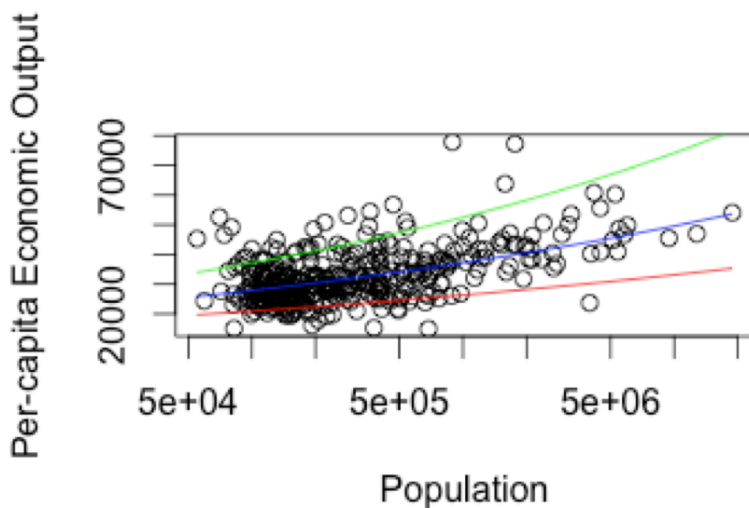


```

---
title: "HW 4"
author: "Autumn Li and UNI ql2280"
date: "Oct 25, 2016"
output: html_document
---
```{r}
gmp <- read.table("~/Desktop/2016 fall/5206/hw4/gmp.txt", header=TRUE, quote="\")
gmp$pop <- round(gmp$gmp/gmp$pcgmp)
names(gmp)
plot(gmppop, gmppcgmp, log = "x", xlab = "Population", ylab = "Per-capita Economic Output")
beta_0 = 6611
beta_1 = 1/8
curve(6611*x^{1/8}, add = TRUE, col = "blue")
curve(6611*x^{0.1}, add = TRUE, col = "red")
curve(6611*x^{0.15}, add = TRUE, col = "green")
```

```



ii. Write a function called `mse()` which calculates the mean squared error if the model on a given dataset.

```

```{r}
v = c(6611, 0.15)
x = gmp$pop
y = gmp$pcgmp
mse1 <- function(v, x=gmp$pop, y=gmp$pcgmp) {
 value = sum((y - x^v[2]*v[1])^2)/length(y)
 return(value)
}

mse1(c(6611, 0.15))

```

```
mse1(c(5000, 0.10))
```

```
...
```

```
> mse1(c(6611,0.15))
```

```
[1] 207057513
```

```
> mse1(c(5000, 0.10))
```

```
[1] 298459914
```

iii. R has several built-in functions for optimization which we'll talk about later on in the course.

```
``{r, warning=FALSE}
```

```
nlm(mse1, c(beta0 = 6611, beta1 = 1/8))
```

```
nlm(mse1, c(beta0 = 6611, beta1 = 0.1))
```

```
nlm(mse1, c(beta0 = 6611, beta1 = 0.15))
```

```
nlm(mse1, c(beta0 = 6611, beta1 = 1/8))$estimate
```

```
nlm(mse1, c(beta0 = 6611, beta1 = 0.1))$estimate
```

```
nlm(mse1, c(beta0 = 6611, beta1 = 0.15))$estimate
```

```
> nlm(mse1, c(beta0 = 6611, beta1 = 0.15))$estimate
```

```
[1] 6610.9999997 0.1263182
```

```
minimum represents the value of the estimated minimum of function.
```

```
estimate represents the point at which the minimum value of function is obtained.
```

```
#
```

```
...
```

iv. Using `nlm()` and the `mse()` function you wrote, write a function `plm()` which estimates the parameters  $\beta_0$  and  $\beta_1$  of the model by minimizing the mean squared error.

```
``{r}
```

```
beta0 = 6611
```

```
beta1 = 0.15
```

```
plm = function(beta0,beta1,x=gmp$pop,y=gmp$pcgmp){
```

```
 v1 = c(beta0,beta1)
```

```
 l3 = mse1(v1,x,y)
```

```
 l1 = nlm(mse1, c(beta0, beta1))$estimate[1]
```

```
 l2 = nlm(mse1, c(beta0, beta1))$estimate[2]
```

```
 value1 = list(l1,l2,l3)
```

```
 return(value1)
```

```
}
```

```
plm(6611,0.15)
```

```
plm(5000,0.1)
```

```
> plm(6611,0.15)
```

```
[[1]]
```

```
[1] 6611
```

```
[[2]]
```

```
[1] 0.1263182
```

```
[[3]]
```

```
[1] 207057513
```

```
> plm(5000,0.1)
```

```
[[1]]
```

```
[1] 5000
```

```
[[2]]
```

```
[1] 0.1475913
```

```
[[3]]
```

```
[1] 298459914
```

```
plm(6611,0.15) has smaller MSE
```

```
...
```

#v. Let's practice the bootstrap in a simple example to convince ourselves, again, that it will work.

(a)

```
```{r}
```

```
mean(y)
```

```
sd(y)
```

```
...
```

```
> mean(y)
```

```
[1] 32922.53
```

```
> sd(y)
```

```
[1] 9219.663
```

(b)

```
```{r}
```

```
v3 = c(1:length(y))
```

```
index.mean = function(v3){
```

```
 value3 = mean(y[v3])
```

```
 return(value3)
```

```
}
```

```
index.mean(c(1,5,1,3))
```

```
...
```

(c) Using the function in (b) create a vector bootstrap.means, which has the mean per-capita GMP for one hundred bootstrap samples.

```
```{r}
```

```
dat = y[sample(100)]
```

```
nboot = 100
```

```
bootstrap.mean <- function(dat, nboot) {
```

```
  bootstat <- NULL
```

```
  for(i in 1:nboot) {
```

```
    truemmean <- mean(dat)
```

```
    samp <- sample(nboot, replace = T)
```

```
    samp.mean = index.mean(samp)
```

```
    bootstat[i] = samp.mean
```

```
  }
```

```
  return(bootstat)
```

```

}

bootstrap.mean(dat,nboot)
```

```

(d) Calculate the standard deviation of the bootstrap.means to approximate the standard error from part (a).

```

```{r}
sd(bootstrap.mean(dat,nboot))

> sd(bootstrap.mean(dat,nboot))
[1] 1052.133

```

#Compares to the part a, part d has a larger standard deviation.

```

```{r}
B = 100
plm.bootstrap = function (beta0,beta1,B,x = gmp$pop,y = gmp$pcgmp) {
 est.beta0 = matrix(NA,nrow = B, ncol = 1)
 est.beta1 = matrix(NA,nrow = B, ncol = 1)
 for(b in 1:B)
 {
 resamp <- sample(1:length(y),size = length(y),replace = T)
 y1=y[resamp]
 x1=x[resamp]
 l1 = plm(beta0, beta1, x1, y1)[[1]]
 l2 = plm(beta0, beta1, x1, y1)[[2]]
 est.beta0[b] = l1
 est.beta1[b] = l2
 }
 est.beta = list(c(sd(est.beta0)/sqrt(B),sd(est.beta1)/sqrt(B)))
 return(est.beta)
}
plm.bootstrap(beta0=6611,beta1=0.15,B=100)
plm.bootstrap(5000,0.1,100)

```

```

> plm.bootstrap(beta0=6611,beta1=0.15,B=100)
[[1]]
[1] 0 0

```

```

> plm.bootstrap(5000,0.1,100)
[[1]]
[1] 0 0

```

# To whom it may concern:

#I know the answer should not be 0. The reason is nlm function generates same value dedpite the different sample size. I think my bootstrap function is right as long as my nlm function could fix above problem.

```

vii. The file gmp-2013.txt contains measurements for 2013 (in contrast to measurements from 2006 in gmp.txt).

```{r}

```
gmp.2013 <- read.table("~/Desktop/2016 fall/5206/hw4/gmp-2013.txt", header=TRUE,
quote="\"")
```

```
x2 = gmp$pop
```

```
y2 = gmp.2013$pcgmp
```

```
plm(6611,0.15,x2,y2)
```

```
plm(5000,0.1,x2,y2)
```

```
plm.bootstrap(611,0.15,100)
```

```
plm.bootstrap(5000,0.1,100)
```

```
> plm(6611,0.15,x2,y2)
```

```
[[1]]
```

```
[1] 6611
```

```
[[2]]
```

```
[1] 0.1263182
```

```
[[3]]
```

```
[1] 217878913
```

```
> plm(5000,0.1,x2,y2)
```

```
[[1]]
```

```
[1] 5000
```

```
[[2]]
```

```
[1] 0.1475913
```

```
[[3]]
```

```
[1] 725717454
```

```
[[1]]
```

```
[1] 0 0
```

```
[[1]]
```

```
[1] 0 0
```

# To whom it may concern:

#The answer above is wrong, because the plm function should return different numbers for different sample size from gmp 2013.

# The reason is nlm function generates same value dedpite the different sample size. I think my plm function and plm.boostrap function are right as long as nlm function could fix above problem.

```

