## HW8

## $Autumn\ Li$

## 11/23/2016

1. Run the following code block to create synthetic regression data, with 100 observations and 10 predictor variables:

```
n <- 100
p <- 10
s <- 3
set.seed(0)
x <- matrix(rnorm(n*p), n, p)
b <- c(-0.7, 0.7, 1, rep(0, p-s))
y <- x %*% b + rt(n, df=2)
data = data.frame(x,y)
corr = cor(data,y= NULL,use="complete.obs")
# From the above correlation, I pick x1, x3 and x4.</pre>
```

2. Verify this by plotting the normal density and the t-density on the same plot, with the latter having 3 degrees of freedom.

```
x1 <- seq(-4, 4, length=100)
hx1 <- dnorm(x1)
degf <- 3
colors <- c("red", "black")
labels <- c("df=3", "normal")

plot(x1, hx1, type="l", lty=2, xlab="x value",
    ylab="Density", main="Comparison of normal and t Distributions")

lines(x1, dt(x1,3), lwd=2, col= "red")
legend("topright", inset=.05, title="Distributions",
    labels, lwd=2, lty=c(1, 1, 1, 1, 2), col=colors)</pre>
```

## Comparison of normal and t Distributions

```
Distributions
                                                                             df=3
      0.3
                                                                             normal
Density
      0.2
      0.1
      0.0
                                                  0
                                                                    2
                               -2
                                                                                       4
                                               x value
                                                                                           3.
 psi <- function(r, c = 1) {</pre>
  return(ifelse(r^2 > c^2, 2*c*abs(r) - c^2, r^2))
huber.loss = function(beta){
  y_hat = x %*% beta
  resid = y - y_hat
psi = psi(r = resid ,c=1)
 result = sum(psi)
 return(result)
library("numDeriv", lib.loc="/Library/Frameworks/R.framework/Versions/3.0/Resources/library")
grad.descent <- function(f, x0, max.iter = 200, step.size = 0.001, stopping.deriv = 0.01, ...) {</pre>
      <- length(x0)
  xmat <- matrix(0, nrow = n, ncol = max.iter)</pre>
  xmat[,1] <- x0</pre>
  for (k in 2:max.iter) {
    # Calculate the gradient
    grad.cur <- grad(f, xmat[,k-1], ...)</pre>
    # Should we stop?
    if (all(abs(grad.cur) < stopping.deriv)) {</pre>
      k <- k-1; break
    \# Move in the opposite direction of the grad
```

 $xmat[ ,k] \leftarrow xmat[ ,k-1] - step.size * grad.cur$ 

```
xmat <- xmat[ ,1:k] # Trim
return(list(x = xmat[,k], xmat = xmat, k = k))
}

x0 <- rep(0,p)
gd <- grad.descent(huber.loss,x0,max.iter = 200, step.size = 0.001, stopping.deriv = 0.1)
gd$x

## [1] -0.87346579    0.61828938    0.87989797    -0.04910821    0.07277491
## [6]    0.10229815    -0.12513246    -0.14559243    -0.11903666    -0.02250130

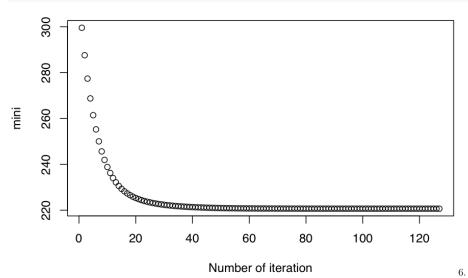
gd$k

## [1] 127</pre>
```

#There are 127 iterations.

5. Using gd, construct a vector obj of the values objective function encountered at each step of gradient descent.

```
mini = NULL
for (i in 1:127){
    a = as.numeric(gd$xmat[,i])
    mini[i] = huber.loss(beta = a)
}
obj = c(c(1:227),mini)
plot(c(1:127),mini,xlab = "Number of iteration")
```



```
x0 \leftarrow rep(0,p)
gd1 <- grad.descent(huber.loss,x0,max.iter = 200, step.size = 0.1, stopping.deriv = 0.1)
gd1$k
## [1] 200
gd1$x
## [1] 1.0740298 -0.7971898 2.8860325 -1.8822687 2.1897562 0.8721260
## [7] -1.0055026 -1.5049278 0.9241456 4.7508245
mini2 = NULL
for (i in 1:50){
   a = as.numeric(gd1$xmat[,i+149])
 mini2[i] = huber.loss(beta = a)
plot(c(150:199),mini2)
             2500
     2000
          150
                        160
                                     170
                                                  180
                                                               190
                                                                            200
                                       c(150:199)
                                                                                7.
sparse.grad.descent = function(f, x0, max.iter = 200, step.size = 0.1, stopping.deriv = 0.05, ...) {
     <- length(x0)
 xmat <- matrix(0, nrow = n, ncol = max.iter)</pre>
 xmat[,1] <- x0</pre>
 for (k in 2:max.iter) {
   # Calculate the gradient
   grad.cur <- grad(f, xmat[ ,k-1],...)</pre>
```

```
# Should we stop?
   if (all(abs(grad.cur) < stopping.deriv)) {</pre>
     k <- k-1; break
   # Move in the opposite direction of the grad
   new.x<-xmat[,k-1] - step.size * grad.cur</pre>
   new.x < -ifelse(abs(new.x) > 0.05, new.x, 0)
   xmat[ ,k] <- new.x</pre>
 xmat <- xmat[ ,1:k] # Trim</pre>
 return(list(x = xmat[,k], xmat = xmat, k = k))
gd2 = sparse.grad.descent(huber.loss,x0,max.iter = 200, step.size = 0.001, stopping.deriv = 0.1)
gd2$k
## [1] 200
gd2$x
coeff = coefficients(lm(y~x,data))[2:11]
mse1 = mean((b-coeff)^2);mse1
## [1] 0.1166408
mse2 = mean((b-gd$x)^2); mse2
## [1] 0.01208955
mse3 = mean((b-gd2$x)^2); mse3
## [1] 0.005610471
set.seed(10)
x_new <- matrix(rnorm(n*p), n, p)</pre>
y_new <- x %*% b + rt(n, df=2)
huber.loss_new <-function(beta){
 y_hat =x_new %*% beta
 resid = y_new - y_hat
psi = psi(r = resid ,c=1)
```

```
result = sum(psi)
return(result)
x0 \leftarrow rep(0,p)
gd3 = sparse.grad.descent(huber.loss_new,x0,max.iter = 200, step.size = 0.001, stopping.deriv = 0.1)
gd4 = grad.descent(huber.loss_new,x0,max.iter = 200, step.size = 0.001, stopping.deriv = 0.1)
mse4 = mean((b-gd3$x)^2); mse4
## [1] 0.198
mse5 = mean((b-gd4$x)^2);mse5
## [1] 0.352788
10.
mse_gd = NULL
mse_sgd = NULL
for (i in 1:10){
x0 \leftarrow rep(0,p)
gd_10 <- grad.descent(huber.loss,x0,max.iter = 200, step.size = 0.001, stopping.deriv = 0.1)
mse_gd[i] = mean((b-gd_10$x)^2)
sparse_gd_10 = sparse.grad.descent(huber.loss,x0,max.iter = 200, step.size = 0.001, stopping.deriv = 0.
mse_sgd[i] = mean((b-sparse_gd_10$x)^2)
mean_mse_gd = mean(mse_gd);mean_mse_gd
## [1] 0.01208955
mean_mse_sgd = mean(mse_sgd);mean_mse_sgd
## [1] 0.005610471
min_mse_gd = min(mse_gd);min_mse_gd
## [1] 0.01208955
min_mse_sgd = min(mse_sgd);min_mse_sgd
## [1] 0.005610471
```