# HW5\_ssoon

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```
# library(quantreg)
# library(quantmod)
# # #1)fetch data from Yahoo
# #AAPL prices
\# apple 08 \leftarrow get Symbols ('AAPL', auto.assign = FALSE, from = '2008-1-1', to = '2008-1-1')
# "2008-12-31")[,6]
# #market proxy
\# rm08 < -getSymbols('^ixic', auto.assign = FALSE, from = '2008-1-1', to = '2008-1-1', to
# "2008-12-31")[,6]
# #log returns of AAPL and market
# logapple08<- na.omit(ROC(apple08)*100)</pre>
# logrm08<-na.omit(ROC(rm08)*100)
\# #OLS for beta estimation
# beta_AAPL_08<-summary(lm(logapple08~logrm08))$coefficients[2,1]</pre>
# #create df from AAPL returns and market returns
# df08<-cbind(logapple08,logrm08)</pre>
# set.seed(666)
# Boot=1000
# sd.boot=rep(0,Boot)
# for(i in 1:Boot){
# # nonparametric bootstrap
# bootdata=df08[sample(nrow(df08), size = 251, replace = TRUE),]
\# sd.boot[i] = coef(summary(lm(AAPL.Adjusted \sim IXIC.Adjusted, data = bootdata)))[2,2]
# sd.boot
```

# Problem 2

#### $\mathbf{a}$

The code uses the wrong variable name while bootstrapping; the linear model should be comparing AAPL.Adjusted~IXIC.Adjusted.

b

```
sensory <- read.delim("https://www2.isye.gatech.edu/~jeffwu/wuhamadabook/data/Sensory.dat",</pre>
                      header = TRUE, sep="\t")
sensory <- sensory[2:nrow(sensory),]</pre>
sensory <- separate(sensory, X, into = c("1", "2", "3", "4", "5", "F"), sep = " ", convert=TRUE)
sensory[!is.na(sensory$F),][1:5] <-sensory[!is.na(sensory$F),][2:6]</pre>
sensory <- sensory[1:5]</pre>
sensory <- melt(sensory)</pre>
## No id variables; using all as measure variables
sensory$variable <- as.numeric(sensory$variable)</pre>
sensory_ops <- split(sensory, sensory$variable)</pre>
boot <- c()
system.time(
 {
c<-1
for(op in sensory_ops){
  bootdata <- c()
  for(i in 1:100){
    bootdata <- c(bootdata, sample(op$value,nrow(op), replace=TRUE))</pre>
    boot <- c(boot, mean(bootdata))</pre>
  print(paste("Estimate for operator", c, ":", mean(boot)))
  c < -c + 1
}
}
)
## [1] "Estimate for operator 1 : 4.55609867956575"
## [1] "Estimate for operator 2 : 4.79179715277645"
## [1] "Estimate for operator 3 : 4.62056940035552"
## [1] "Estimate for operator 4 : 4.77543841712621"
## [1] "Estimate for operator 5 : 4.67538736650596"
      user system elapsed
##
      0.01
              0.00
##
# print("Bootstrap set:")
# boot
```

# Problem 3

#### $\mathbf{a}$

There are 4 roots in the given graph.

My function will return the latex calculated  $x_1$  value if it fails to converge.

```
tol = 1e-5
f <- function(x){</pre>
  if(x > 100){
  x <- as.brob(x)
  return((3^x - \sin(x) + \cos(5*x) + x^2 - 1.5)/(3^x + \log(3) - \cos(x) - \sin(5*x) + 5 + 2*x))
}
df <- function(x){</pre>
}
newton <- function(x0, iter = 0){</pre>
  if(iter >= 100){
   # print(paste("Max number of iterations reached. Current value:", x0))
    return(x0)
  }else{
    x1 < x0- f(x0)
    #if(is.na(x1)){print(paste(x0, iter))}
    if(abs(x1-x0) \le 1e-5){
      return(x1)
    }
    else{
      return(newton(x1, iter+1))
    }
  }
}
newton(0)
## [1] -0.862233
b
```

```
vec <- seq(-3,2.5,by=5.5/999)
system.time(sapply(vec, newton, iter=0))</pre>
```

```
## user system elapsed
## 5.22 0.00 5.38
```

# Problem 4

```
\#a
mse <- function(y,yhat, n){</pre>
      return(sum((y - yhat)^2)/n)
  }
grad <- function(dat, start1, start2, step, tol, it, n, b) {</pre>
  b1 <- start1
  b0 <- start2
  # mse_prev <- 100
  diff <- 100
  i <- 0
  x \leftarrow dat[1]
  y <- dat[2]
  while( i < it) {</pre>
    yhat \leftarrow b1*x + b0
    \#mse1 \leftarrow mse(y, yhat, n)
    b1 \leftarrow b1 - step * sum((yhat - y) * x)/n
    b0 \leftarrow b0 - step * sum(yhat - y)/n
    yhat2 < -b1 * x + b0
    #mse2 <- mse(y,yhat2,n)
    #print(paste(mse1, mse2))
    diff \leftarrow abs(sum((y - yhat)^2)/n - sum((y - yhat2)^2)/n)
    if(!isTRUE(diff) && diff < tol){</pre>
      break
    }
    #print(is.na(diff))
    i<-i+1
  }
  if(b==0){
    return(b0)
  }
  else{
    return(b1)
  }
}
#grad(sensory, 0.05, 4, 1e-7, 1e-9, 1, nrow(sensory))
```

## b

My stopping rule is that the algorithm returns the latest estimates regardless of proximity if either the tolerance threshold is met, or the number of iterations exceed a certain number. If the true values of the parameters were known, then I would stop when the algorithm finds values of b1 and b0 close enough to said values. A potential problem could be that variance within data means that some samples will not fit the true

values well, or that the algorithm finds a local minimum instead of a global minimum. For a guess of inital value, I would use the true values of parameters.

#### $\mathbf{c}$

Using larger step/tolerance to reduce runtime on my laptop

```
mod <- lm(value ~., sensory)</pre>
summary(mod)
##
## Call:
## lm(formula = value ~ ., data = sensory)
## Residuals:
##
      Min
              1Q Median
                            3Q
                                  Max
## -3.861 -1.684 0.048 1.335 4.796
##
## Coefficients:
##
               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 4.81367 0.41170 11.692 <2e-16 ***
## variable
              -0.05233
                           0.12413 -0.422
                                               0.674
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.15 on 148 degrees of freedom
## Multiple R-squared: 0.001199, Adjusted R-squared:
## F-statistic: 0.1777 on 1 and 148 DF, p-value: 0.6739
s<- 1e-7
t <- 1e-9
b0 <- mod$coefficients[1]
b1 <- mod$coefficients[2]
range0 \leftarrow seq(b0 - 1, b0 + 1, length.out=1000)
range1 <- seq(b1 - 1, b1 + 1, length.out=1000)
g <- expand.grid(range0, range1)
cores <- detectCores() - 1</pre>
cores <- max(1, detectCores() - 1)</pre>
cl <- makeCluster(cores)</pre>
map0 <- clusterMap(cl, grad, dat=sensory, range1, range0, step=1e-7, tol=1e-9, it=5e+4, n=nrow(sensory)
map1 <- clusterMap(cl, grad, dat=sensory, range1, range0, step=1e-7, tol=1e-9, it=5e+4, n=nrow(sensory)
stopCluster(cl)
```

```
hat0 <- unlist(map0)
hat1 <- unlist(map1)</pre>
```

### $\mathbf{d}$

From the given plots, it seems that the algorithm did succeed in smoothing the predicted  $\beta$  values to be closer to the true value. This method looks good for approximating the true parameters using an observed sample, though it seems to require quite a bit of computation time.

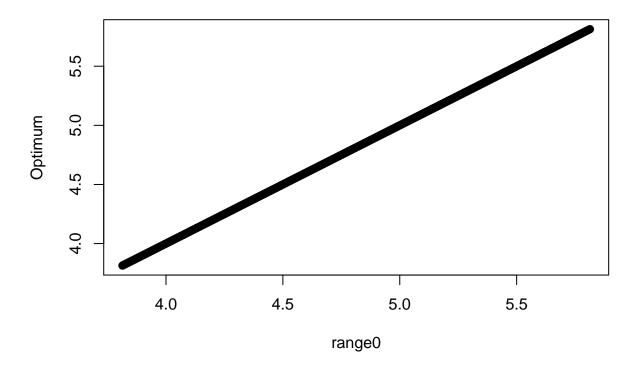
```
plot(hat0~ range0, x_lab="Start", ylab="Optimum")
```

```
## Warning in plot.window(...): "x_lab" is not a graphical parameter
## Warning in plot.xy(xy, type, ...): "x_lab" is not a graphical parameter
## Warning in axis(side = side, at = at, labels = labels, ...): "x_lab" is not a
## graphical parameter

## Warning in axis(side = side, at = at, labels = labels, ...): "x_lab" is not a
## graphical parameter

## Warning in box(...): "x_lab" is not a graphical parameter

## Warning in title(...): "x_lab" is not a graphical parameter
```



```
plot(hat1~ range1, x_lab="Start", ylab="Optimum")
```

## Warning in plot.window(...): "x\_lab" is not a graphical parameter

```
## Warning in plot.xy(xy, type, ...): "x_lab" is not a graphical parameter
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## Warning in title(...): "x_lab" is not a graphical parameter
```

