W271 - Homework 4

Lei Yang, Ron Cordell, Subhashini Raghunathan

Feb 25, 2016

The Data

The file athletics.RData contains a two-year panel of data on 59 universities. Some variables relate to admissions, while others related to atheletic performance. You will use this dataset to investigate whether athletic success causes more students to apply to a university.

This data was made available by Wooldridge, and collected by Patrick Tulloch, then an economics student at MSU. It may have been further modified to test your proficiency. Sources are as follows:

1. Peterson's Guide to Four Year Colleges*, 1994 and 1995 (24th and 25th editions). Princeton University Press. Princeton, NJ.
2. The Official 1995 College Basketball Records Book*, 1994, NCAA.
3. 1995 Information Please Sports Almanac (6th edition)*. Houghton Mifflin. New York, NY.

```
# load packages
knitr::opts_chunk$set(echo = TRUE)
library(car)
library(ggplot2)
library(lattice)
library(car)
library(lmtest)
library(sandwich)
# set work dir, clear workspace, load data, show description
setwd("~/Desktop/W271Data")
rm(list=ls())
```

Question 1:

Examine and summarize the dataset. Note that the actual data is found in the data object, while descriptions can be found in the desc object. How many observations and variables are there?

```
load('athletics.Rdata')
desc
```

```
##    variable                          label
## 1      year                   1992 or 1993
## 2      apps        # applics for admission
## 3     top25  perc frsh class in 25 hs perc
## 4    ver500 perc frsh >= 500 on verbal SAT
## 5    mth500   perc frsh >= 500 on math SAT
## 6    stufac          student-faculty ratio
## 7      bowl    = 1 if bowl game in prev yr
## 8    btitle  = 1 if men's cnf chmps prv yr
```

```
## 9   finfour    = 1 if men's final 4 prv yr
## 10    lapps                      log(apps)
## 11   avg500              (ver500+mth500)/2
## 12   school             name of university
## 13    bball        =1 if btitle or finfour
```

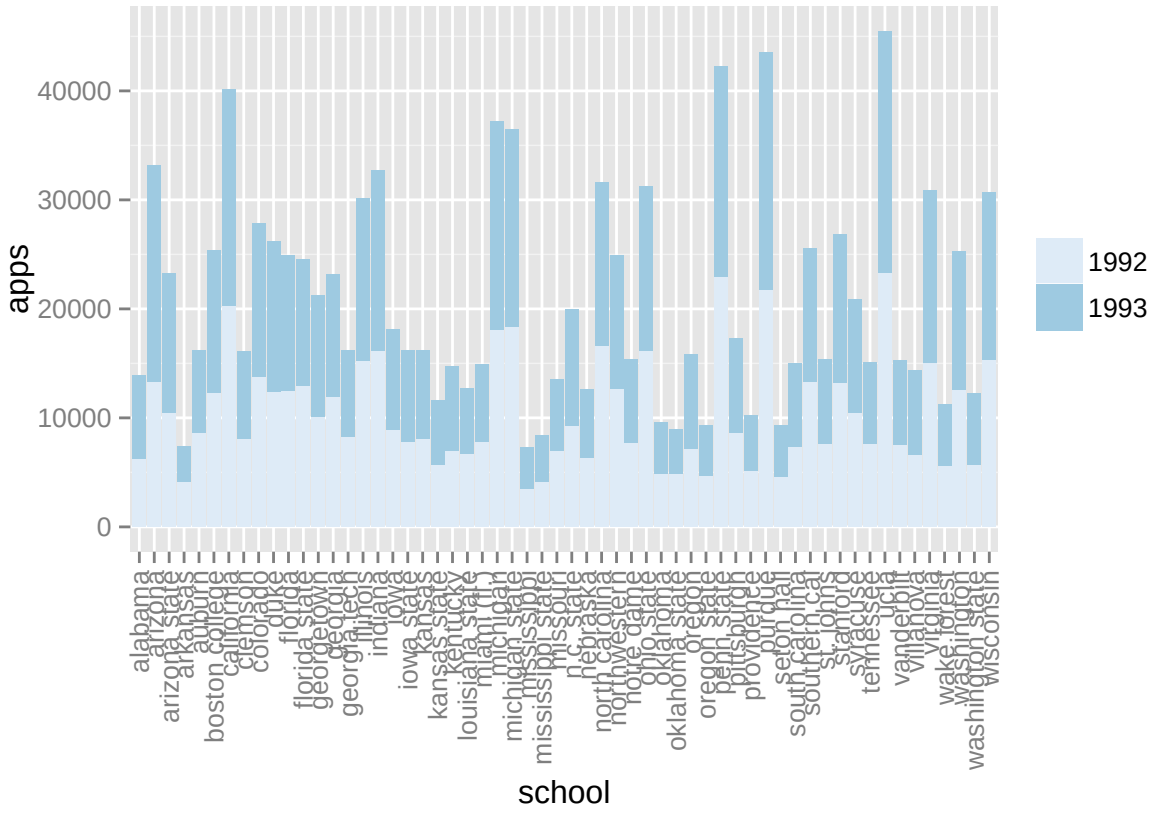
```
str(data)
```

```
## 'data.frame':    116 obs. of  14 variables:
##  $ year   : int  1992 1993 1992 1993 1992 1993 1992 1993 1992 1993 ...
##  $ apps   : int  6245 7677 13327 19860 10422 12809 4103 3303 8661 7548 ...
##  $ top25  : int  49 58 57 57 37 49 60 67 54 54 ...
##  $ ver500 : int  NA NA 36 36 28 31 NA NA 46 51 ...
##  $ mth500 : int  NA NA 58 58 58 62 NA NA 86 83 ...
##  $ stufac : int  20 15 16 16 20 14 16 18 16 16 ...
##  $ bowl   : int  1 1 0 1 0 0 1 0 0 0 ...
##  $ btitle : int  0 0 0 1 0 0 1 0 0 0 ...
##  $ finfour: int  0 0 0 0 0 0 0 0 0 0 ...
##  $ lapps  : num  8.74 8.95 9.5 9.9 9.25 ...
##  $ avg500 : num  NA NA 47 47 43 46.5 NA NA 66 67 ...
##  $ school : chr  "alabama" "alabama" "arizona" "arizona" ...
##  $ bball  : int  0 0 0 1 0 0 1 0 0 0 ...
##  $ perf   : int  1 1 0 2 0 0 2 0 0 0 ...
```

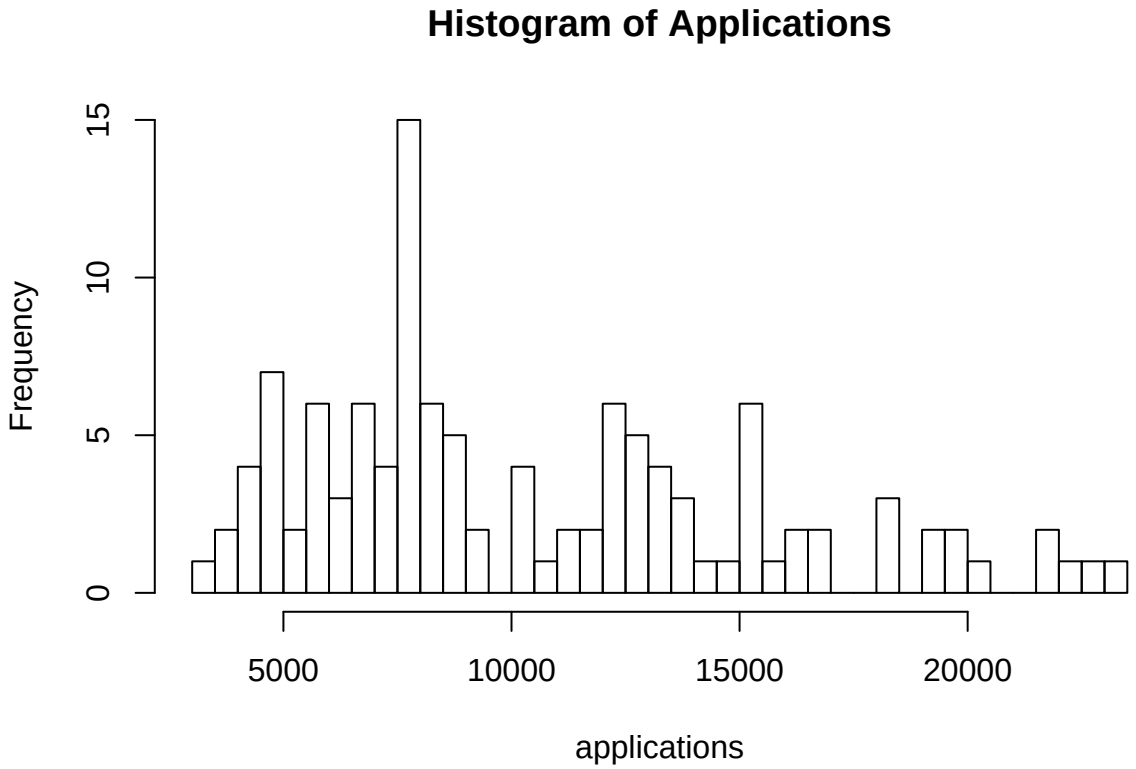
There are `116` observations evenly divided across two years: 1992 and 1993, and `14` variables in the data.

Examine the variables of key interest: apps represents the number of applications for admission. bowl, btitle, and finfour are indicators of athletic success. The three athletic performance variables are all lagged by one year. Intuitively, this is because we expect a school's athletic success in the previous year to affect how many applications it recieves in the current year.

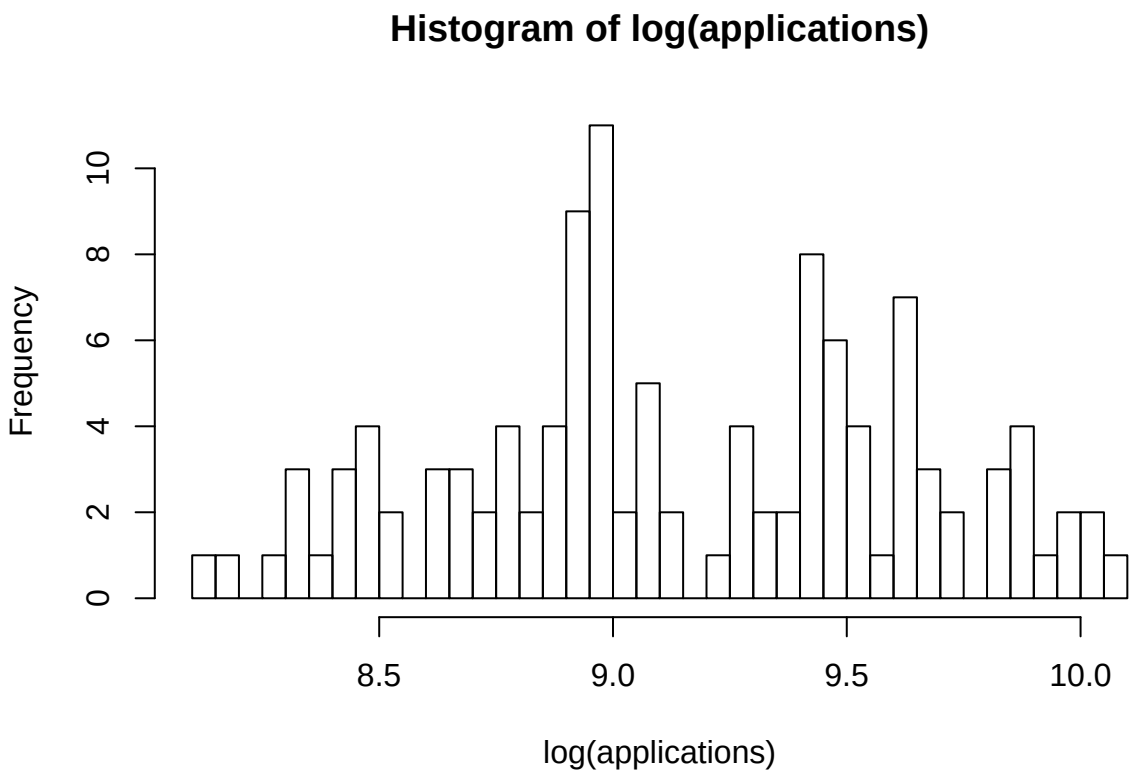
The year column is an integer as opposed to a label or level, so we may need to change that. An examination of the data doesn't reveal anything out of place. A scatterplot of applications by school for both years shows that schools received relatively similar numbers of applications for each year.



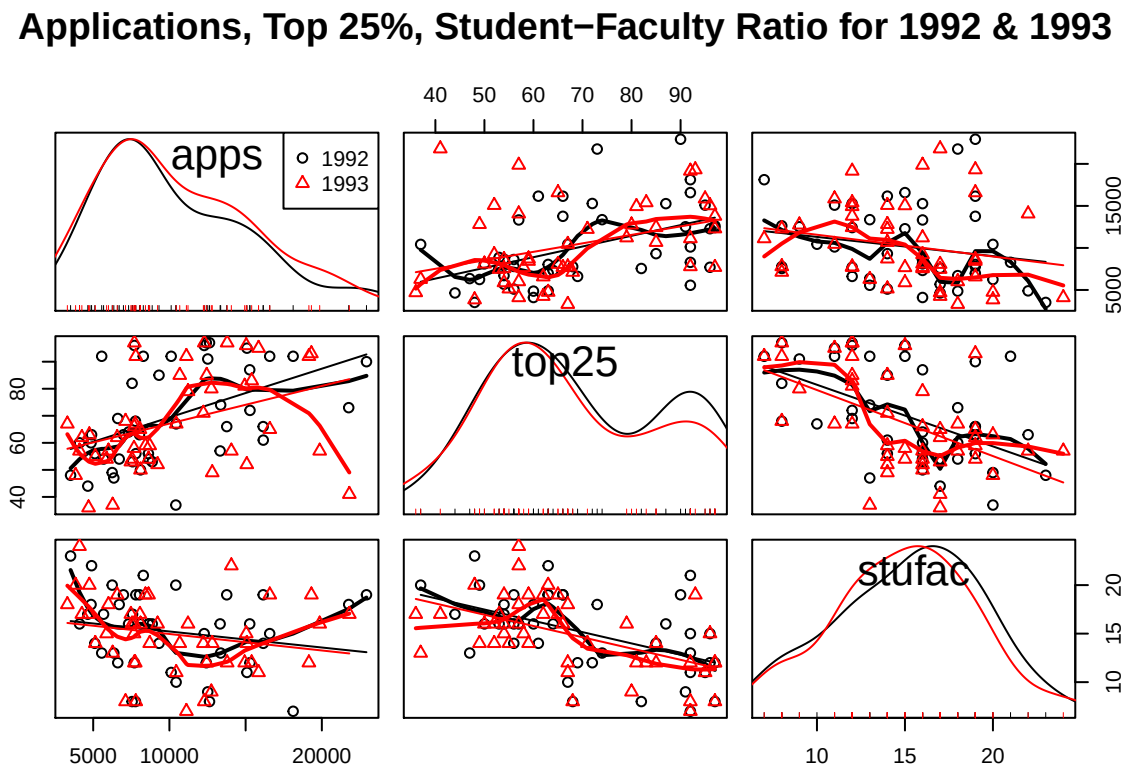
When we examine the histogram of the apps variable we can see that it has a skewed distribution.



Taking a look at the lapps (log(apps)) variable correct the skewness of the applications variable distribution but the distribution almost appears bimodal.



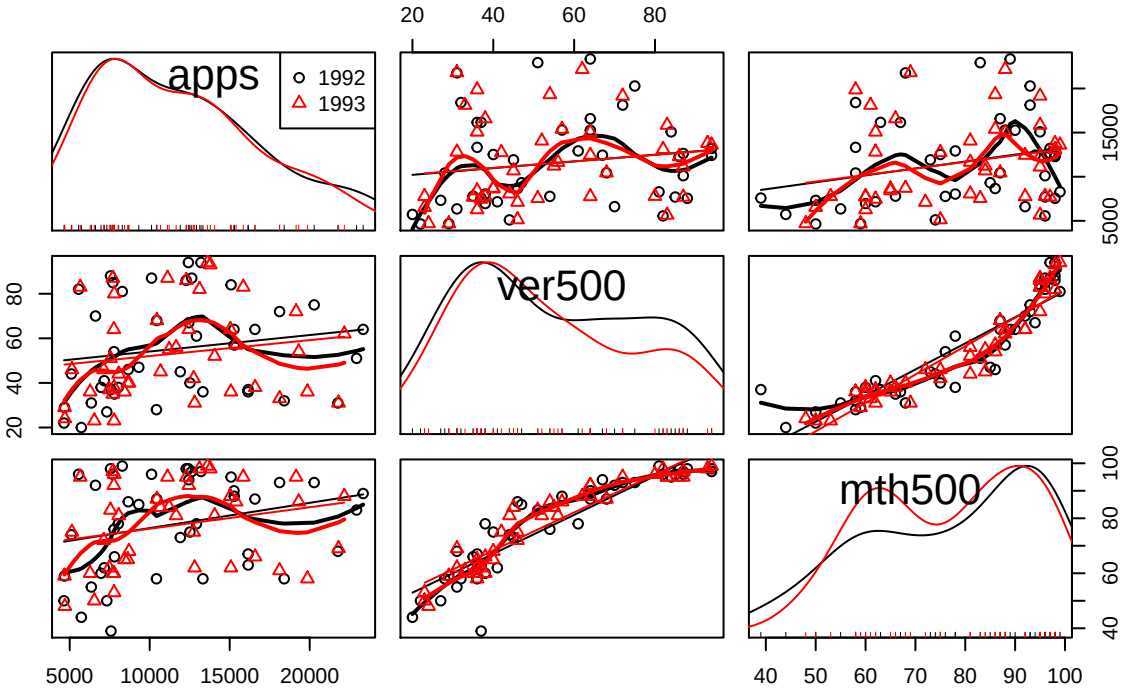
Exploring the Applications a little more we compare the lapps variable to the other continuous variables in the data set using a couple of scatterplot matrices. The first matrix compares applications, top 25% and student faculty ratio grouping by year. There don't appear to be any significant correlations between the variables on visual inspection.



The second matrix compares log(apps) with SAT scores. There is a very strong correlation between the

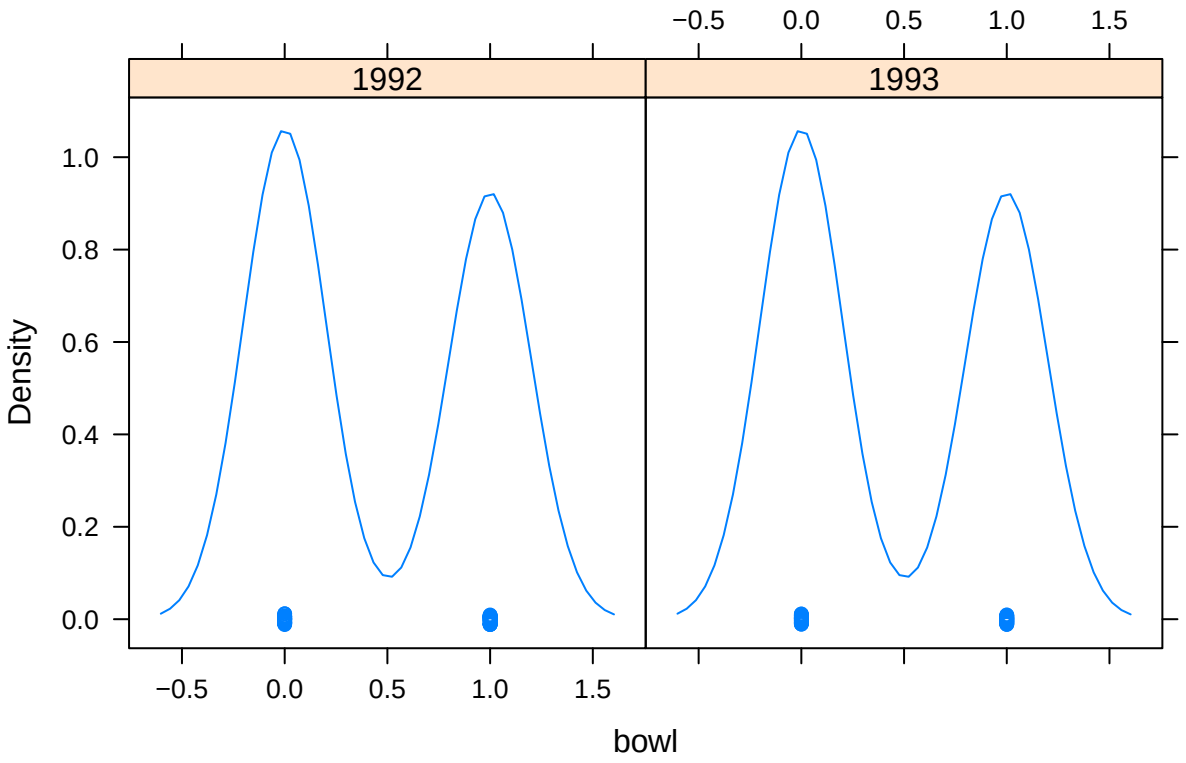
verbal and math SAT scores but neither appears to correlate with the apps variable

Applications, SAT Verbal > 500, SAT Math > 500 for 1992 & 1993

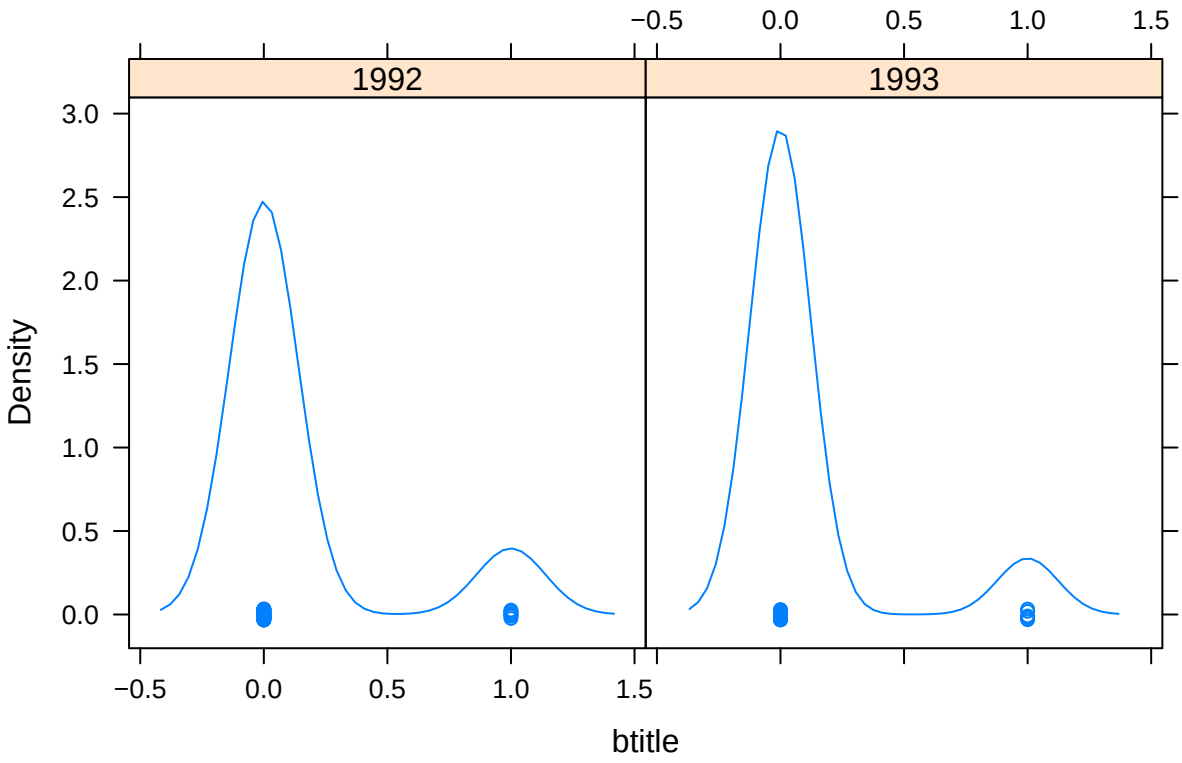


Exploring the athletic univariate data of bowl, btitle and finfour, showing a stats summary and density plot for each by year:

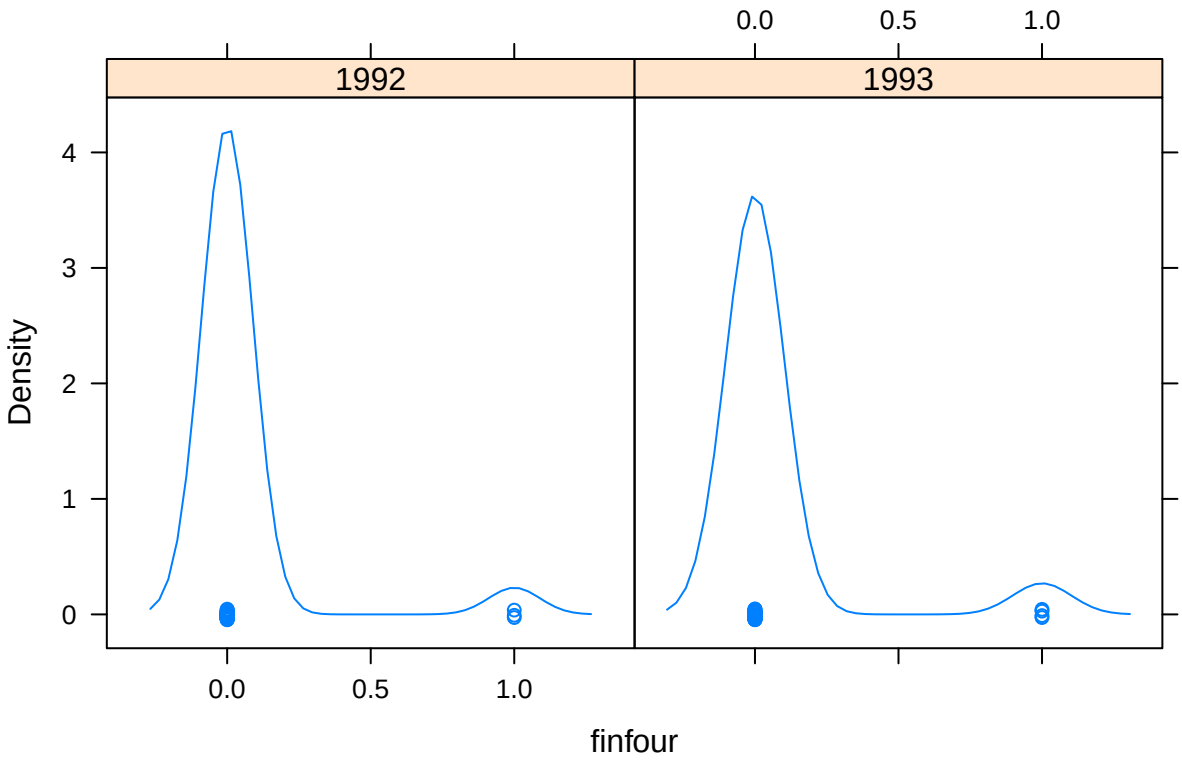
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  0.0000  0.4655  1.0000  1.0000
```



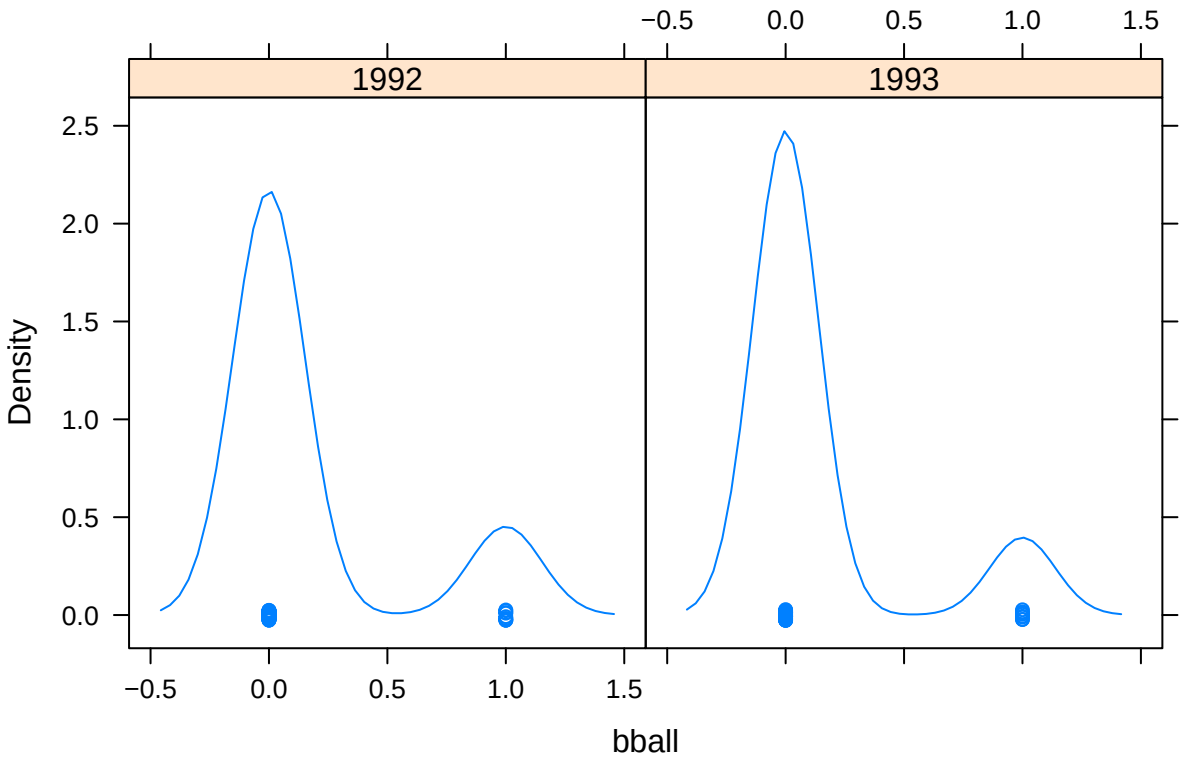

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  0.0000  0.1207  0.0000  1.0000
```



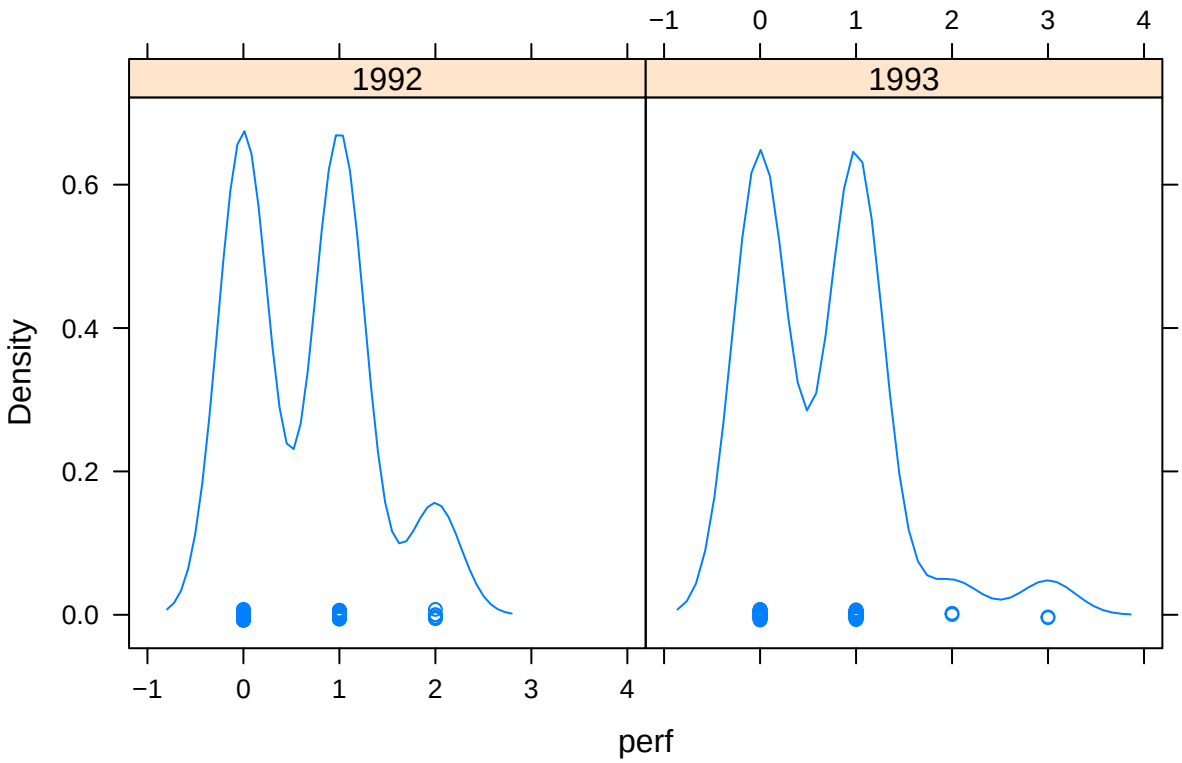

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.00000 0.00000 0.00000 0.06034 0.00000 1.00000
```




```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  0.0000  0.1552  0.0000  1.0000
```




```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  1.0000  0.6466  1.0000  3.0000
```



The bowl athletic success variable appears relatively even across the two years but the btitle and finfour variables are heavily skewed to 1992. This matches the expectation as set out in Question 1 in that previous year's atheletic indicators are more apparent for the current year's applications.

Question 2:

Note that the dataset is in long format, with a separate row for each year for each school. To prepare for a difference-in-difference analysis, transfer the dataset to wide-format. Each school should have a single row of data, with separate variables for 1992 and 1993. For example, you should have an apps.1992 variable and an apps.1993 variable to record the number of applications in either year.

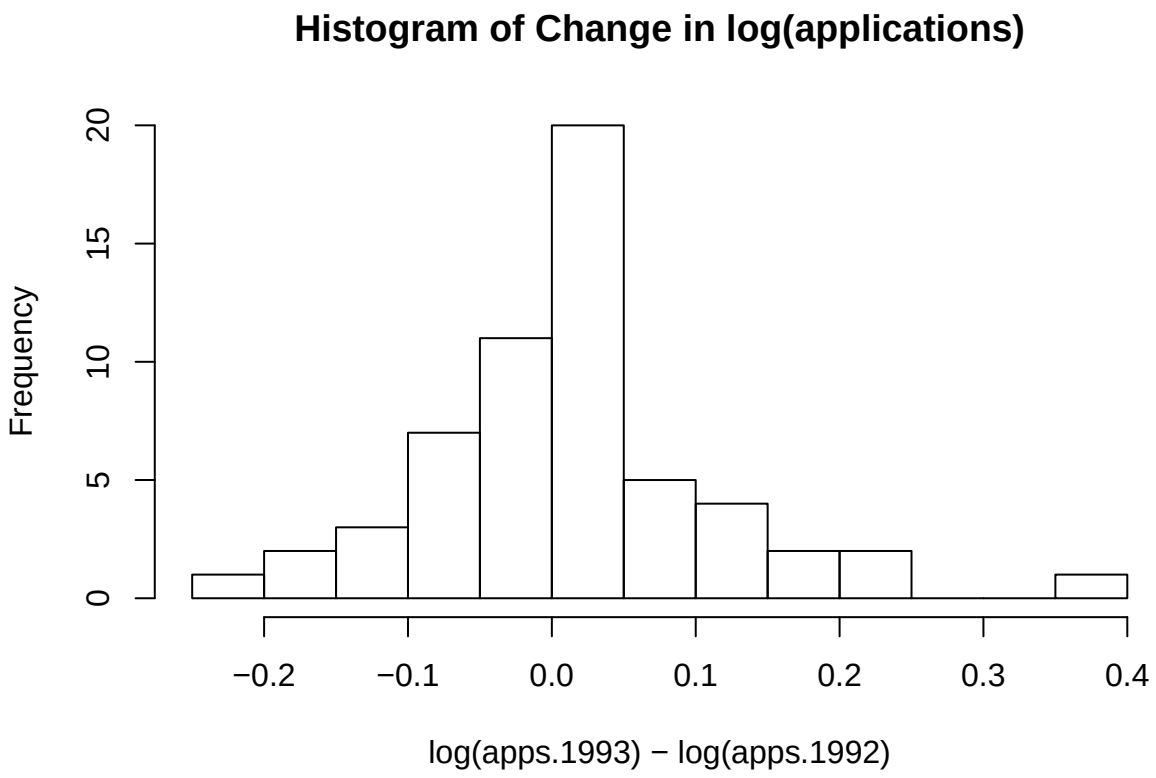
```
# create wideData variable for wide format on year
wideData <- reshape(data, timevar="year", idvar=c("school"), direction="wide")
```

Create a new variable, clapps to represent the change in the log of the number of applications from 1992 to 1993. Examine this variable and its distribution. Which schools had the greatest increase and the greatest decrease in number of log applications?

```
# create clapps variable
wideData$clapps<-log(wideData$apps.1993) - log(wideData$apps.1992)
summary(wideData$clapps)
```

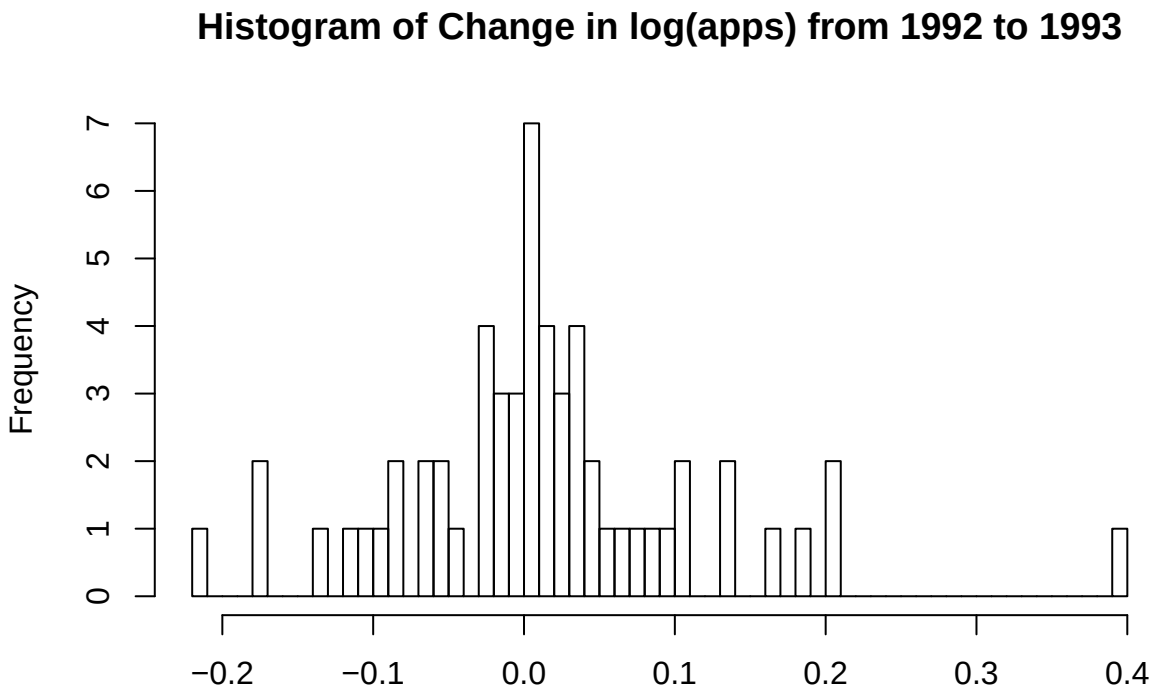
```
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## -0.216900 -0.026630  0.006774  0.014210  0.049490  0.398900
```

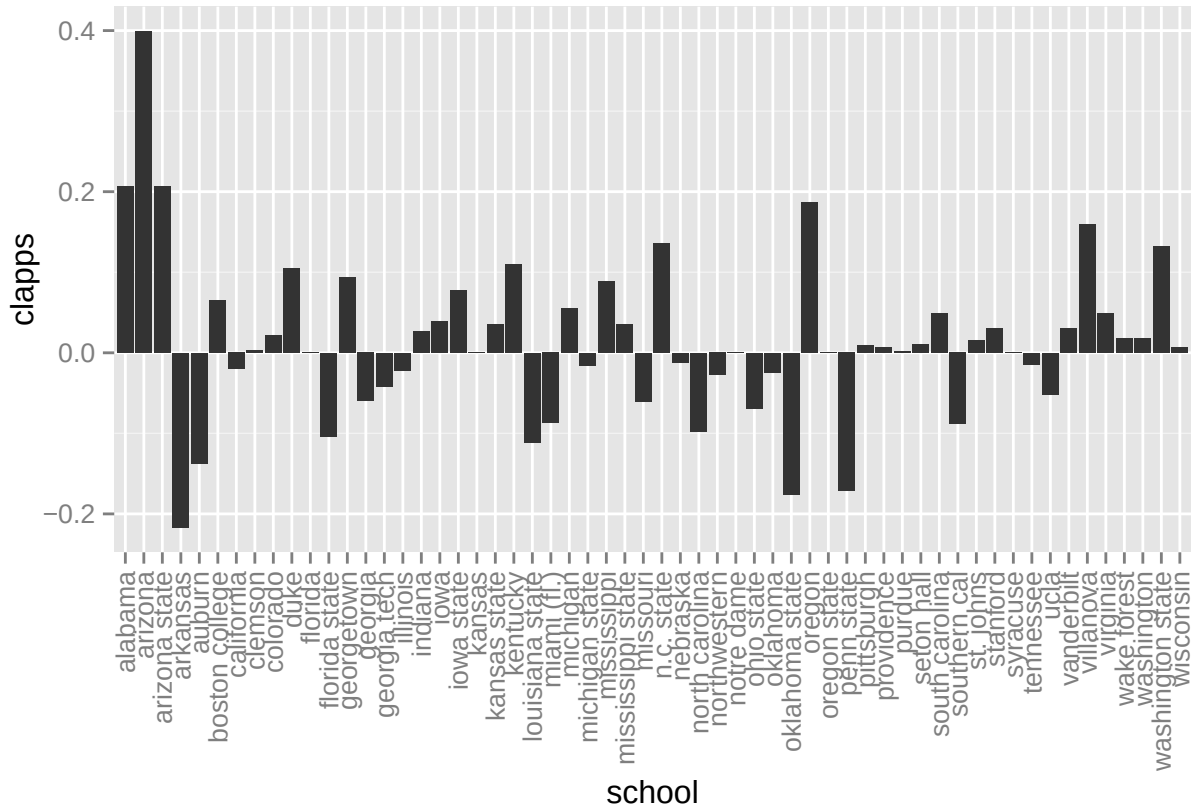
```
# plot histogram
hist(wideData$clapps, breaks=20, main="Histogram of Change in log(applications)",
     xlab="log(apps.1993) - log(apps.1992)")
```




```
# greatest increase
cmax <- max(wideData$clapps)
inc <- wideData[cmax==wideData$clapps, c("school")]
# greatest decrease
cmin <- min(wideData$clapps)
dec <- wideData[cmin==wideData$clapps, c("school")]
```

For the number of applications, **arizona** has the greatest increase of `0.40`, and **arkansas** has the greatest decrease of `-0.22`.


Histogram of Change in log(apps) from 1992 to 1993
Frequency
0
1
2
3
4
5
6
7
−0.2
−0.1
0.0
0.1
0.2
0.3
0.4
Change in log(apps)


clapps
0.4
0.2
0.0
−0.2
alabama
arizona
arizona state
arkansas
auburn
boston college
california
clemson
colorado
duke
florida
florida state
georgetown
georgia
georgia tech
illinois
indiana
iowa
iowa state
kansas
kansas state
kentucky
louisiana state
miami (fl)
michigan
michigan state
mississippi
mississippi state
missouri
n.c. state
nebraska
north carolina
northwestern
notre dame
ohio state
oklahoma
oklahoma state
oregon
oregon state
penn state
pittsburgh
providence
purdue
seton hall
south carolina
southern cal
st. johns
stanford
syracuse
tennessee
ucla
vanderbilt
villanova
virginia
wake forest
washington
washington state
wisconsin
school

Question 3:

**Similarly to above, create three variables, *cperf*, *cbball*, and *cbowl* to represent the changes in the three athletic success variables. Since these variables are lagged by one year, you are actually computing the change in athletic success from 1991 to 1992.

Which of these variables has the highest variance?**

```
#create cperf, cbball, and cbowl
wideData$cperf <- wideData$perf.1993 - wideData$perf.1992
wideData$cbball <- wideData$bball.1993 - wideData$bball.1992
wideData$cbowl <- wideData$bowl.1993 - wideData$bowl.1992
wideData$cbtitle <- wideData$btitle.1993 - wideData$btitle.1992
wideData$cfinfour <- wideData$finfour.1993 - wideData$finfour.1992
```

Summary statistics and variances are calculated as:

```
summary(wideData$cperf)
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -2.00000  0.00000  0.00000 -0.01724  0.00000  3.00000
```

```
summary(wideData$cbball)
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -1.00000  0.00000  0.00000 -0.03448  0.00000  1.00000
```

```
summary(wideData$cbowl)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      -1       0       0       0       0       1
```

```
var(wideData[c('cperf','cbball','cbowl')])
```

```
##            cperf     cbball      cbowl
## cperf  0.8242589 0.28009679 0.42105263
## cbball 0.2800968 0.17422868 0.07017544
## cbowl  0.4210526 0.07017544 0.31578947
```

From the variance calculation on each of the new variables it appears that the *cperf* variable has the highest variance. However, the *cperf* variance is not negatively correlated with the component years like *cbball* and *cbowl*:

```
var(wideData[c('cperf','perf.1992','perf.1993')])
```

```
##                cperf   perf.1992  perf.1993
## cperf      0.8242589 -0.37447066 0.44978826
## perf.1992 -0.3744707  0.44041137 0.06594071
## perf.1993  0.4497883  0.06594071 0.51572898
```

There is a negative covariance between *cbball* and *bball.1992*

```
var(wideData[c('cbball','bball.1992','bball.1993')])
```

```
##                 cbball  bball.1992 bball.1993
## cbball      0.17422868 -0.09921355 0.07501512
## bball.1992 -0.09921355  0.14519056 0.04597701
## bball.1993  0.07501512  0.04597701 0.12099214
```

There is a negative covariance between *cbowl* and *bowl.1992*:

```
var(wideData[c('cbowl','bowl.1992','bowl.1993')])
```

```
##                cbowl   bowl.1992  bowl.1993
## cbowl      0.3157895 -0.15789474 0.15789474
## bowl.1992 -0.1578947  0.25317604 0.09528131
## bowl.1993  0.1578947  0.09528131 0.25317604
```

Question 4:

We are interested in a population model,

$$lapps_i = \gamma_0 + \beta_0 I_{1993} + \beta_1 bowl_i + \beta_2 btitle_i + \beta_3 finfour_i + a_i + u_{it}$$

Here, I_{1993} is an indicator variable for the year 1993. a_i is the time-constant effect of school i. u_{it} is the idiosyncratic effect of school i at time t. The athletic success indicators are all lagged by one year as discussed above.

At this point, we assume that (1) all data points are independent random draws from this population model (2) there is no perfect multicollinearity (3) $E(a_i) = E(u_{it}) = 0$

You will estimate the first-difference equation,

$$clapps_i = \beta_0 + \beta_1 cbowl_i + \beta_2 cbtitle_i + \beta_3 finfour_i + a_i + cu_i$$

where $cu_i = u_{i1993} - u_{i1992}$ is the change in the idiosyncratic term from 1992 to 1993.

a) - What additional assumption is needed for this population model to be causal? Write this in mathematical notation and also explain it intuitively in English.

The difference equation contains the a_i term should be removed by taking the differences between the equation

The additional assumption for causality is

$$cov(\Delta u, \Delta \mathbf{X_i}) = 0$$

or stated differently:

$$E(\Delta u_i \mid cbowl, cbtitle, cfinfour) = 0$$

There must be no correlation between the residual error term and any of the random variables. If there is correlation between Δu and $\Delta \mathbf{X_i}$ then there will be bias in the estimators.

In addition, the assignment of predictor variables should be random, this is equivalent to conducting a randomized experiment to collect the data.

b) - What additional assumption is needed for OLS to consistently estimate the first-difference model? Write this in mathematical notation and also explain it intuitively in English. Comment on whether this assumption is plausible in this setting.

The additional assumption of OLS to consistently estimate the first difference model is there must be some variance in the random variables across the time periods.

$$var(\Delta \mathbf{X}_i) > 0)$$

And to reduce bias, the change in the idiosyncratic terms at any different time should not be correlated with the change in sports performance. Mathematically:

$$cov(\Delta u, \Delta \mathbf{X_i}) = 0$$

Question 5:

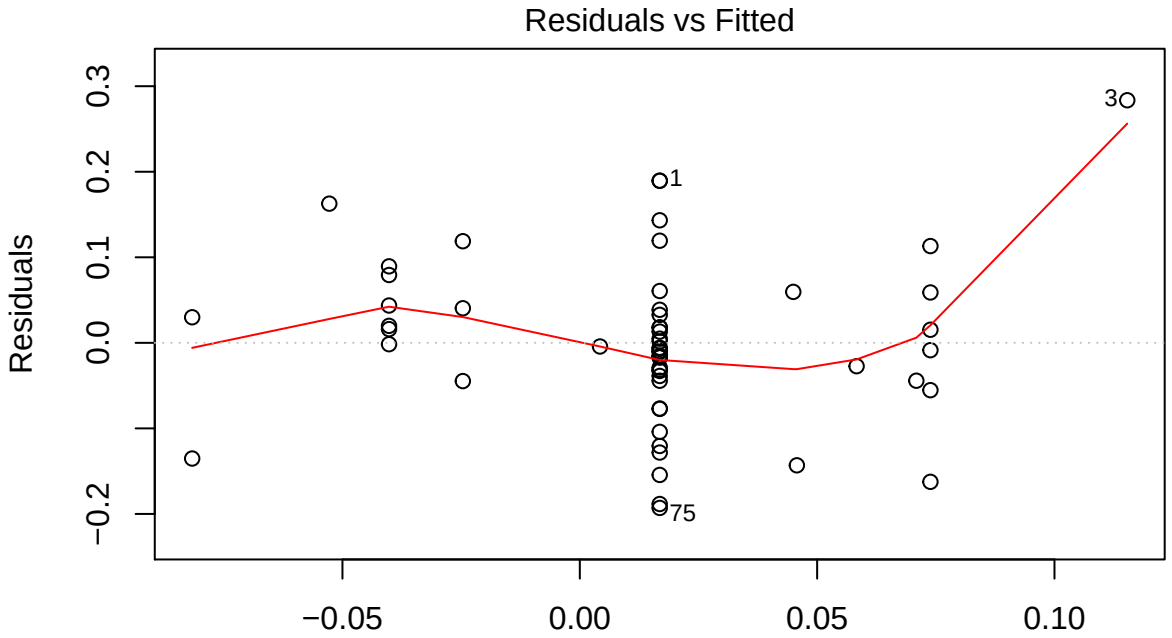
Estimate the first-difference model given above. Using the best practices descibed in class, interpret the slope coefficients and comment on their statistical significance and practical significance.

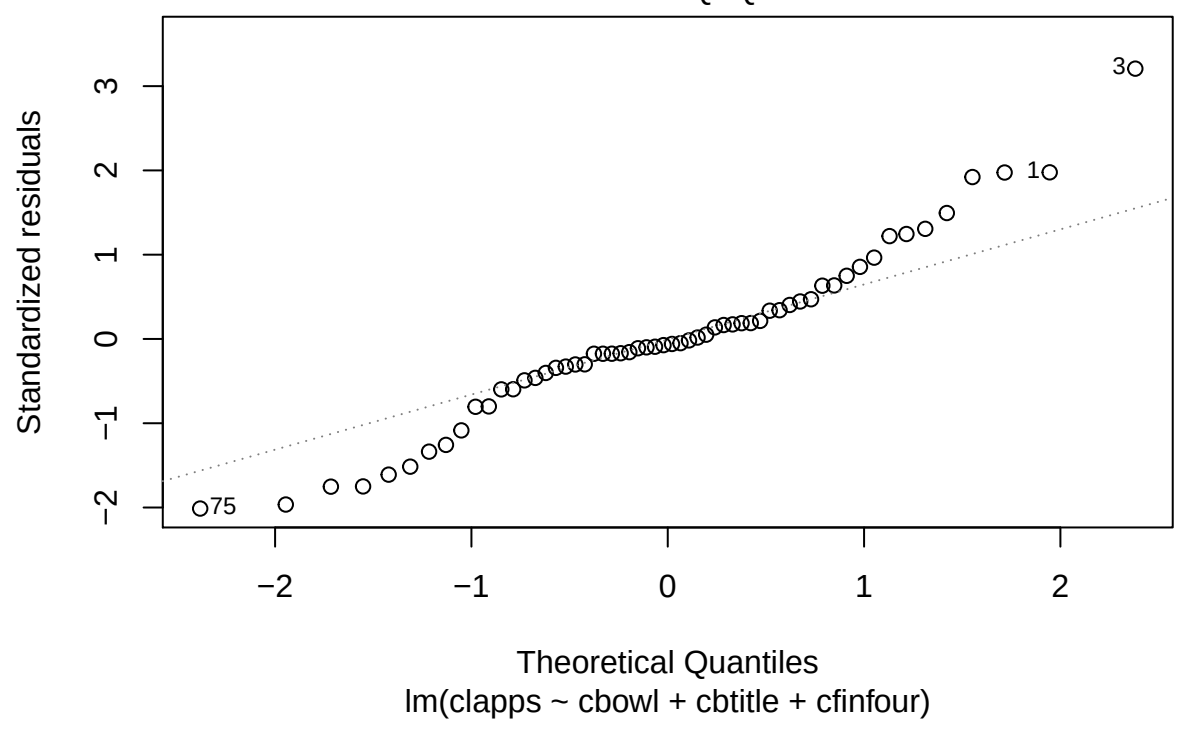
```
# fit first-difference equation
m5 <- lm(clapps ~ cbowl+cbtitle+cfinfour, data=wideData)
summary(m5)
```

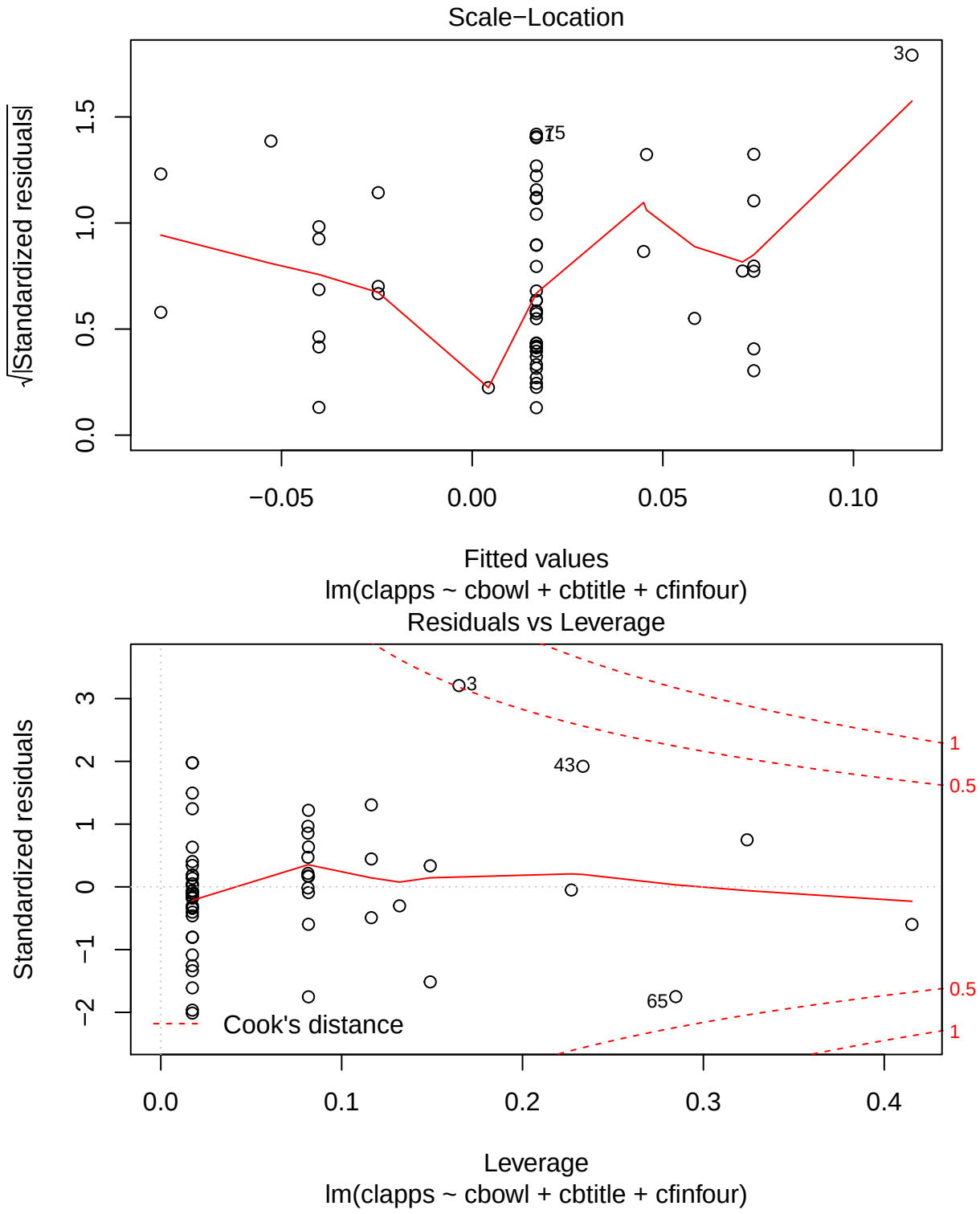
```
##
## Call:
## lm(formula = clapps ~ cbowl + cbtitle + cfinfour, data = wideData)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.192965 -0.042868 -0.006367  0.040005  0.283577
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.01684    0.01278   1.318   0.1932
## cbowl        0.05702    0.02448   2.329   0.0236 *
## cbtitle      0.04148    0.03161   1.312   0.1950
## cfinfour    -0.06961    0.04585  -1.518   0.1348
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.09674 on 54 degrees of freedom
## Multiple R-squared:  0.1428, Adjusted R-squared:  0.09513
## F-statistic: 2.998 on 3 and 54 DF,  p-value: 0.03855
```

From the coefficients, the improvement in bowl game has statistically significant impact on application number, which will increase **5.70%** if a school has played in a bowl game the previous year while hasn't in the year before. Meanwhile, earning a men's conference title can also increase application by **4.15%**, but the effect is not statistically significant. Finally the model suggests that being in Final Four would actually decrease the application by **-6.96%**, this is clearly unreasonable and further model diagnostic is needed to evaluate the validity of the model.

```r
# model diagnostic
plot(m5)
```







it seems the model has violation in both zero-conditional mean and homoskedasticity. From the fitted value plot, there ar a lot of points having the same prediction, this may be an indication that we don't have a good variation in the predictors of our data. In addition, school #3 (**arizona**) has the number of an outlier. Let's remove this data point and refit our model again:

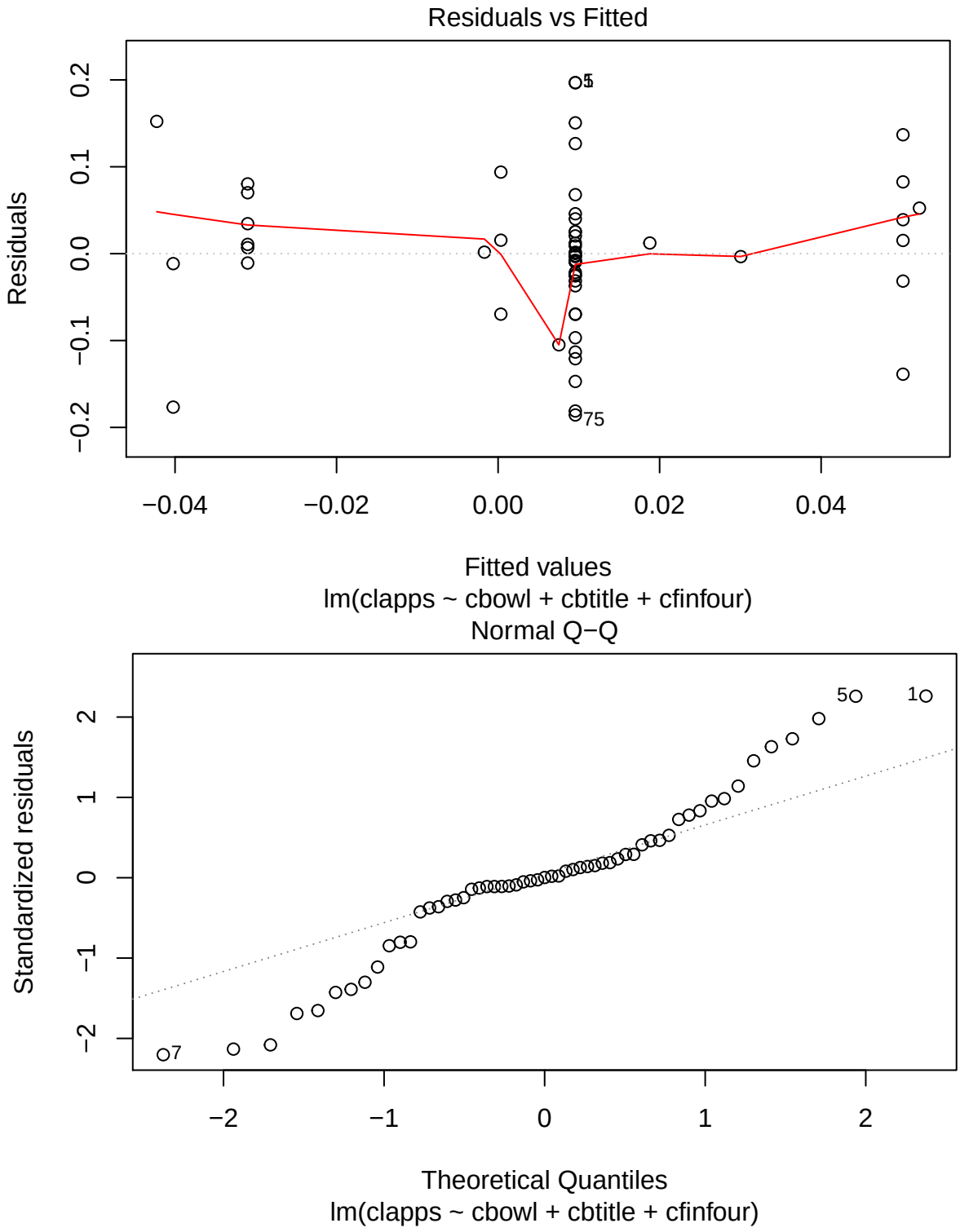
```r
wideData2 <- wideData[wideData$school != "arizona",]
m5.2 <- lm(clapps ~ cbowl+cbtitle+cfinfour, data=wideData2)
summary(m5.2)
```

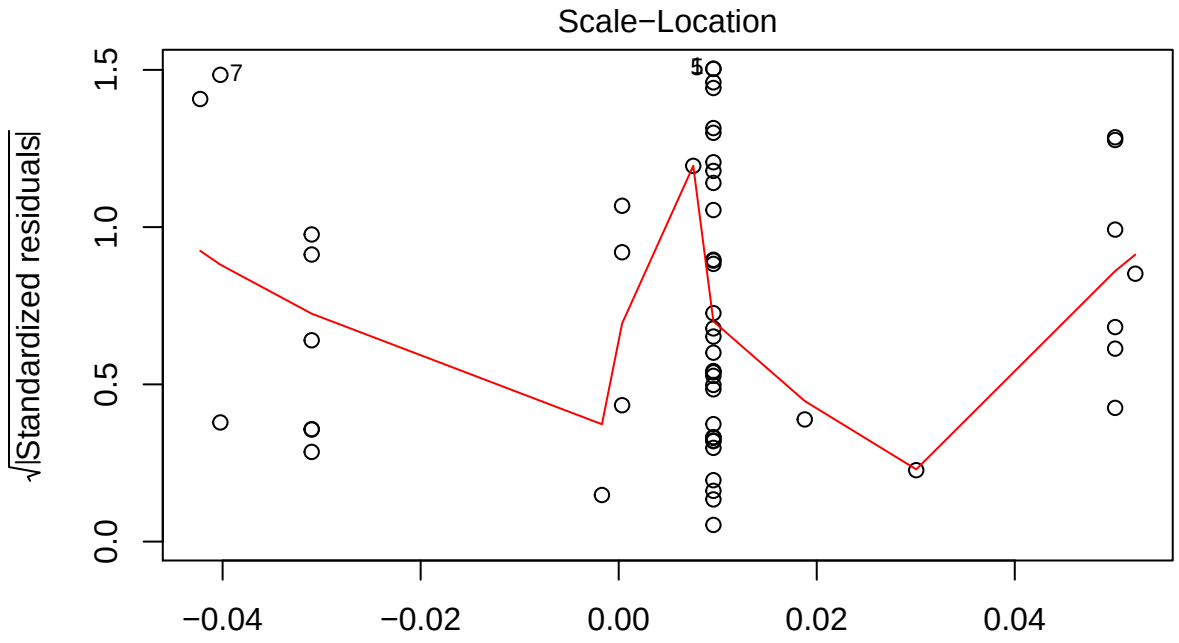
```
##
## Call:
## lm(formula = clapps ~ cbowl + cbtitle + cfinfour, data = wideData2)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.185692 -0.031415  0.000244  0.039051  0.196882
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.009566   0.011787   0.812   0.4207
## cbowl        0.040573   0.022717   1.786   0.0798 .
## cbtitle      0.009223   0.030122   0.306   0.7607
## cfinfour    -0.051833   0.041939  -1.236   0.2219
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.08785 on 53 degrees of freedom
## Multiple R-squared:  0.06801,    Adjusted R-squared:  0.01526
## F-statistic: 1.289 on 3 and 53 DF,  p-value: 0.2876
```

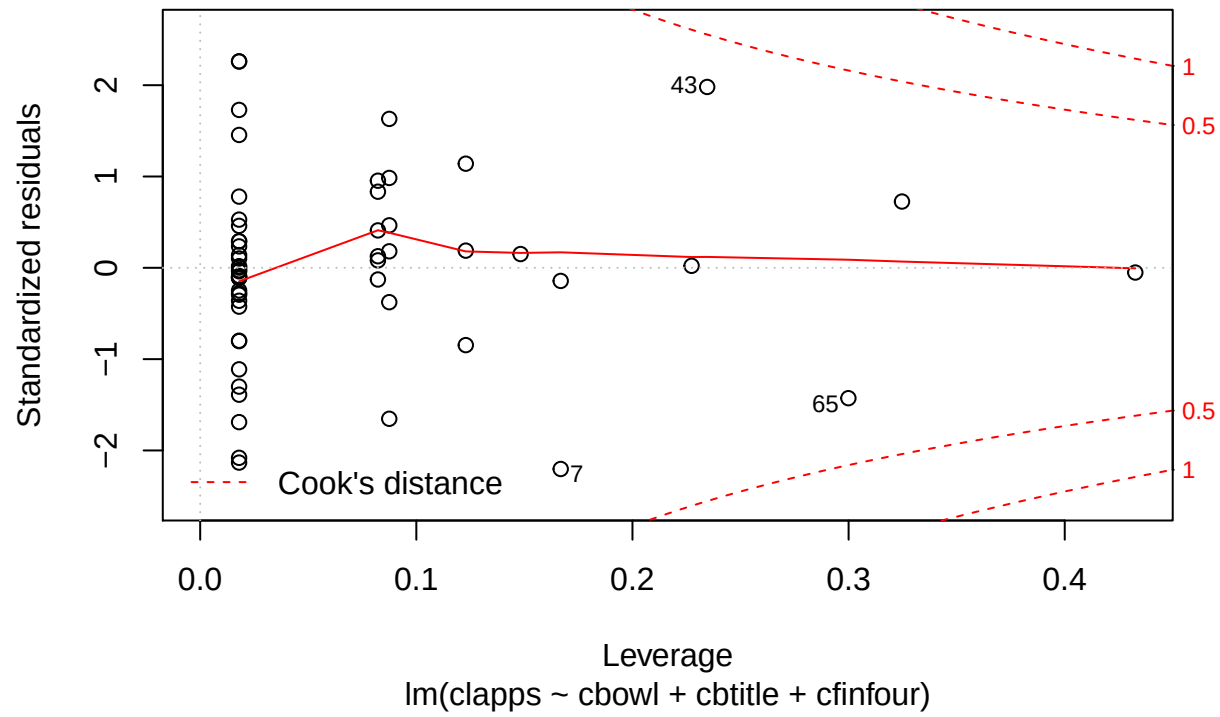
we can see that after removing this outlier, all three coefficients are not significant anymore. From data we can see the application of **arizona** has increased from 13327 to 19860 (**4.9%**), which coincidentally happened with a bowl game appearance. In addition, the impact of conference title becomes much smaller in the new model.

And there is no significant improvement in the zero-condition mean and heteraskadasticity assumptions from the diagnostic plots below.

```r
plot(m5.2)
```


Residuals vs Fitted
Residuals
0.2
0.1
0.0
−0.1
−0.2
−0.04
−0.02
0.00
0.02
0.04
75
Fitted values
lm(clapps ~ cbowl + cbtitle + cfinfour)
Normal Q−Q
Standardized residuals
2
1
0
−1
−2
5
1
7
−2
−1
0
1
2
Theoretical Quantiles
lm(clapps ~ cbowl + cbtitle + cfinfour)





Finally, we check the joint hypothesis that : $H_0 : \beta_2, \beta_3 = 0$ using the F test between the unrestricted model RSS and the restricted model RSS.

```
m5.r <- lm(clapps ~ cbowl, data=wideData)
rss.r = sum(residuals(m5.r)^2)
rss.ur = sum(residuals(m5)^2)
```

```r
linearHypothesis(m5, c("cbtitle","cfinfour"), vcov=vcovHC)
```

```
## Linear hypothesis test
##
## Hypothesis:
## cbtitle = 0
## cfinfour = 0
##
## Model 1: restricted model
## Model 2: clapps ~ cbowl + cbtitle + cfinfour
##
## Note: Coefficient covariance matrix supplied.
##
##   Res.Df Df      F Pr(>F)
## 1     56
## 2     54  2 0.9207 0.4044
```

We can't reject the null hypothesis that β_2 and β_3 are statistically different than 0.

Question 6:

Test the joint signifance of the three indicator variables. This is the test of the overall model. What impact does the result have on your conclusions?

```r
waldtest(m5, test='F', vcov=vcovHC)
```

```
## Wald test
##
## Model 1: clapps ~ cbowl + cbtitle + cfinfour
## Model 2: clapps ~ 1
##   Res.Df Df      F Pr(>F)
## 1     54
## 2     57 -3 1.4717 0.2325
```

The result is consistent with previous conclusions that the overall changes in sports performance do not have significant impact on the change in school application.