pct.hhinc.womort + pct.foreignborn + pct.born.samestate +
pct.samehouse1985 + pct.samecity1985 + pct.samestate1985 +
           land.area + pop.density + pct.use.publictransit
```

#### ii:

```
fr}
fit.min.lm <- lm(lm.input, data=train_data)
lm.output <- coef(fit.min.lm)
model_q4_2_2 = summary(fit.min.lm)

{r}
test_q4_2_2 = predict(fit.min.lm,test_data)

{r}
cat("Training RMSE:", mean(model_q4_2_2$residuals^2), "\n")
cat("Training R-squared:", mean(model_q4_2_2$residuals^2), "\n")
cat("Testing RMSE:", RMSE(test_q4_2_2, test_data$violentcrimes.perpop), "\n")
cat("Testing R-squared:", R2(test_q4_2_2, test_data$violentcrimes.perpop), "\n")
Training RMSE: 74413.41
Training R-squared: 74413.41
Testing RMSE: 442.6142
Testing R-squared: 0.6268232</pre>
```

#### iii:

```
my_model = as.data.frame(summary(fit.min.lm)$coefficients)
var = rownames(my_model[my_model$'Pr(>|t|)'<0.05,])
lm.input <- as.formula(paste("violentcrimes.perpop", "~", paste(var, collapse = "+")))

violentcrimes.perpop ~ race.pctblack + age.pct12to21 + pct.pubasst.inc +
    indian.percap + pct.less9thgrade + pct.not.hsgrad + male.pct.nvrmarried +
    pct.kids2parents + pct.pop.immig8 + pct.no.english.well +
    pct.people.ownoccup.hh + pct.house.nophone + med.owncost.as.pct.hhinc.womort +
    land.area</pre>
```

#### iv:

```
fit.min.lm <- lm(lm.input, data=train_data)
lm.output <- coef(fit.min.lm)
model_q4_2_4 = summary(fit.min.lm)

fr}
test_q4_2_4 = predict(fit.min.lm, test_data)

{r}
cat("Training RMSE:", mean(model_q4_2_4$residuals^2), "\n")
cat("Training R-squared:", mean(model_q4_2_4$r.squared), "\n")
cat("Testing RMSE:", RMSE(test_q4_2_4, test_data$violentcrimes.perpop), "\n")
cat("Testing R-squared:", R2(test_q4_2_4, test_data$violentcrimes.perpop), "\n")</pre>
```

Training RMSE: 70752.12 Training R-squared: 0.8340532 Testing RMSE: 463.0018 Testing R-squared: 0.6056186