

Q1.

a)

$$\frac{f(x)}{g(x)} = \frac{\frac{\exp(-x^2/2)}{\sqrt{\pi}(1-\Phi(b))}}{b \exp(-b(x-b))} = \frac{1}{\sqrt{\pi}(1-\Phi(b)) \cdot b} e^{-x^2/2 + bx - b^2}$$

$$= \frac{e^{-\frac{x^2}{2} + bx - b^2}}{\sqrt{\pi}(1-\Phi(b)) b} = p(b) \cdot e^{-\frac{x^2}{2} + bx - b^2}$$

where  $p(b)$  should be constant and independent of  $x$ .)

$$M = \max_x \frac{f(x)}{g(x)}, \text{ we want to max } p(b) \cdot e^{-\frac{x^2}{2} + bx}$$

$$\Rightarrow \max_x e^{-\frac{x^2}{2} + bx} \Rightarrow \max_x -\frac{x^2}{2} + bx$$

take derivative  $-x + b = 0$ ,  $b = x$  ( $\frac{f(x)}{g(x)}$  has greatest value)

$$\text{Then, we have } M = p(b) \cdot e^{-\frac{b^2}{2} + b^2 - b^2} = p(b) \cdot e^{-\frac{b^2}{2}}$$

$$U \text{ should satisfy } U \leq \frac{f(x)}{Mg(x)}$$

$$U \leq p(b) \cdot e^{-\frac{x^2}{2} + bx - b^2} \cdot \frac{1}{p(b) e^{-\frac{b^2}{2}}}$$

$$U \leq e^{-\frac{x^2}{2} + bx - b^2 + \frac{b^2}{2}}$$

$$U \leq e^{-\frac{x^2}{2} + bx - \frac{b^2}{2}}$$

$$U \leq e^{-\frac{1}{2}(x-b)^2}$$

Then we accept  $X = b + \frac{Y}{b}$  if

$$U \leq e^{-\frac{1}{2} \left( b + \frac{Y}{b} - b \right)^2}$$

$$U \leq e^{-\frac{1}{2} \cdot \left( \frac{Y}{b} \right)^2}$$

$$\ln U \leq -\frac{1}{2} \left( \frac{Y}{b} \right)^2$$

$$-2 \ln U \geq \frac{Y^2}{b^2}$$

b).

$$\text{probability of acceptance: } \frac{1}{M} = \frac{\sqrt{\pi} b (1 - \Phi(b))}{\exp(-b^2/2)}$$

$$\lim_{b \rightarrow \infty} \frac{\sqrt{\pi} b (1 - \Phi(b))}{\exp(-b^2/2)} = \lim_{b \rightarrow \infty} \frac{\frac{d}{db} (\sqrt{\pi} b (1 - \Phi(b)))}{\frac{d}{db} \exp(-b^2/2)} \quad \text{by L'Hopital Rule}$$

$$\Rightarrow \lim_{b \rightarrow \infty} \frac{\sqrt{\pi} (1 - \Phi(b)) - \sqrt{\pi} b \phi(b)}{-b e^{-\frac{1}{2}b^2}} \quad \left[ \begin{array}{l} \text{note: } \Phi \text{ is CDF of } N(0,1) \\ \phi \text{ is pdf of } N(0,1) \end{array} \right]$$

by Mills's ratio

$$1 - \Phi(b) \approx \frac{1}{b} \phi(b) \quad \& \quad \phi(b) = \frac{1}{\sqrt{2\pi}} e^{-b^2/2}$$

$$\begin{aligned} & \lim_{b \rightarrow \infty} \frac{\sqrt{\pi} \frac{1}{b} \phi(b) - \sqrt{\pi} b \phi(b)}{-b e^{-\frac{1}{2}b^2}} \\ &= \lim_{b \rightarrow \infty} \frac{\frac{1}{b} e^{-b^2/2} - b e^{-b^2/2}}{-b e^{-\frac{1}{2}b^2}} \end{aligned}$$

$$= \lim_{b \rightarrow \infty} \frac{1}{b^2} + 1 = 1$$

The probability equals 1.

$$c) \min_{\lambda > 0} \max_{x \geq b} \frac{f(x)}{g_{\lambda}(x)} = \max_{x \geq b} \left( \min_{\lambda > 0} \frac{f(x)}{g_{\lambda}(x)} \right)$$

$$\begin{aligned} \max_{x \geq b} \min_{\lambda > 0} \ln f(x) - \ln g_{\lambda}(x) &= \ln f(x) - \ln(\lambda \exp(-\lambda(x-b))) \\ &= \ln f(x) - \ln \lambda + \lambda x - \lambda b \end{aligned}$$

take derivative to find min.

$$\frac{d}{d\lambda} \ln f(x) - \ln \lambda + \lambda x - \lambda b = 0$$

$$-\frac{1}{\lambda} + x - b = 0$$

$$-\frac{1}{\lambda} = b - x$$

$$\lambda = (x - b)^{-1}$$

plug  $\lambda = (x - b)^{-1}$  into function

$$\ln f(x) - \ln[(x - b)^{-1} \exp((x - b)^{-1}(x - b))]$$

$$= \ln \frac{\exp(-x^2/2)}{\sqrt{2\pi} (1 - \Phi(b))} - \ln (x - b)^{-1} + 1$$

$$= -\frac{x^2}{2} - \ln[\sqrt{2\pi} (1 - \Phi(b))] - \ln (x - b)^{-1} + 1$$

take derivative to find maximum.

$$\frac{d}{dx} \left[ -\frac{x^2}{2} - \ln[\sqrt{\pi}(1-\Phi(b))] - \ln(x-b)^{-1} + 1 \right] = 0$$

$$\frac{d}{dx} \left[ -\frac{x^2}{2} - \ln[\sqrt{\pi}(1-\Phi(b))] + \ln(x-b) + 1 \right] = 0$$

$$\text{Since } \ln(x-b)^{-1} = -\ln(x-b)$$

$$-x + \frac{1}{x-b} = 0$$

$$x^2 - bx - 1 = 0$$

$$x = \frac{b + \sqrt{b^2 + 4}}{2} \quad (x \geq b, b \geq 0)$$

$$\lambda = \lambda(b) = (x - b)^{-1} = \left( \frac{b + \sqrt{b^2 + 4}}{2} - b \right)^{-1}$$

$$= \left( \frac{-b + \sqrt{b^2 + 4}}{2} \right)^{-1}$$

$$= \frac{2}{-b + \sqrt{b^2 + 4}}$$

Thus,  $\lambda = \frac{2}{-b + \sqrt{b^2 + 4}}$  maximizes the probability of acceptance

Q2.

1) We have  $y_i = a \times i + b$ , assume  $\theta_i = y_i$ ,

$$\begin{aligned}\theta_{i+1} - 2\theta_i + \theta_{i-1} &= y_{i+1} - 2y_i + y_{i-1} \\ &= a(i+1) + b - 2(ai + b) + a(i-1) + b \\ &= ai + a + b - 2ai - 2b + ai - a + b \\ &= 0\end{aligned}$$

Thus, when  $\hat{\theta}_i = y_i$

$$\sum_{i=1}^n (y_i - \theta_i)^2 + \lambda \sum_{i=2}^{n-1} (\theta_{i+1} - 2\theta_i + \theta_{i-1})^2 = \sum_{i=1}^n 0 + \lambda \sum_{i=2}^{n-1} 0 = 0$$

which is minimized.

2b)  $\hat{\theta} = y_i$  for all  $i$  minimize  $\|y^* - x\theta\|^2$

$$\sum_{i=1}^n (y_i - \theta_i)^2 + \lambda \sum_{i=2}^{n-1} (\theta_{i+1} - 2\theta_i + \theta_{i-1})^2 = 0$$

$$\left\| \begin{pmatrix} y_1 - \theta_1 \\ \vdots \\ y_n - \theta_n \\ \sqrt{\lambda}(\theta_3 - 2\theta_2 + \theta_1) \\ \vdots \\ \sqrt{\lambda}(\theta_n - 2\theta_{n-1} + \theta_{n-2}) \end{pmatrix} \right\|^2 \Rightarrow y^* = \begin{pmatrix} y_1 \\ \vdots \\ y_n \\ 0 \\ \vdots \\ 0 \end{pmatrix}_{(2n-2) \times 1}$$

$$X = \begin{bmatrix} 1 & 0 & \cdots & \cdots & \cdots & \cdots & 0 \\ 0 & 1 & 0 & \cdots & \cdots & \cdots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & 0 & \ddots & \ddots & \ddots & \ddots & 1 \\ \sqrt{\lambda} & -2\sqrt{\lambda} & \sqrt{\lambda} & 0 & \cdots & \cdots & 0 \\ 0 & \sqrt{\lambda} & -2\sqrt{\lambda} & \sqrt{\lambda} & 0 & \cdots & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & \ddots & \ddots & \ddots & \ddots & \sqrt{\lambda} & -2\sqrt{\lambda} & \sqrt{\lambda} \end{bmatrix}_{(2n-2) \times n}$$

$$\therefore y^* - X\theta = \begin{pmatrix} y_1 \\ \vdots \\ y_n \\ 0 \\ \vdots \\ 0 \end{pmatrix} - \begin{bmatrix} 1 & 0 & \cdots & \cdots & \cdots & \cdots & 0 \\ 0 & 1 & 0 & \cdots & \cdots & \cdots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & 0 & \ddots & \ddots & \ddots & \ddots & 1 \\ \sqrt{\lambda} & -2\sqrt{\lambda} & \sqrt{\lambda} & 0 & \cdots & \cdots & 0 \\ 0 & \sqrt{\lambda} & -2\sqrt{\lambda} & \sqrt{\lambda} & 0 & \cdots & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & \ddots & \ddots & \ddots & \ddots & \sqrt{\lambda} & -2\sqrt{\lambda} & \sqrt{\lambda} \end{bmatrix} \begin{pmatrix} \theta_1 \\ \vdots \\ \theta_n \end{pmatrix}_{n \times 1}$$

c).

At  $i$ th iteration, the minimize function we have is.

$$\|y^* - X_{\bar{w}} \hat{\theta}_{\bar{w}(i)} - X_w \theta_{w(i)}\|$$

And for  $i+1$  iteration, we want to minimize

$$\|y^* - X_{\bar{w}} \hat{\theta}_{\bar{w}(i)} - X_w \theta_w\|$$

then we have

$$\|y^* - X_{\bar{w}} \hat{\theta}_{\bar{w}(i)} - X_w \hat{\theta}_{w(i+1)}\| \leq \|y^* - X_{\bar{w}} \hat{\theta}_{\bar{w}(i)} - X_w \hat{\theta}_{w(i)}\|$$

Thus, the objective function is non-increasing from one iteration to the next.



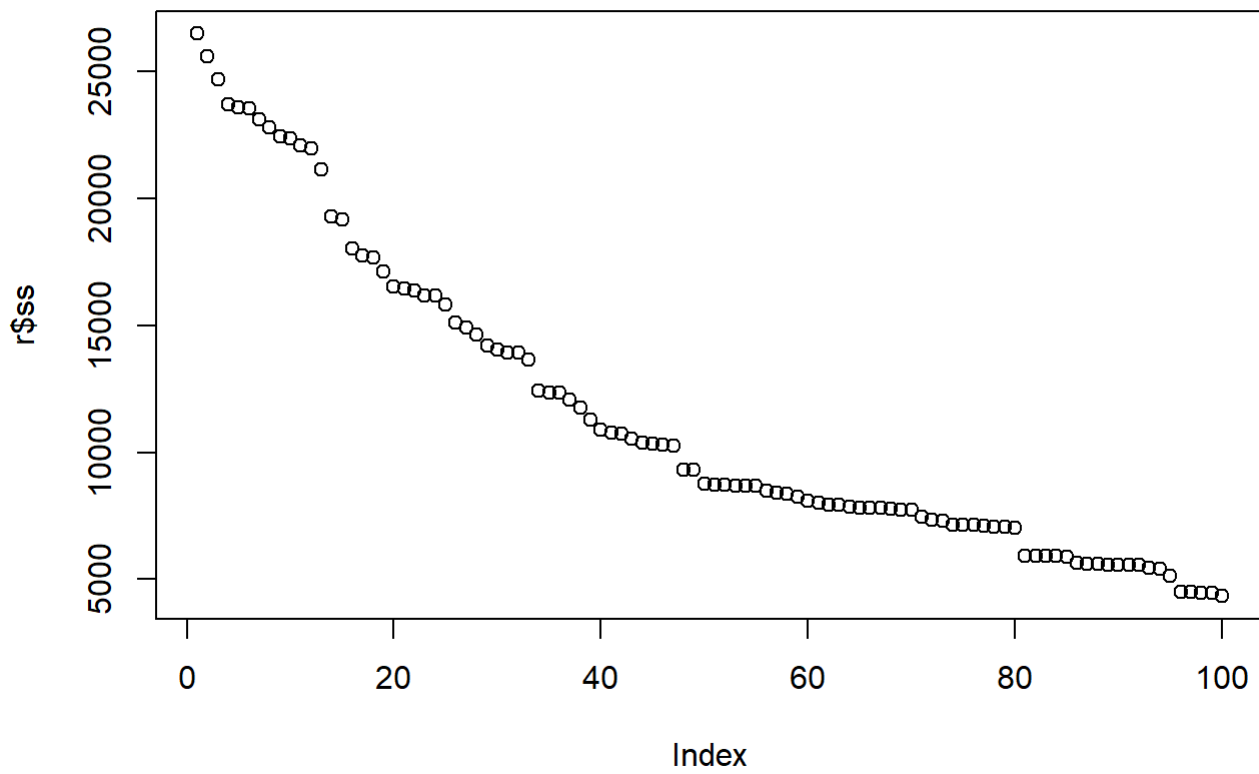
# STA410 A2

```
HP <- function(x, lambda, p=20, niter=200) {  
  n <- length(x)  
  a <- c(1, -2, 1)  
  aa <- c(a, rep(0, n-2))  
  aaa <- c(rep(aa, n-3), a)  
  mat <- matrix(aaa, ncol=n, byrow=T)  
  mat <- rbind(diag(rep(1, n)), sqrt(lambda)*mat)  
  xhat <- x  
  x <- c(x, rep(0, n-2))  
  sumofsquares <- NULL  
  for (i in 1:niter) {  
    w <- sort(sample(c(1:n), size=p))  
    xx <- mat[, w]  
    y <- x - mat[, -w] %*% xhat[-w]  
    r <- lsfit(xx, y, intercept=F)  
    xhat[w] <- r$coef  
    sumofsquares <- c(sumofsquares, sum(r$residuals^2))  
  }  
  r <- list(xhat=xhat, ss=sumofsquares)  
  r  
}
```

```
data<-scan("C:/Users/WLJY8/Desktop/Courses/YEAR 4/STA410/A2/yield.txt")
```

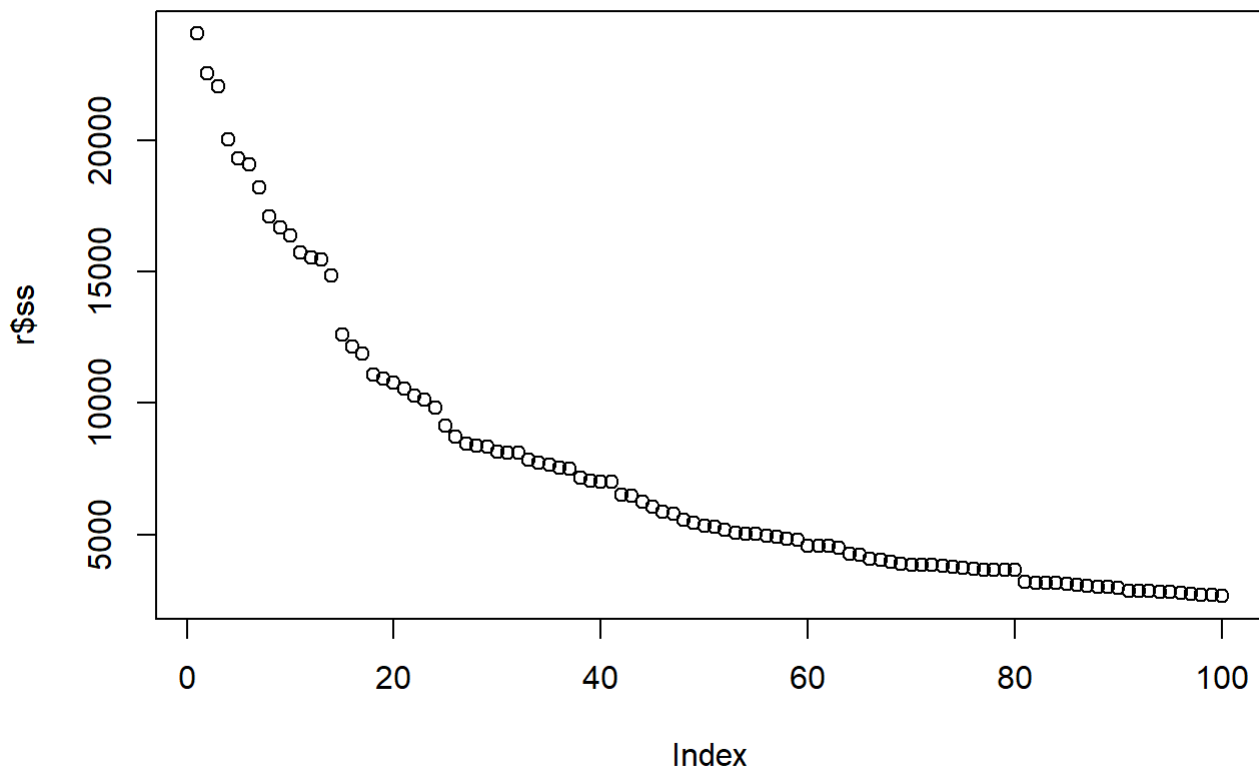
**p=5**

```
r <- HP(data, lambda=2000, p=5, niter=100)  
plot(r$ss)
```



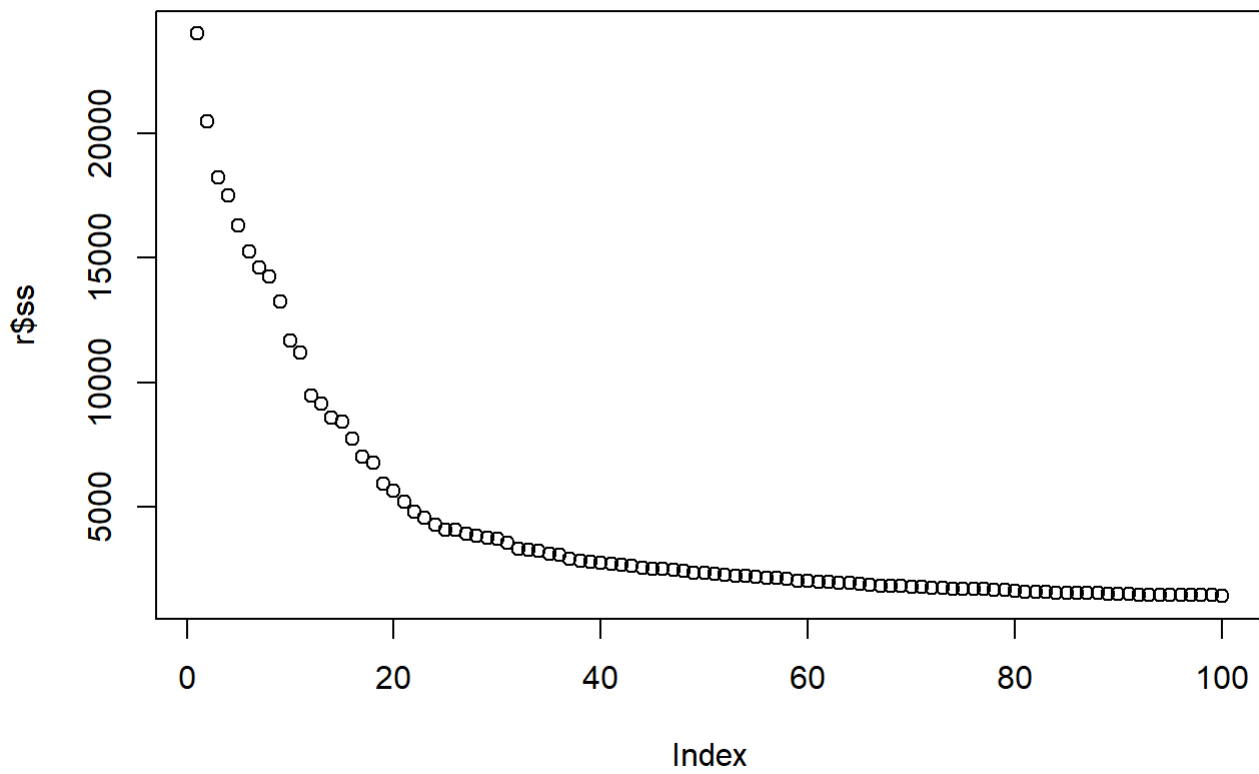
p=10

```
r <- HP(data, lambda=2000, p=10, niter=100)
plot(r$ss)
```



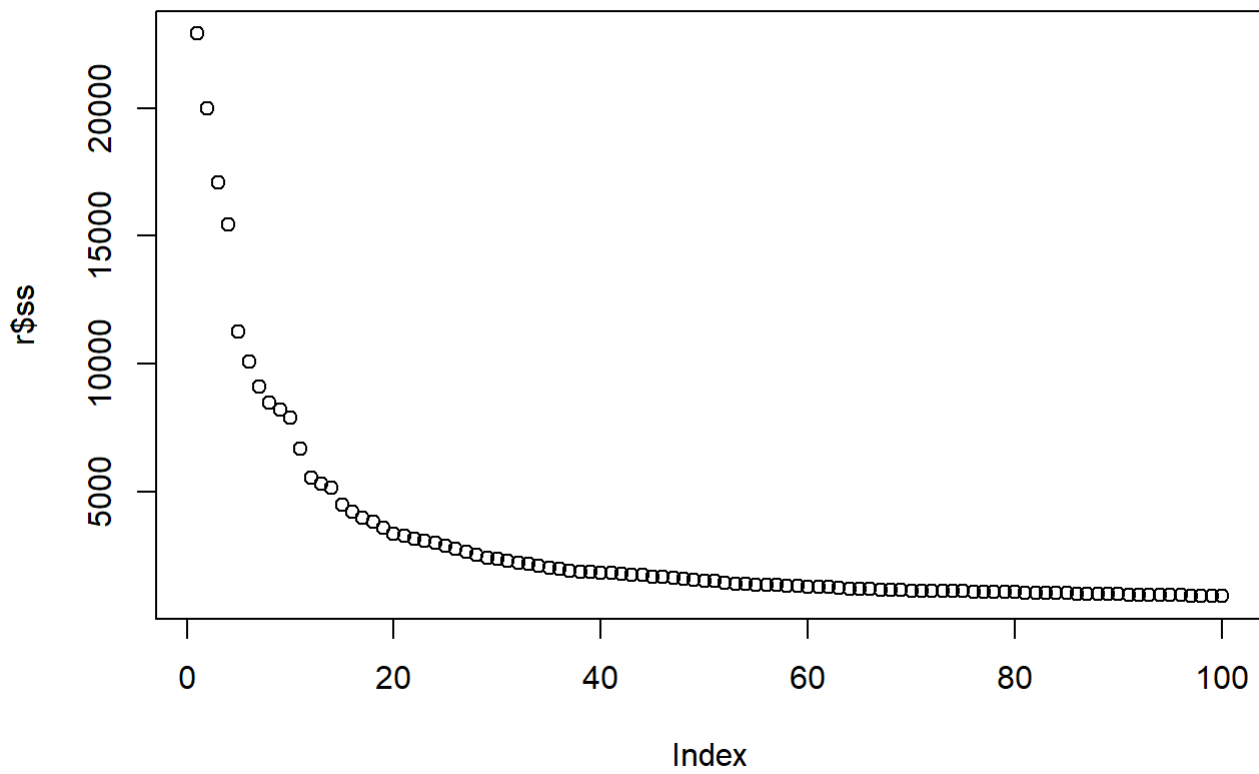
p=20

```
r <- HP(data, lambda=2000, p=20, niter=100)
plot(r$ss)
```



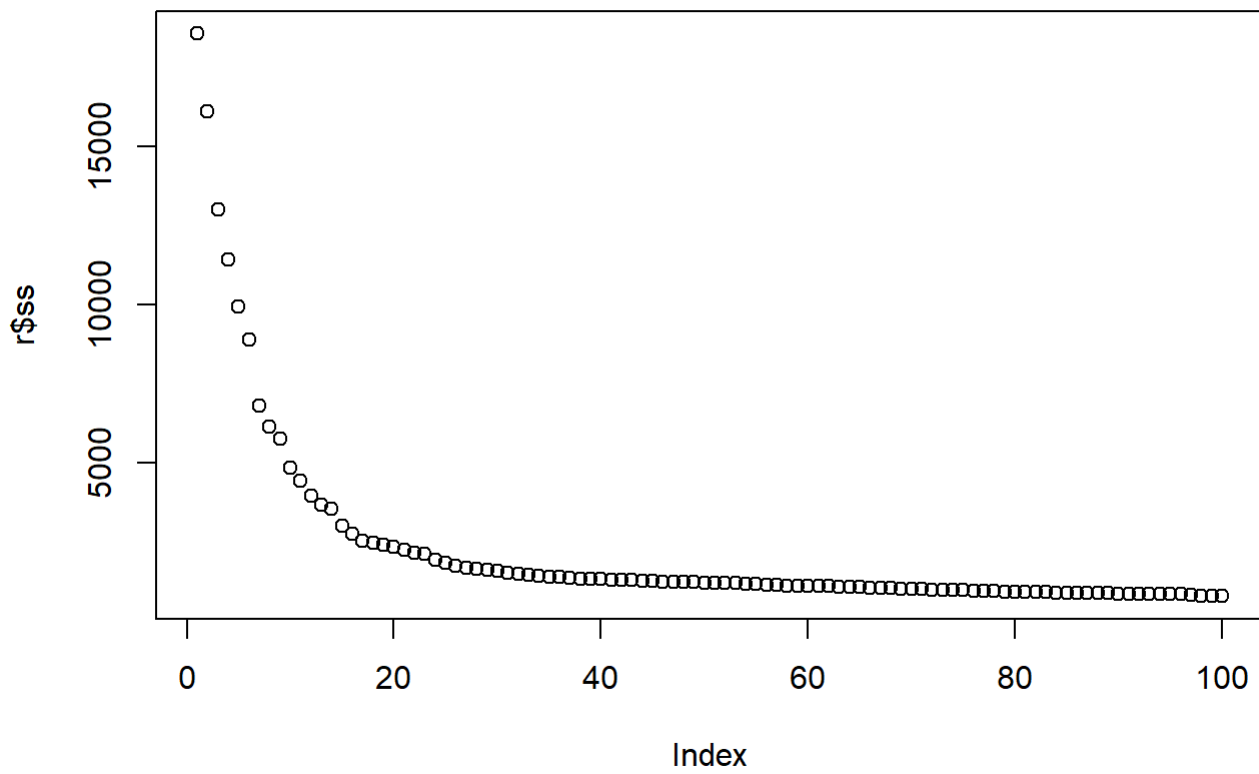
p=30

```
r <- HP(data, lambda=2000, p=30, niter=100)
plot(r$ss)
```



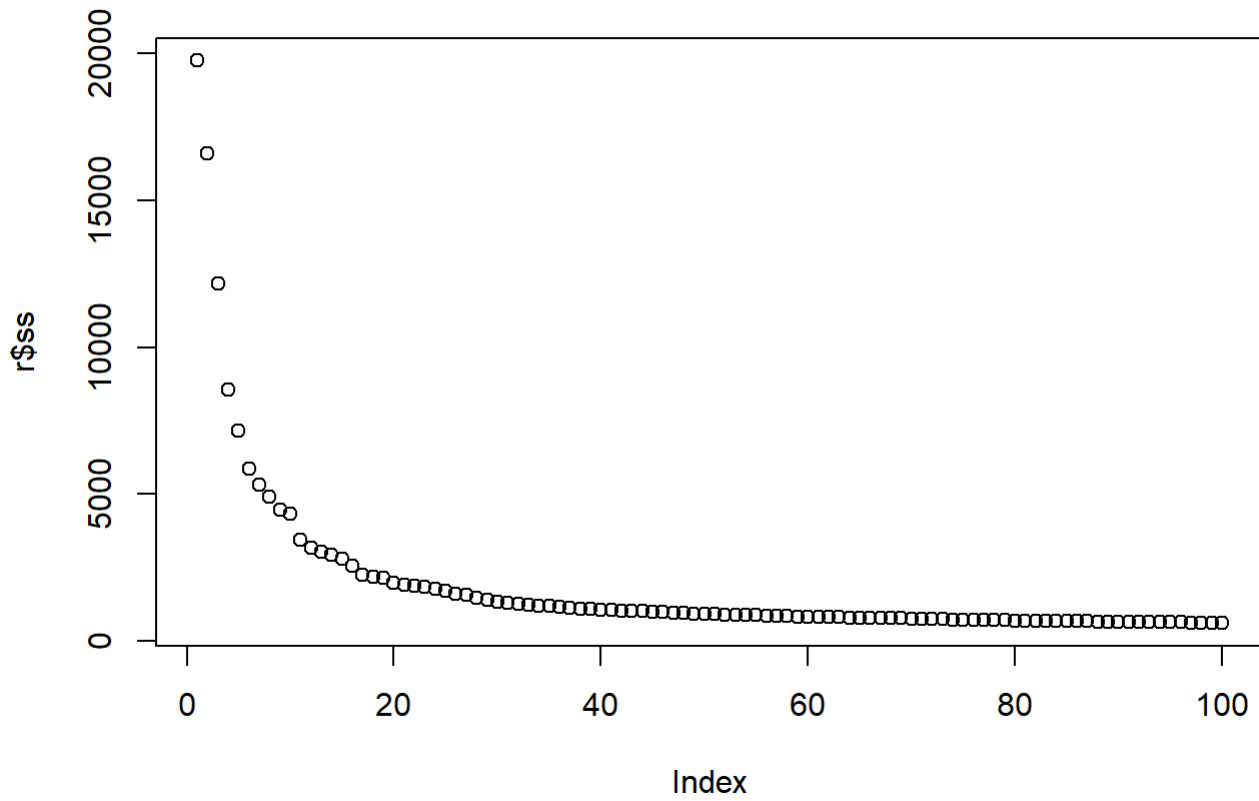
p=40

```
r <- HP(data, lambda=2000, p=40, niter=100)
plot(r$ss)
```



p=50

```
r <- HP(data, lambda=2000, p=50, niter=100)
plot(r$ss)
```



As  $p$  increases, the objective function value decreases more quickly as a function of the number of iterations.