

5361_stat_hw_Qi_You

Question 1b

Equations

$$l(\theta) \tag{1}$$

$$= \ln \prod_{i=1}^n \frac{1}{\pi[1 + (x - \theta)^2]} \tag{2}$$

$$= \sum_{i=1}^n \ln \frac{1}{\pi[1 + (x - \theta)^2]} \tag{3}$$

$$= \sum_{i=1}^n \left[\ln \frac{1}{\pi} + \ln \frac{1}{1 + (x - \theta)^2} \right] \tag{4}$$

$$= -n \ln \pi - \sum_{i=1}^n \ln[1 + (x - \theta)^2] \tag{5}$$

$$\tag{6}$$

$$l'(\theta) \tag{7}$$

$$= 0 - \sum_{i=1}^n \frac{2(\theta - x_i)}{1 + (\theta - x_i)^2} \tag{8}$$

$$= -2 \sum_{i=1}^n \frac{\theta - x_i}{1 + (\theta - x_i)^2} \tag{9}$$

$$\tag{10}$$

$$l''(\theta) \tag{11}$$

$$= -2 \sum_{i=1}^n \frac{1 + (\theta - x_i)^2 - 2(\theta - x_i)(\theta - x_i)}{[1 + (\theta - x_i)^2]^2} \tag{12}$$

$$= -2 \sum_{i=1}^n \frac{1 - (\theta - x_i)^2}{[1 + (\theta - x_i)^2]^2} \tag{13}$$

$$\tag{14}$$

We can set x to be $\tan(x)$. In this way we can compute the value of I easily

$$I(\theta) \tag{15}$$

$$= n \int \frac{\{p'(x)\}^2}{p(x)} dx \tag{16}$$

$$= n \int \frac{4(x-\theta)^2}{\pi[1+(x-\theta)^2]^4} * \pi[1+(x-\theta)^2] dx \tag{17}$$

$$= \frac{4n}{\pi} \int_{-\infty}^{\infty} \frac{(x-\theta)^2}{[1+(x-\theta)^2]^3} dx \tag{18}$$

$$= \frac{4n}{\pi} \int_{-\infty}^{\infty} \frac{x^2}{(1+x^2)^3} dx \tag{19}$$

$$= \frac{4n}{\pi} \int_{-\infty}^{\infty} [(\frac{1}{(1+x^2)^2} - \frac{1}{(1+x^2)^3})] dx \tag{20}$$

$$= \frac{4n}{\pi} (\int_{-\infty}^{\infty} \frac{1}{(1+x^2)^2} dx - \int_{-\infty}^{\infty} \frac{1}{(1+x^2)^3} dx) \tag{21}$$

$$= \frac{4n}{\pi} [\int_{-\infty}^{\infty} \frac{1}{(1+x^2)^2} dx - (\frac{x}{4(x^2+1)^2} |_{-\infty}^{\infty} + \frac{3}{4} \int_{-\infty}^{\infty} \frac{dx}{(x^2+1)^2})] \tag{22}$$

$$= \frac{4n}{\pi} (\int_{-\infty}^{\infty} \frac{1}{4(1+x^2)^2} dx - \frac{x}{4(x^2+1)^2} |_{-\infty}^{\infty}) \tag{23}$$

$$= \frac{4n}{\pi} [\frac{1}{4} (\frac{x}{2(x^2+1)} |_{-\infty}^{\infty} + \frac{1}{2} \int_{-\infty}^{\infty} \frac{1}{1+x^2} dx) - \frac{x}{4(x^2+1)^2} |_{-\infty}^{\infty}] \tag{24}$$

$$= \frac{4n}{\pi} (\frac{x(x^2-1)}{8(x^2+1)^2} |_{-\infty}^{\infty} + \frac{1}{8} \int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} \frac{\sec^2 t}{1+\tan^2 t} dt) \tag{25}$$

$$= \frac{4n}{\pi} (0 + \frac{\pi}{8}) \tag{26}$$

$$= \frac{n}{2} \tag{27}$$

$$\tag{28}$$

Functions I setup

```

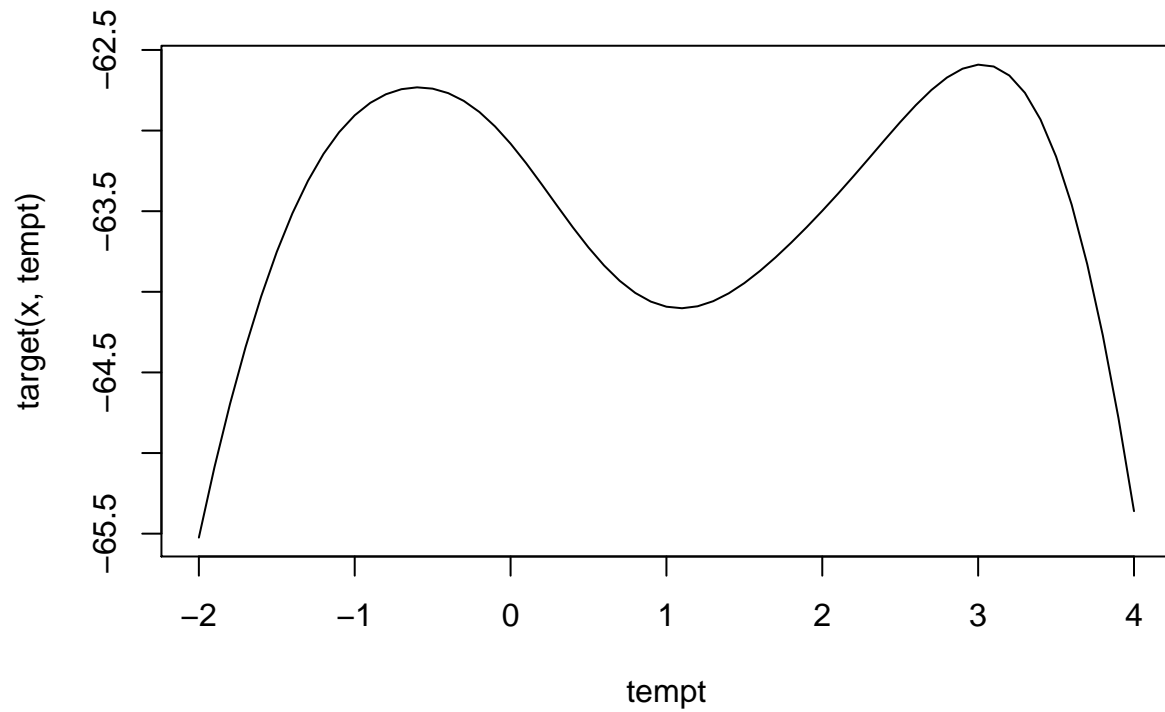
derivative1 <- function(x,sita){
  value <- 0
  for (i in 1:length(x)){
    value <- value-2*(sita-x[i])/(1+(sita-x[i])^2)
  }
  return(value)
}

derivative2 <- function(s,sita){
  value <- 0
  for (i in 1:length(x)){
    value <- value-2*((1-(sita-x[i])^2)/(1+(sita-x[i])^2)^2)
  }
  return(value)
}

```

Plots(1b)

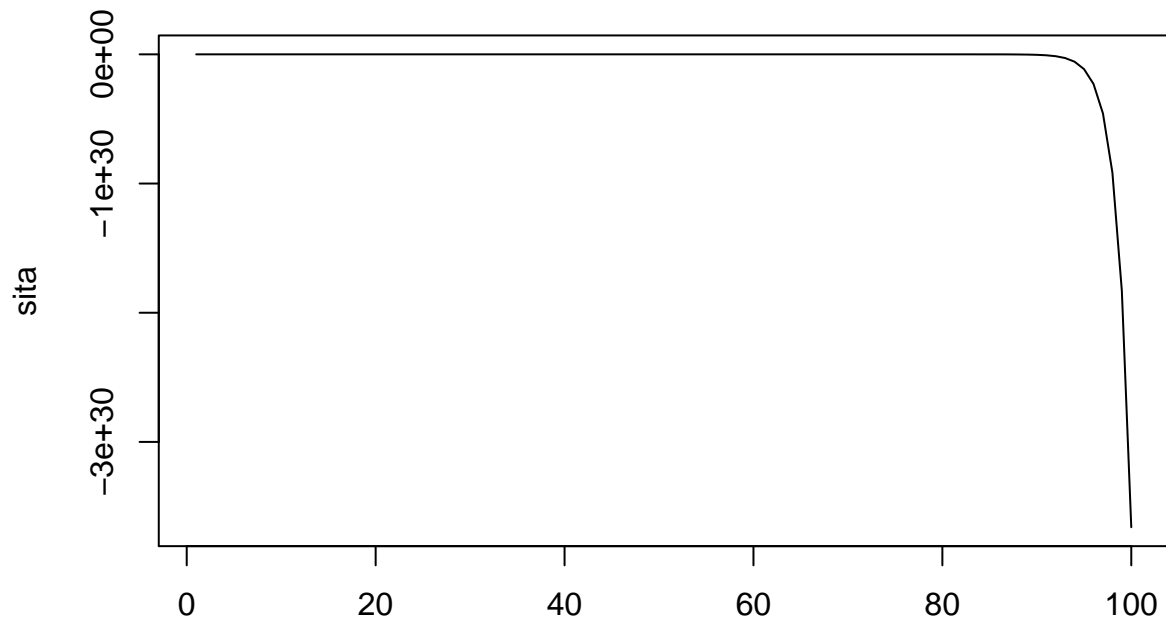
Here are the plots of my result



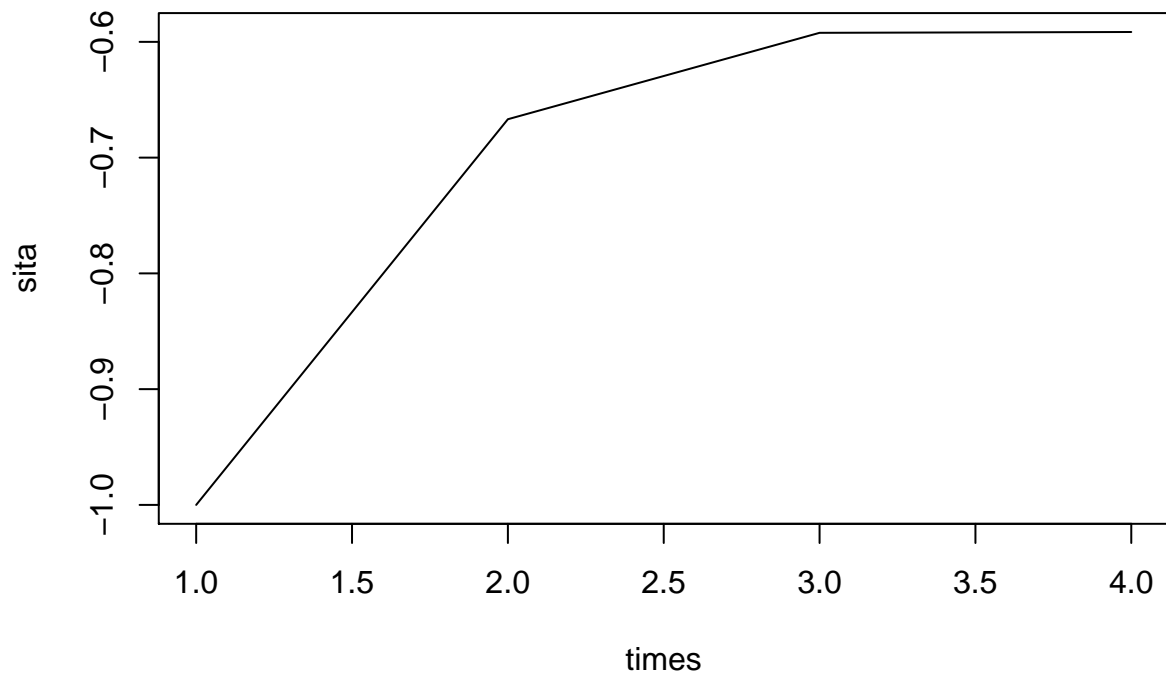
Here are the plots of mutiple start points

```
for(i in 1:length(start_points)){  
  estimate(start_points[i])  
}
```

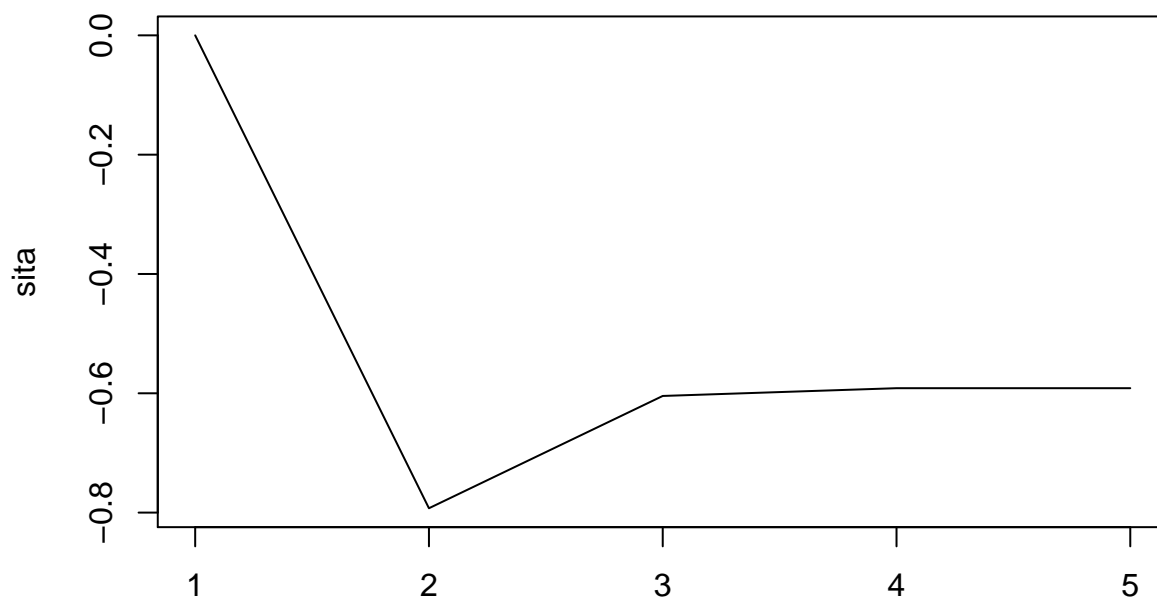
-11



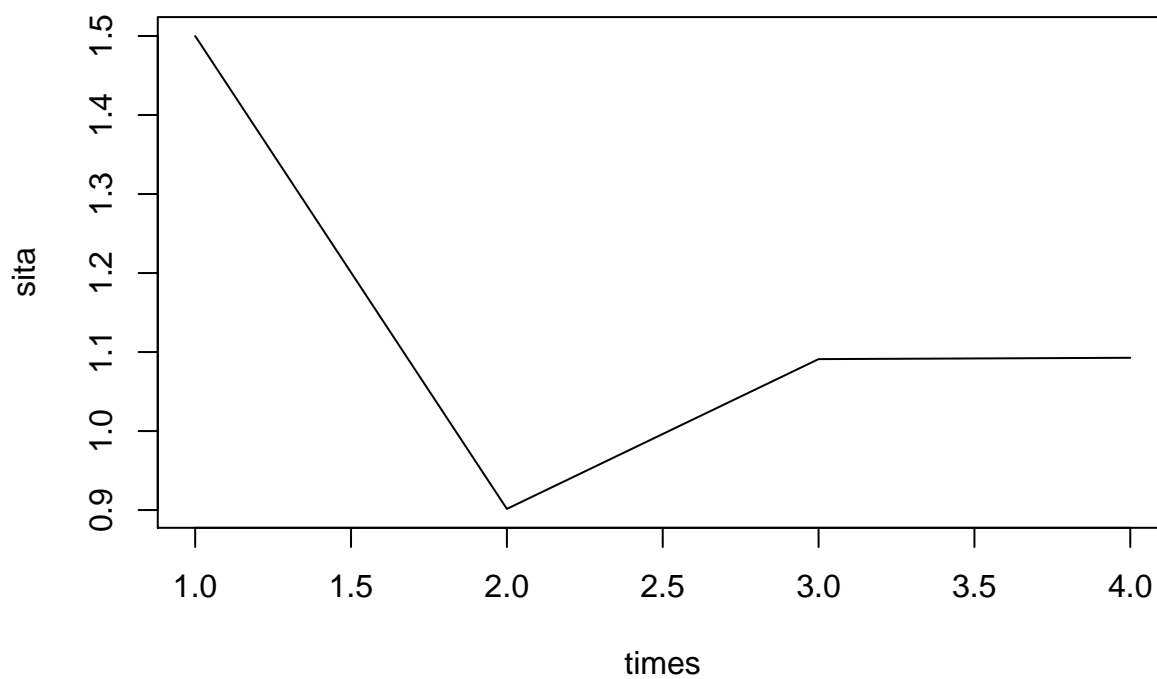
times
-1



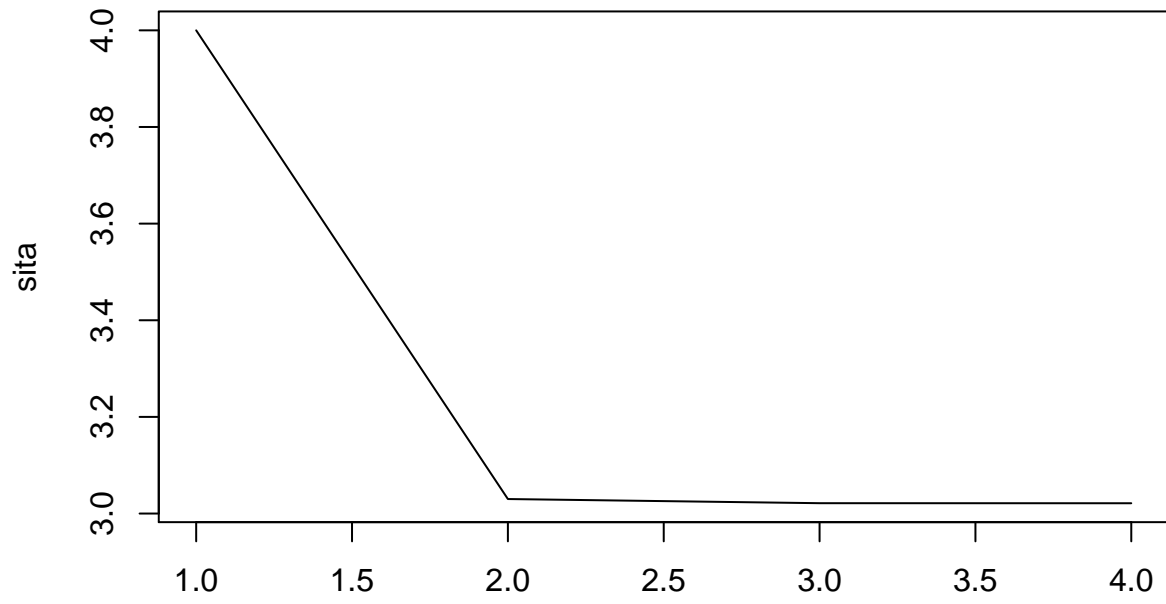
0



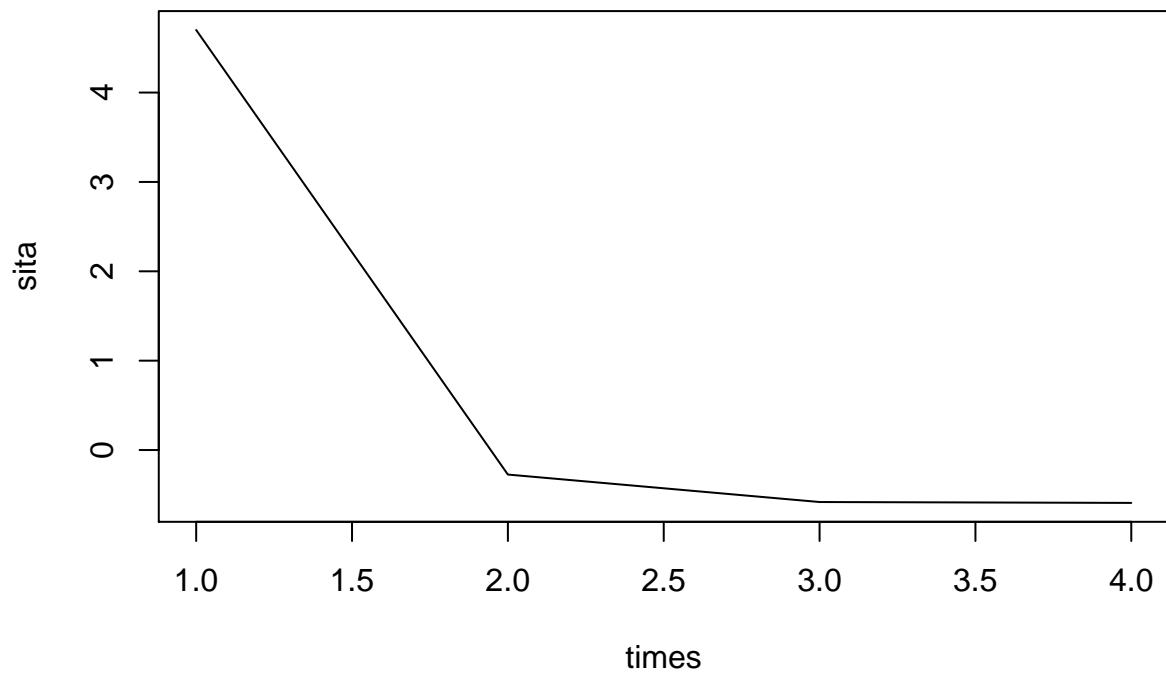
times
1.5



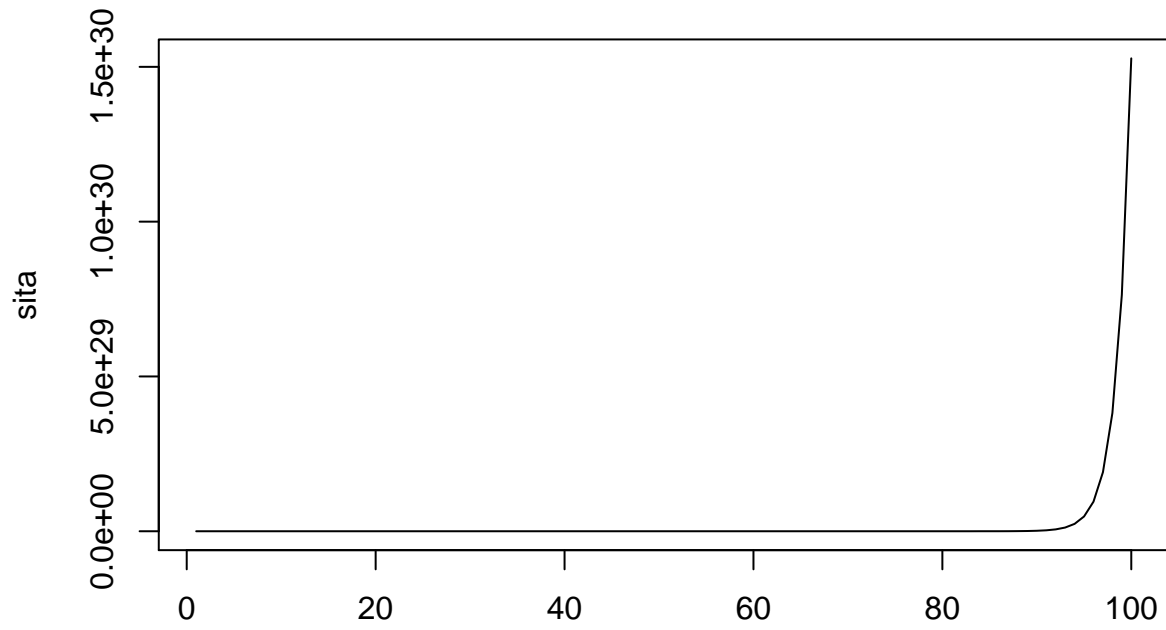
4



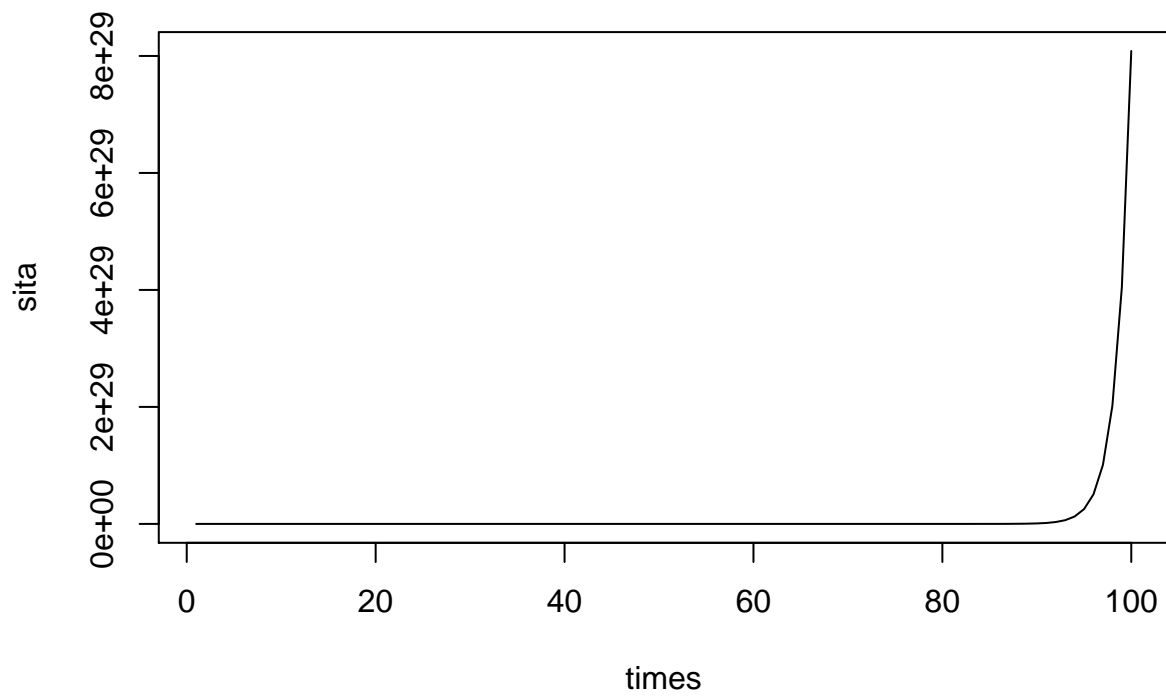
times
4.7



7



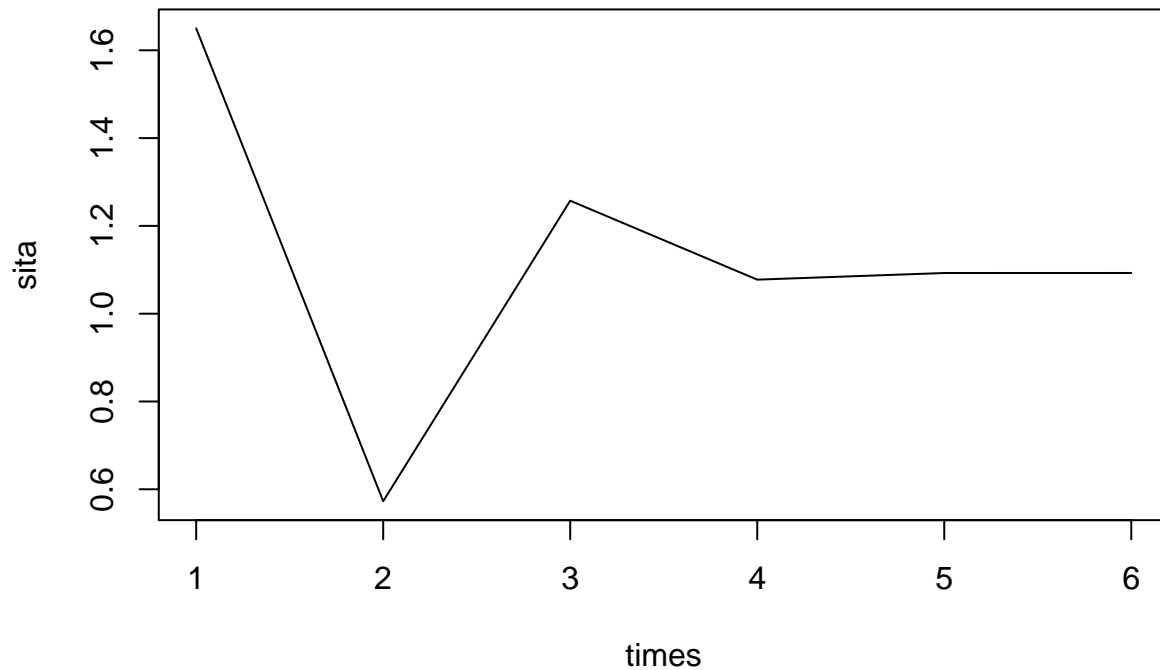
times
8



This is the plot of mean

```
estimate(mean(start_points))
```

1.65



Question 1(c)

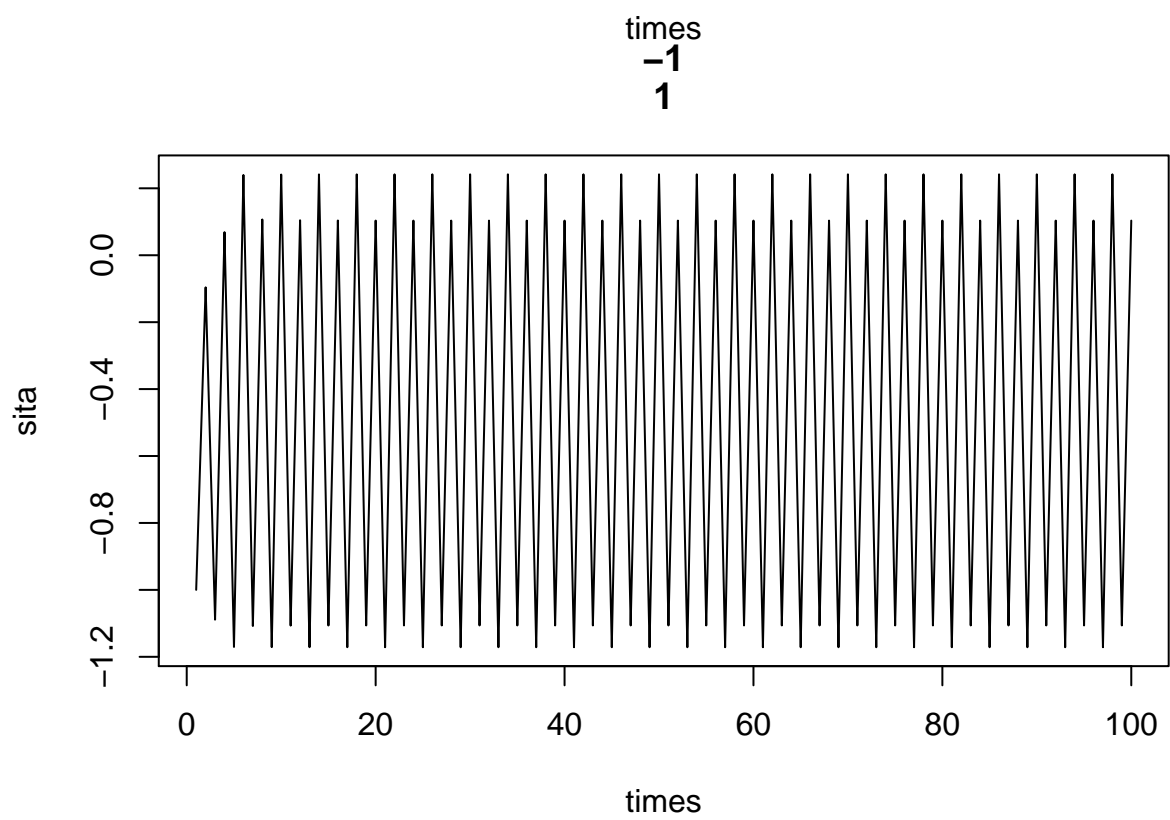
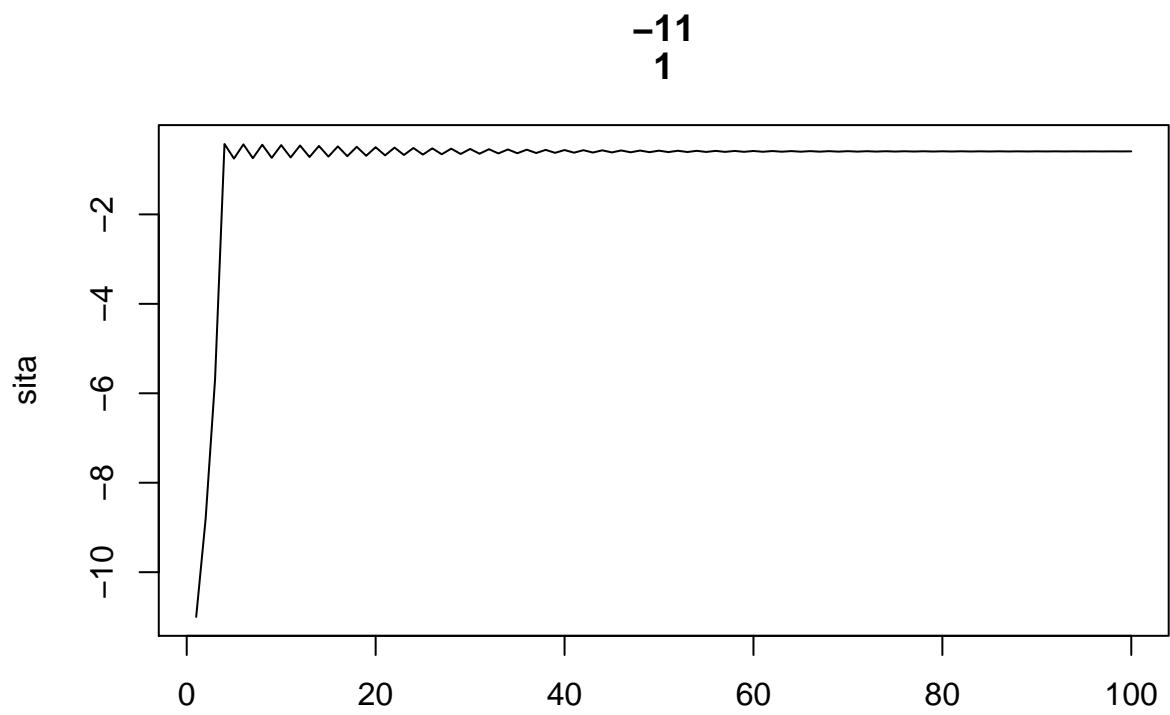
This time we use fixed points

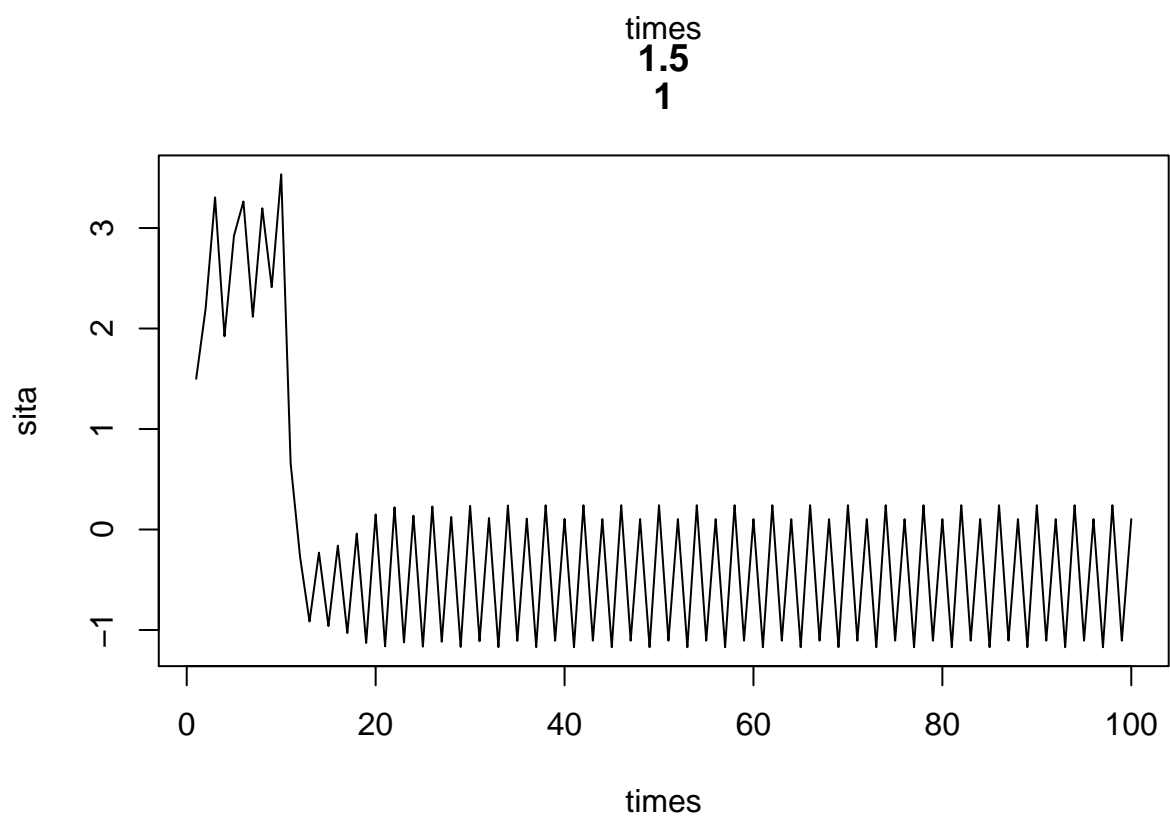
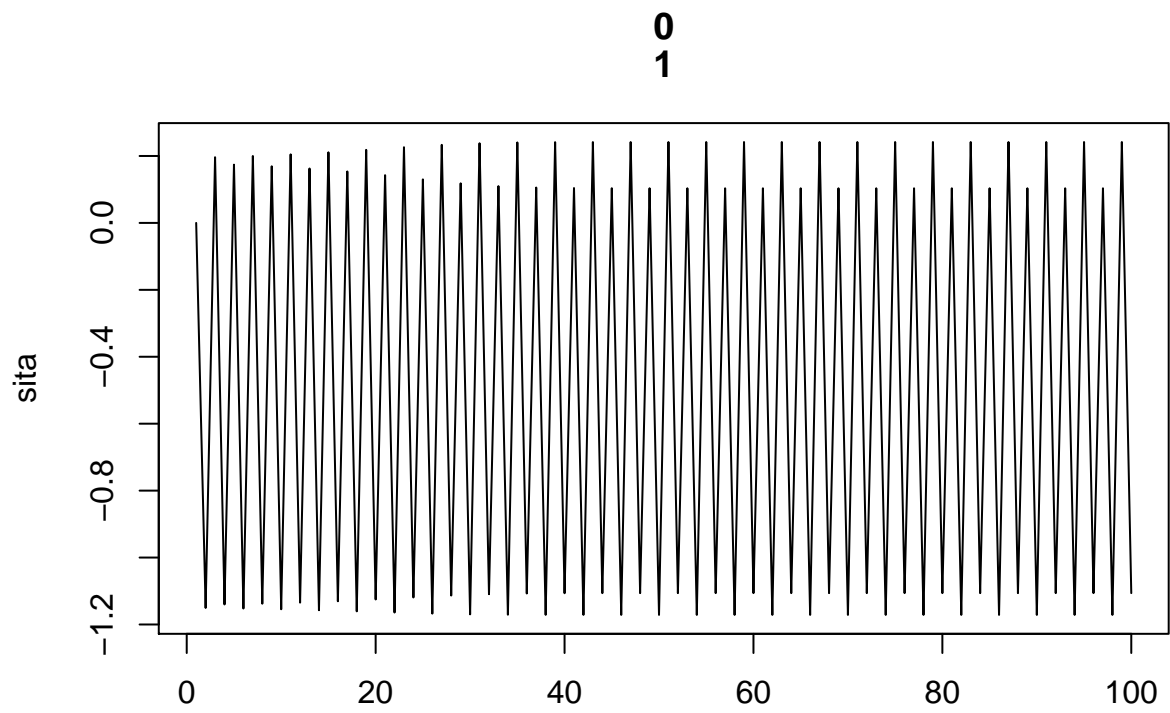
These are functions I established to compute derivation

```
derivitive1 <- function(x,sita){  
  value <- 0  
  for (i in 1:length(x)){  
    value <- value-2*(sita-x[i])/(1+(sita-x[i])^2)  
  }  
  return(value)  
}  
  
G <- function(alpha,x,sita){  
  value <- alpha*derivitive1(x,sita)+sita  
  return(value)  
}
```

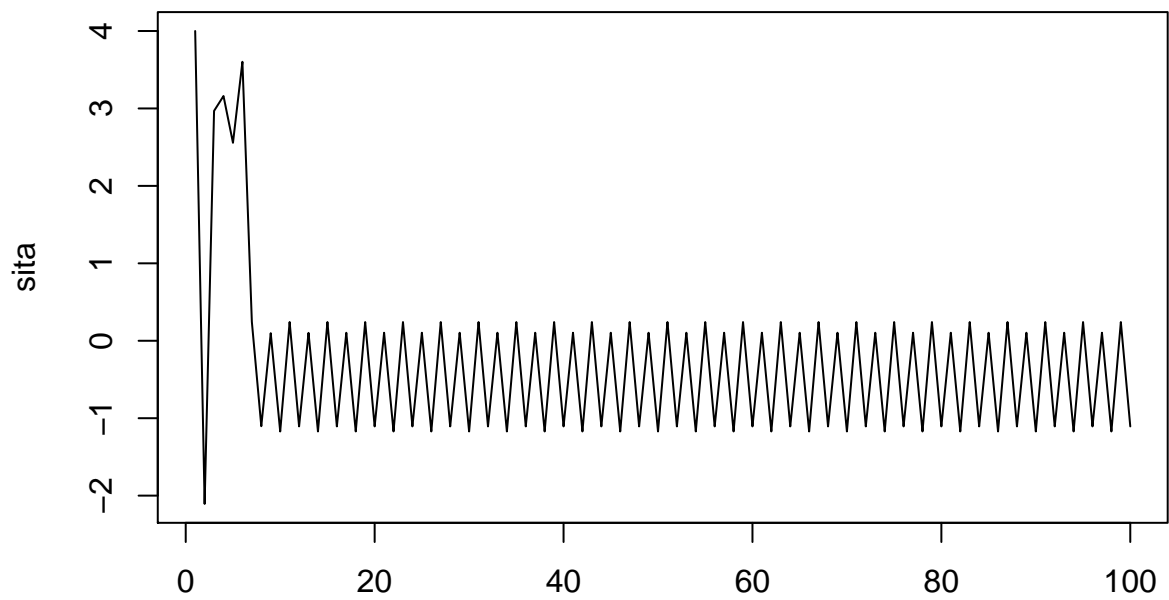
Here are plots1(c)

These plots are using different alphas and start points

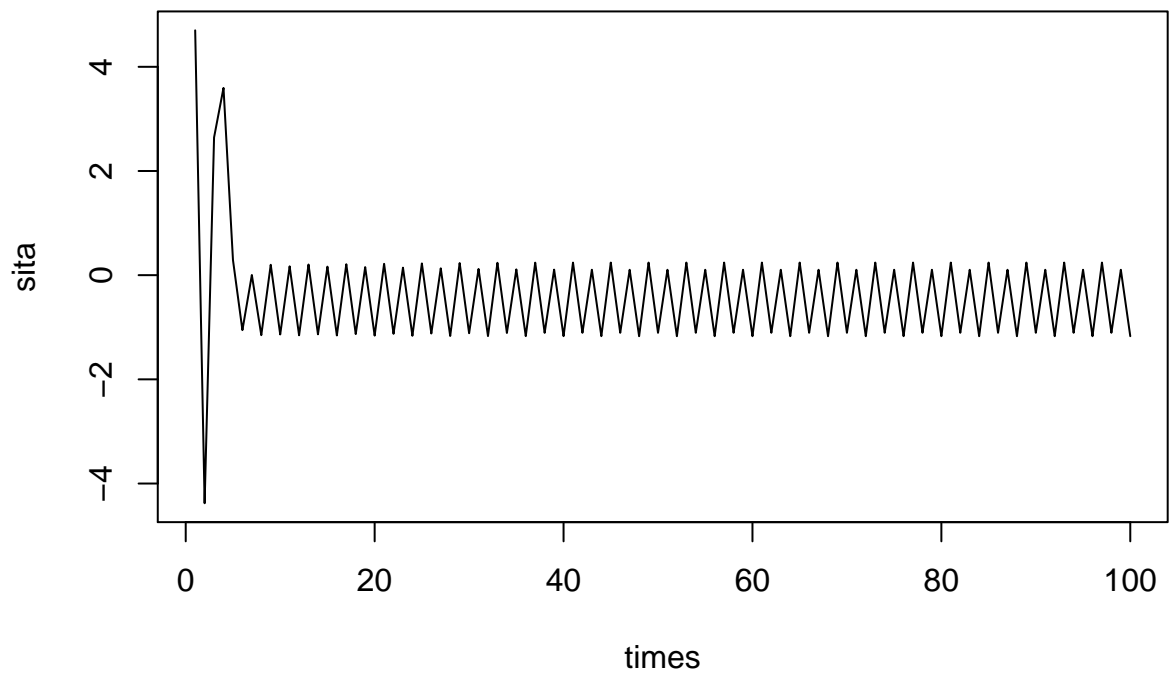




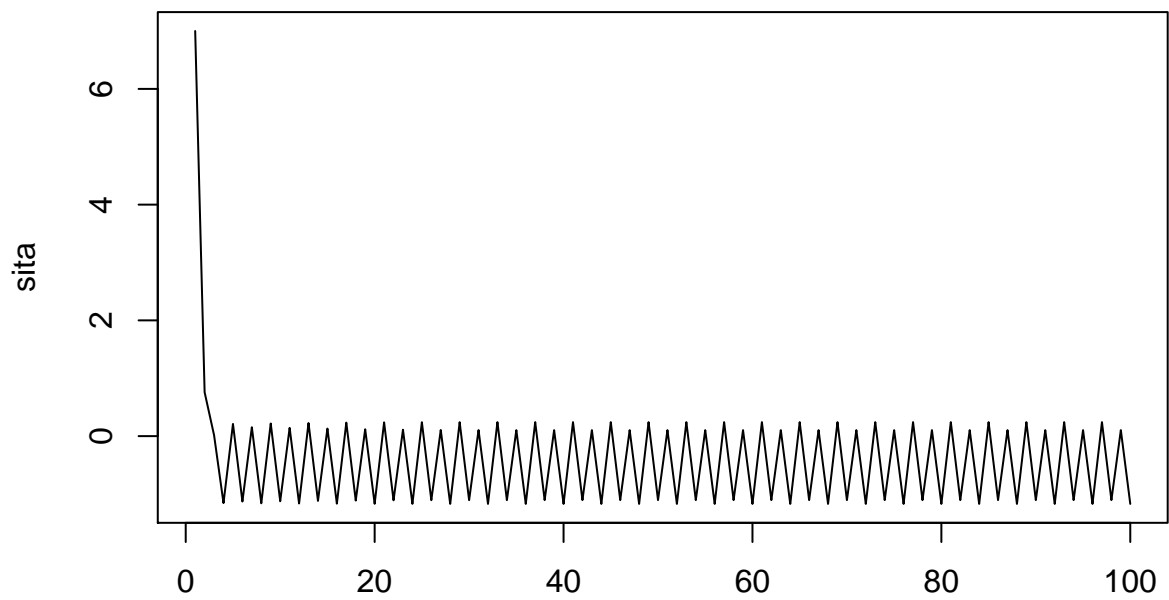
4
1



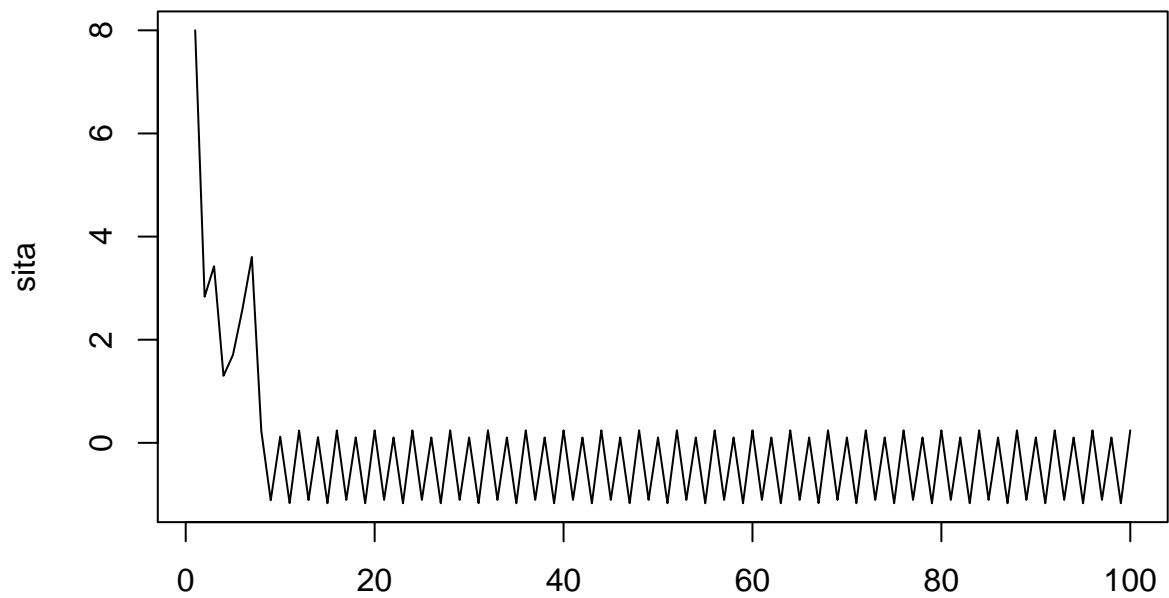
times
4.7
1



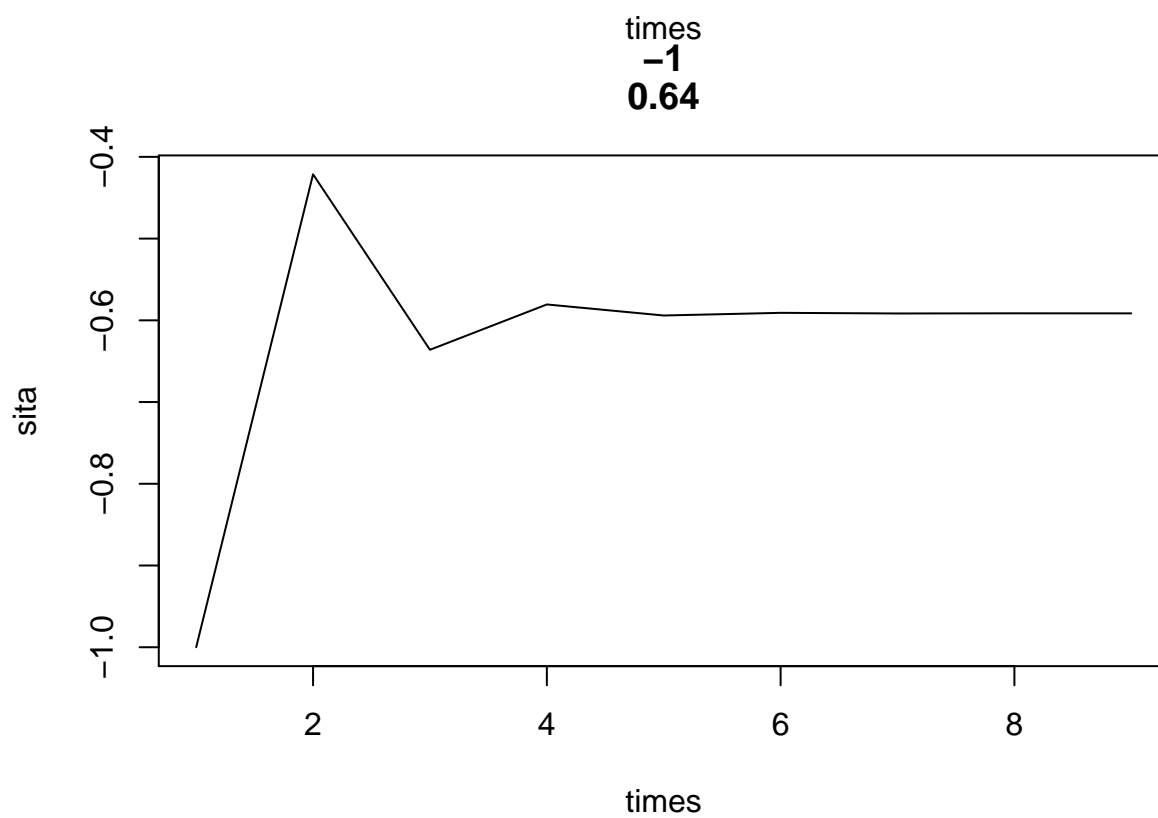
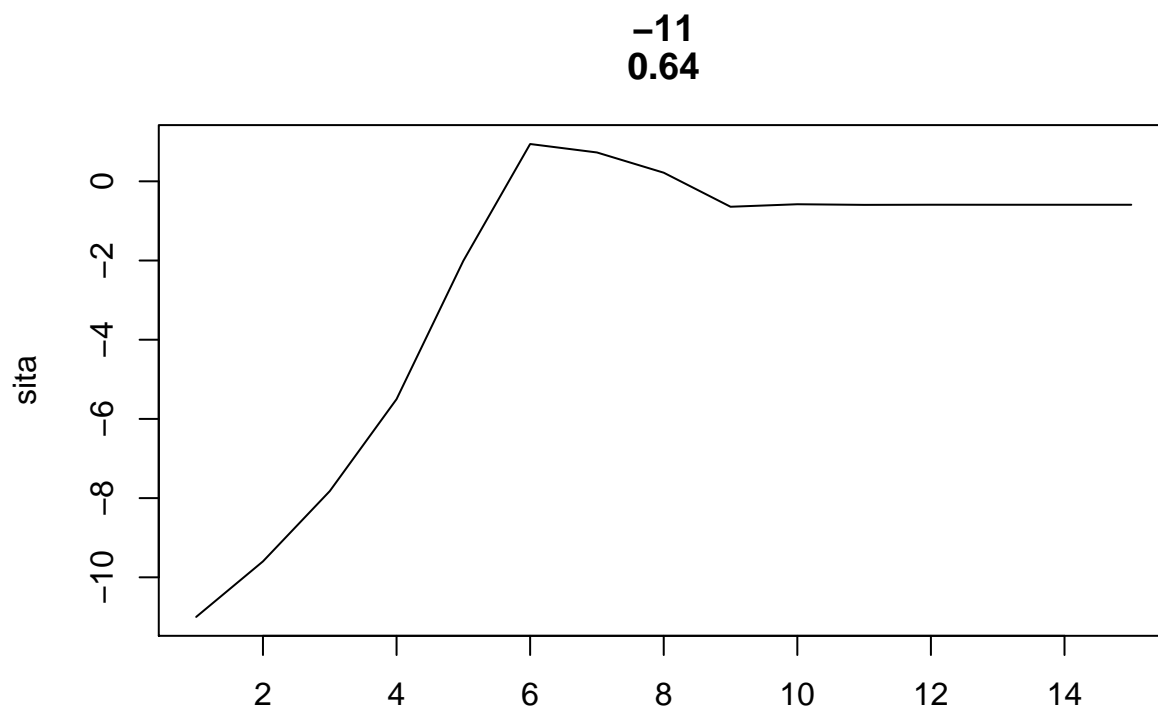
7
1

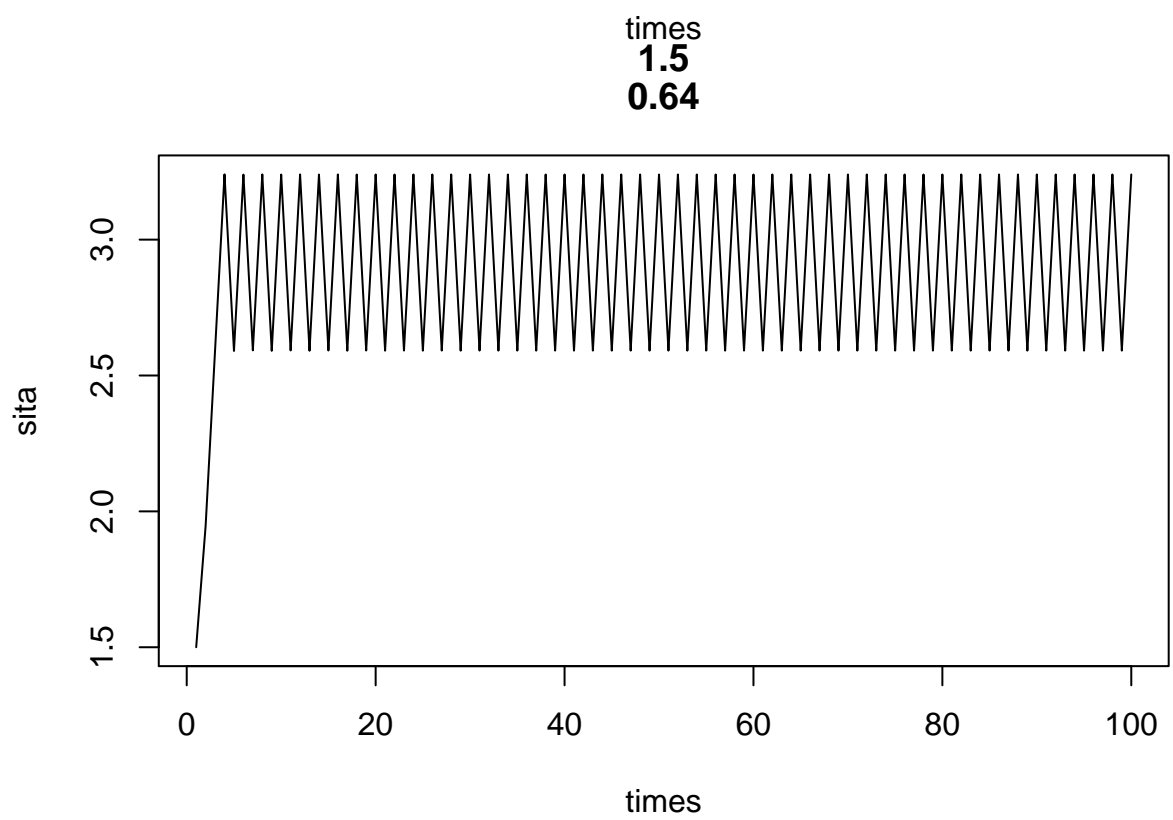
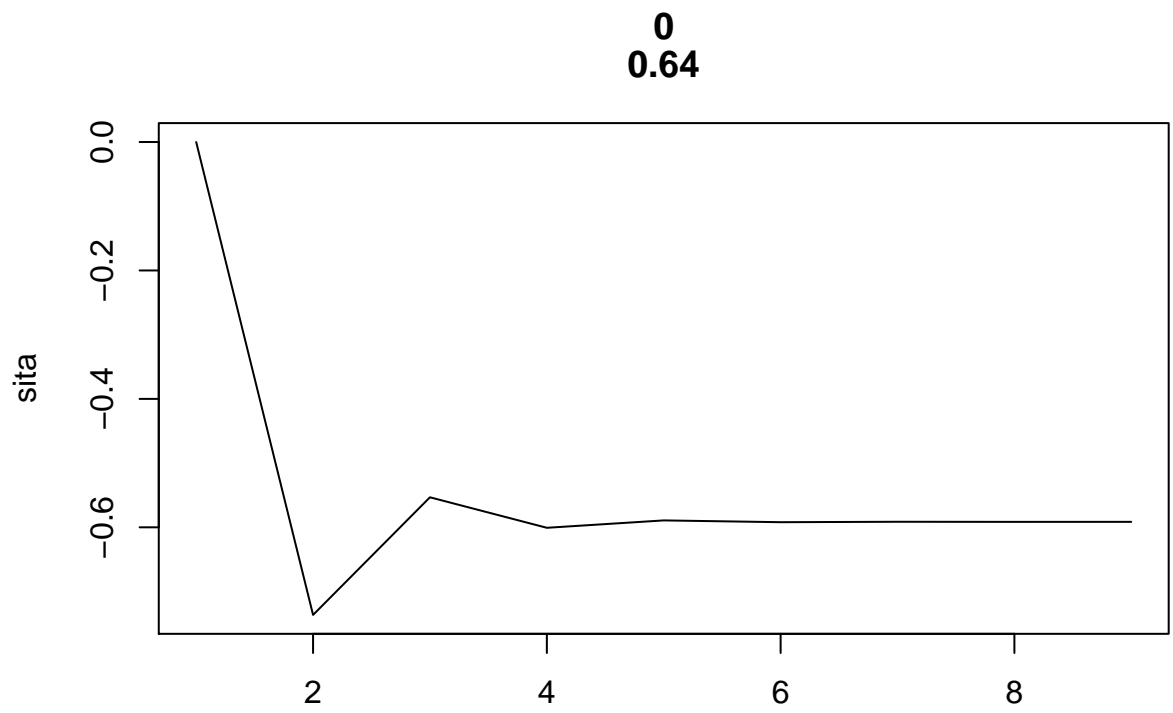


times
8
1

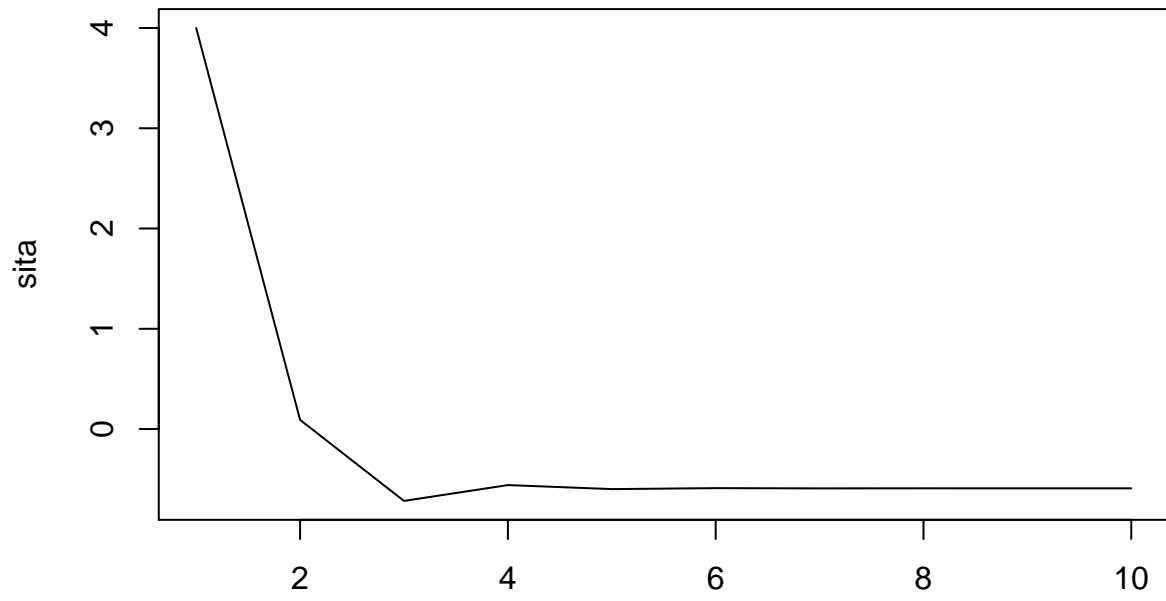


times

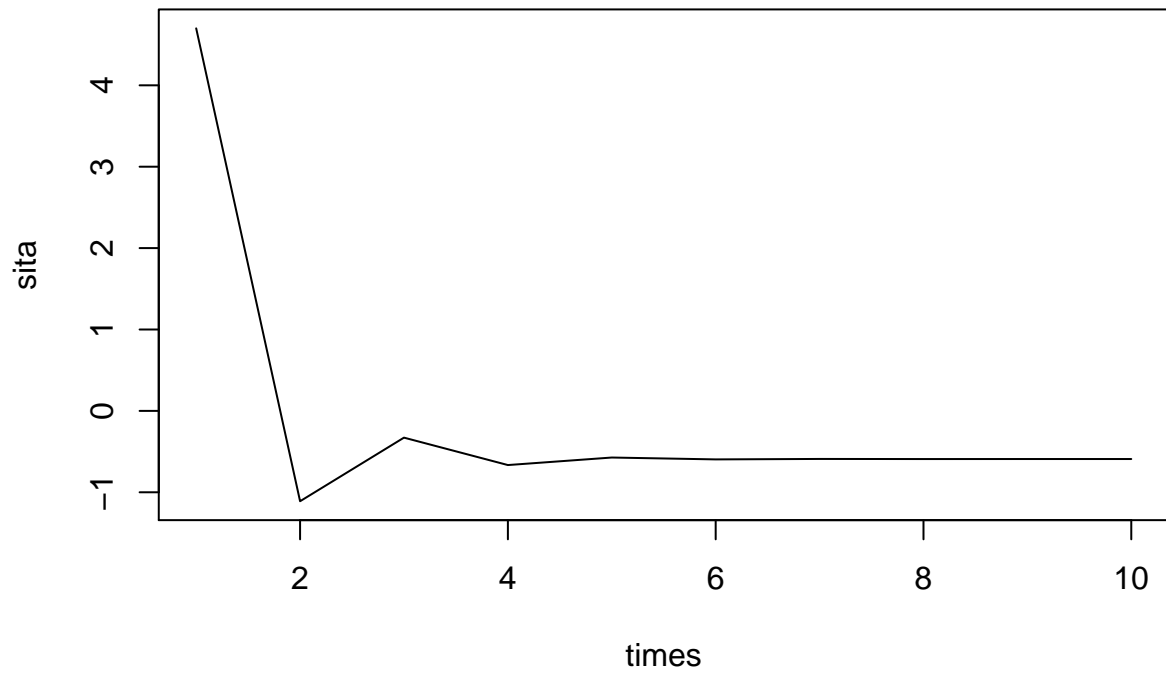




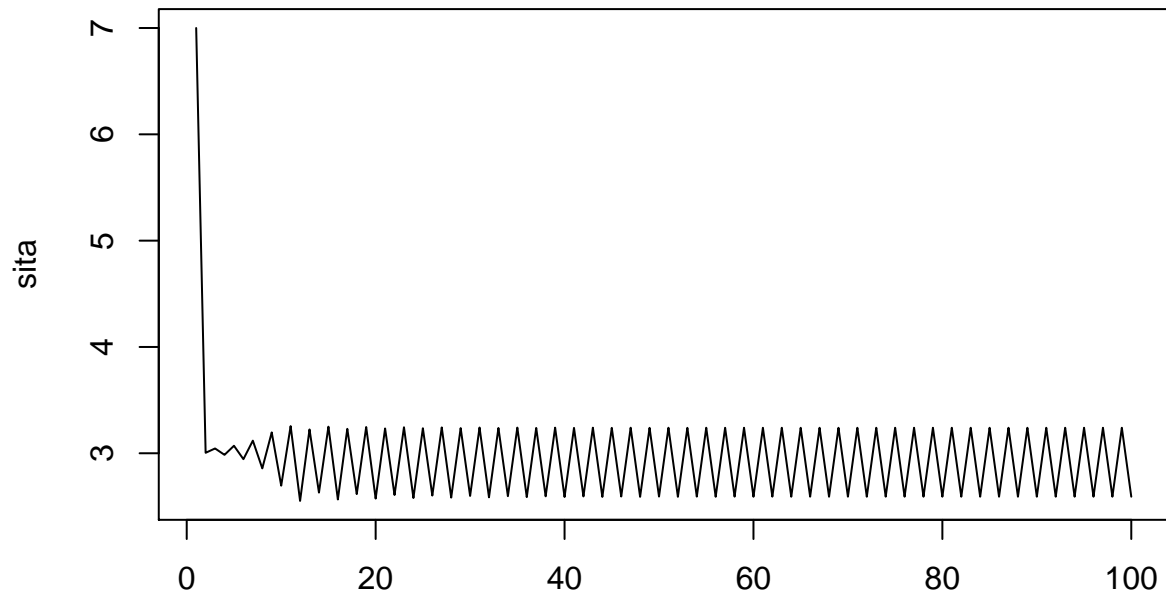
4
0.64



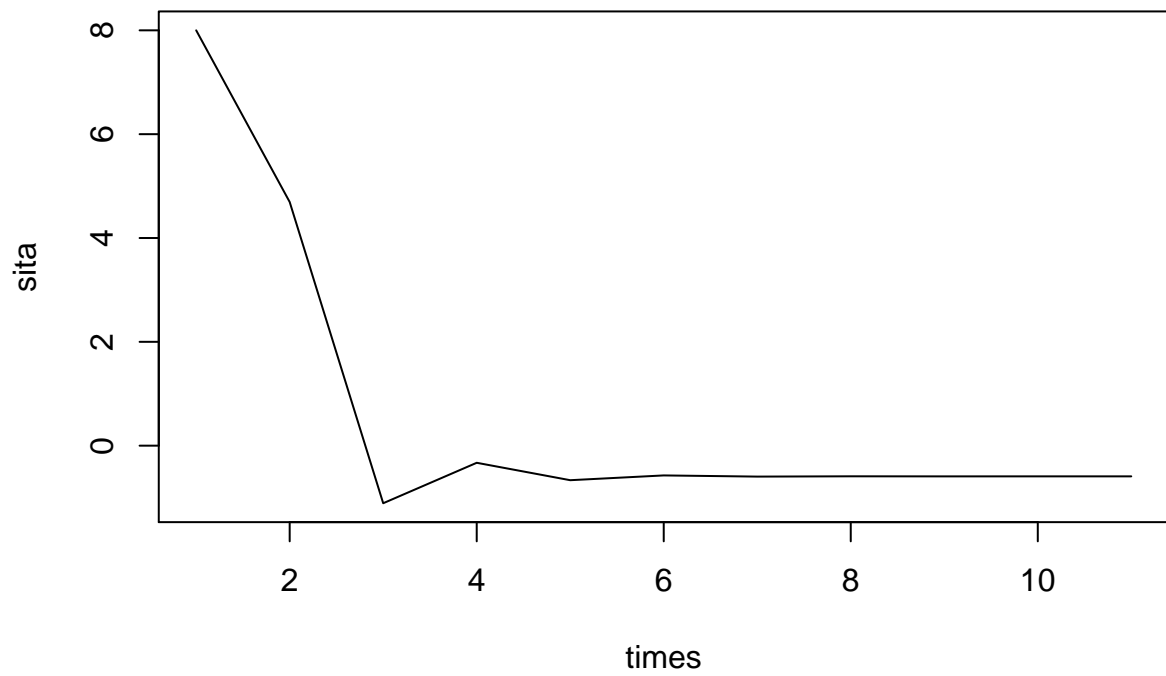
times
4.7
0.64

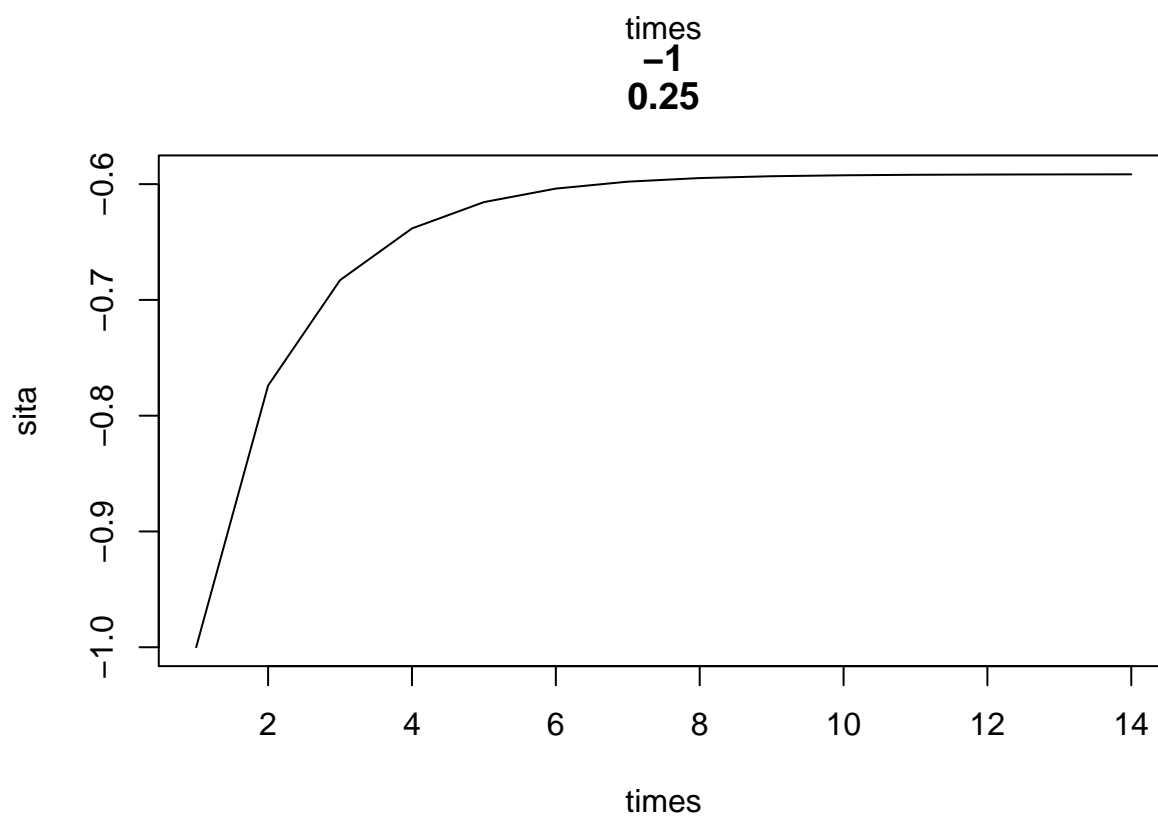
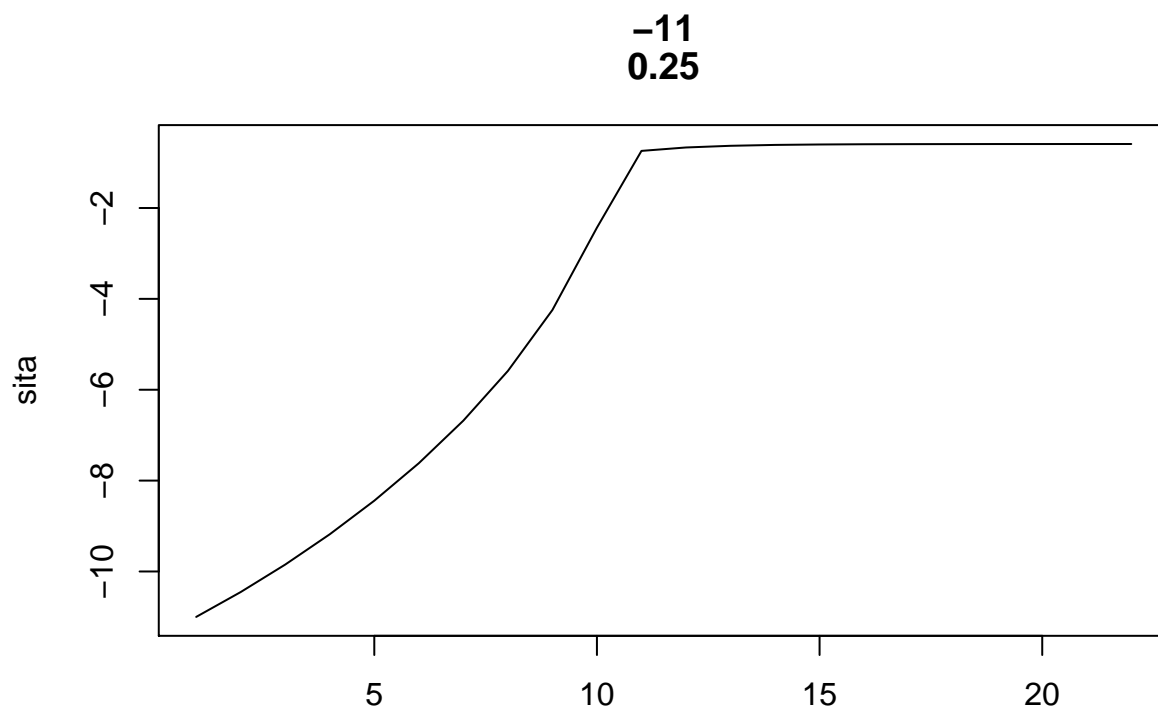


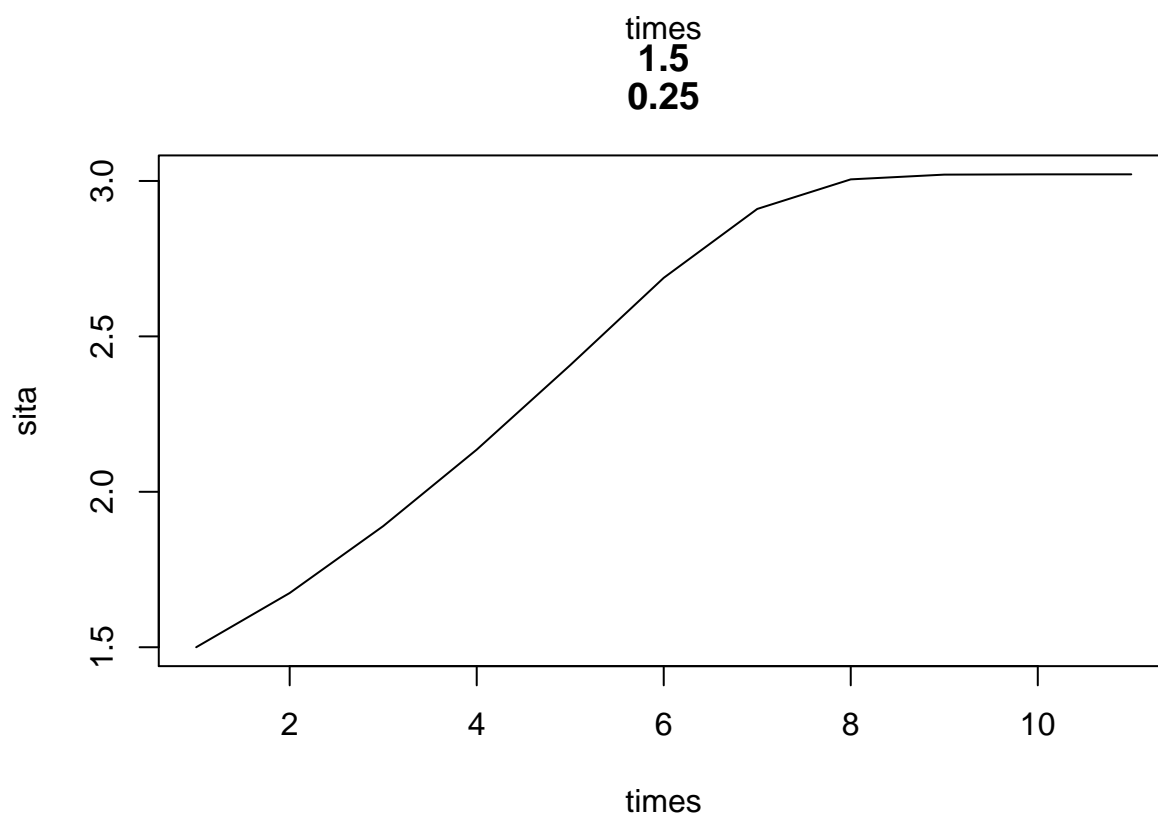
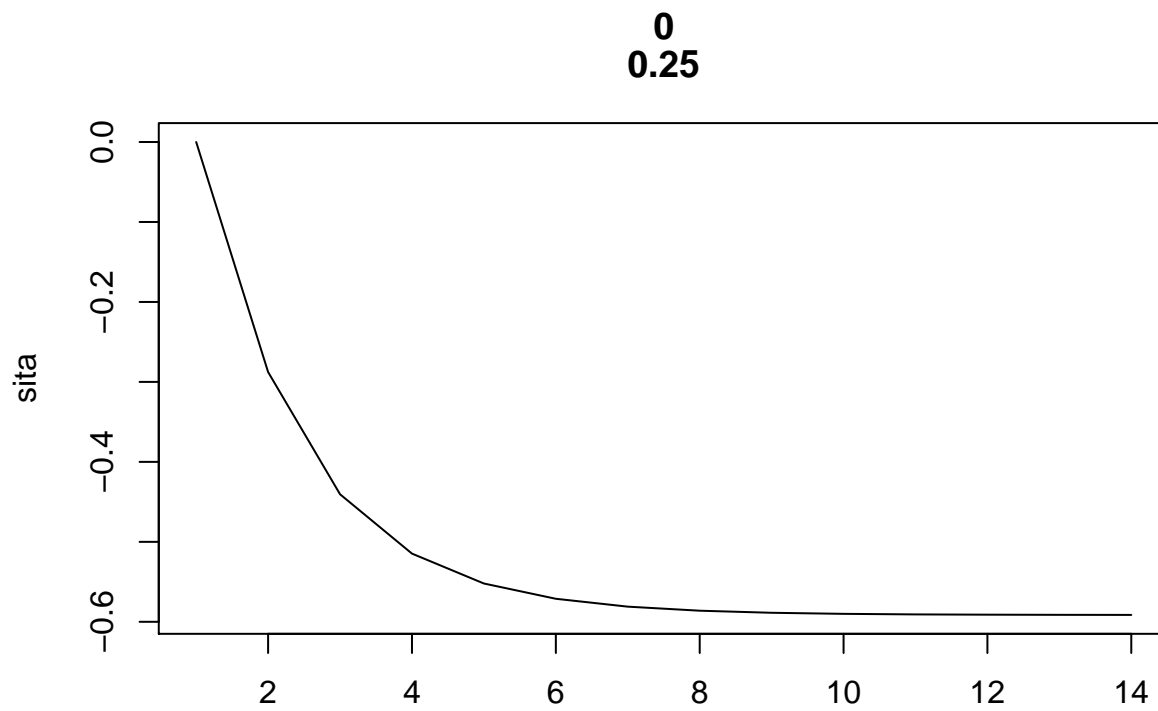
7
0.64



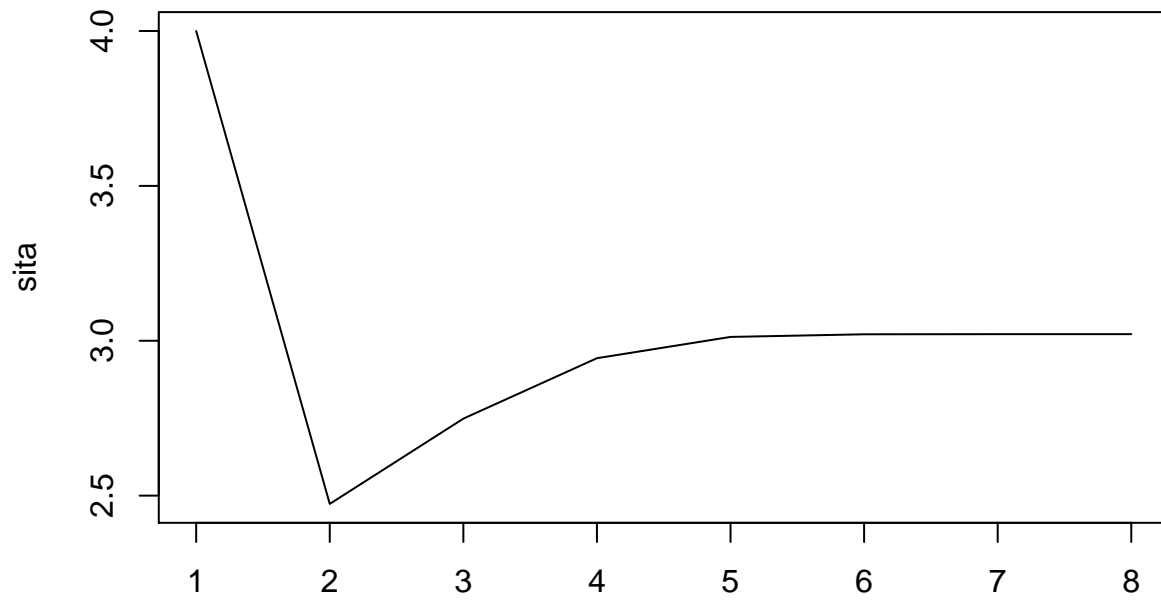
times
8
0.64



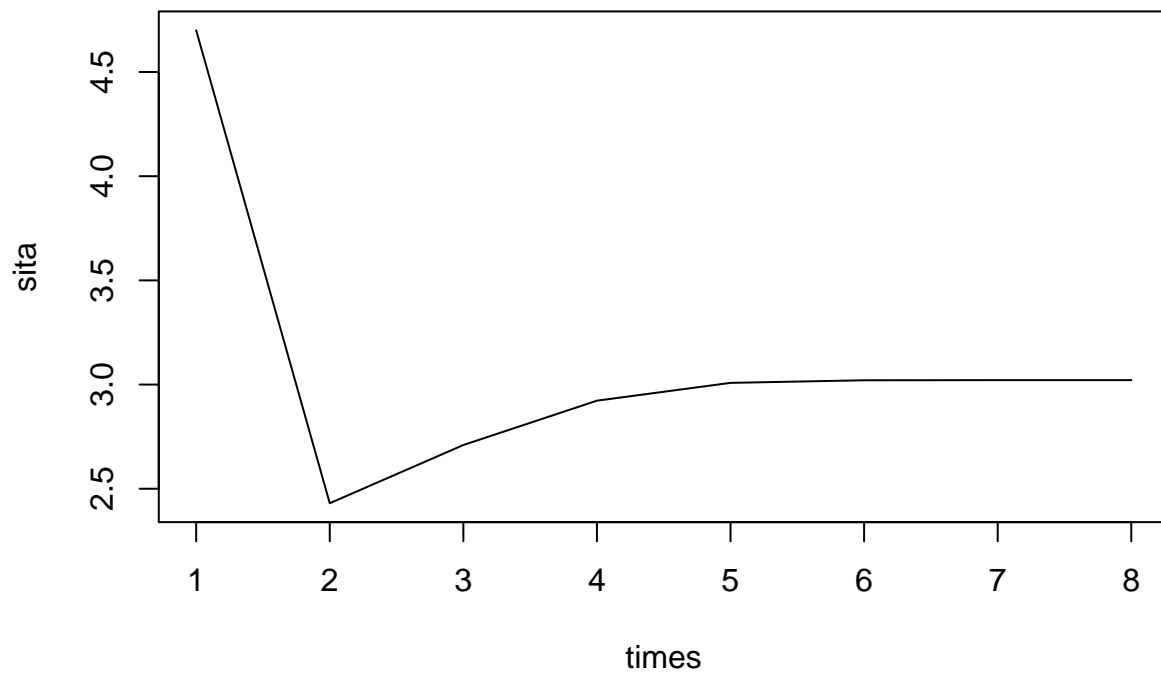


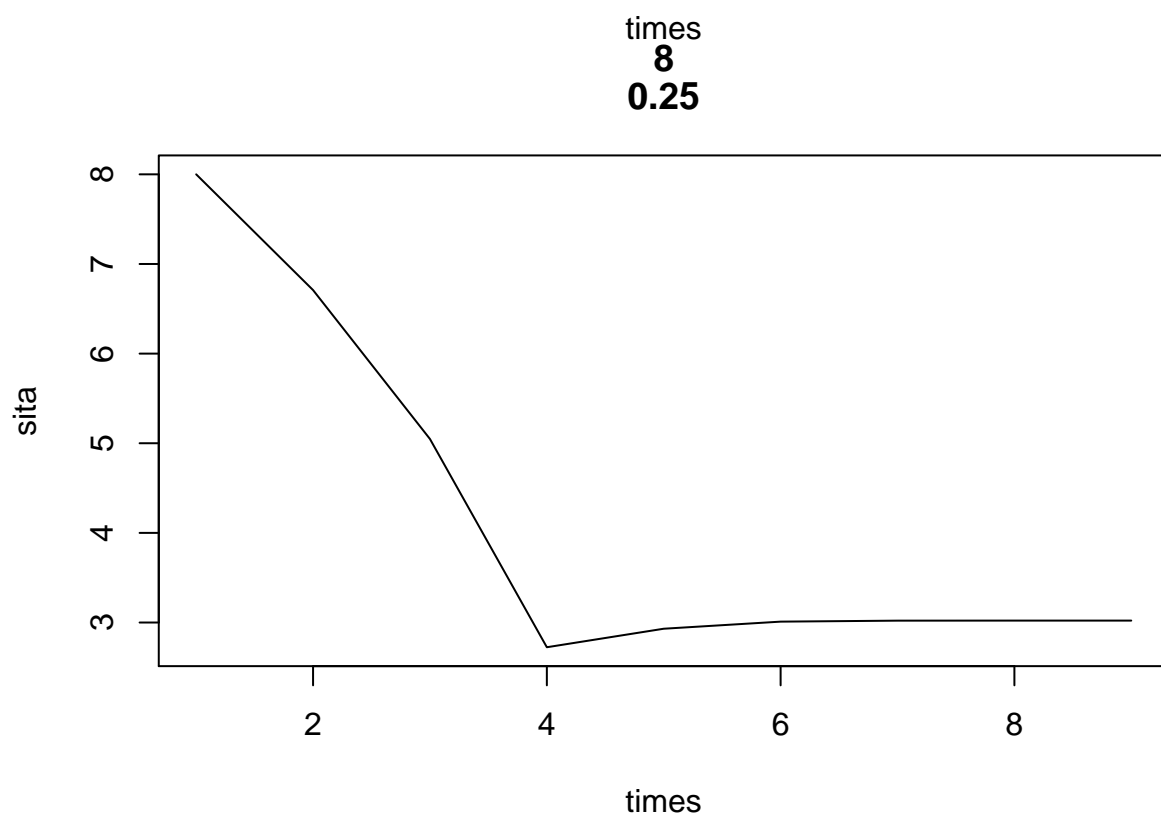
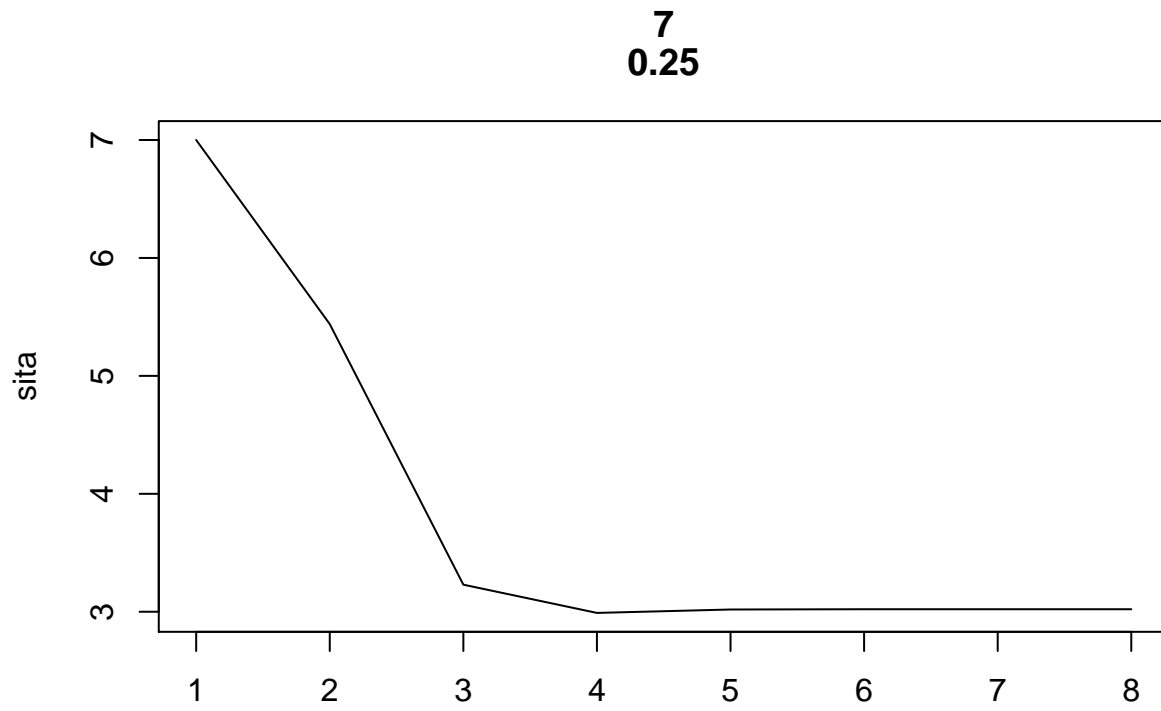


4
0.25



4.7
0.25





Question 1(d)

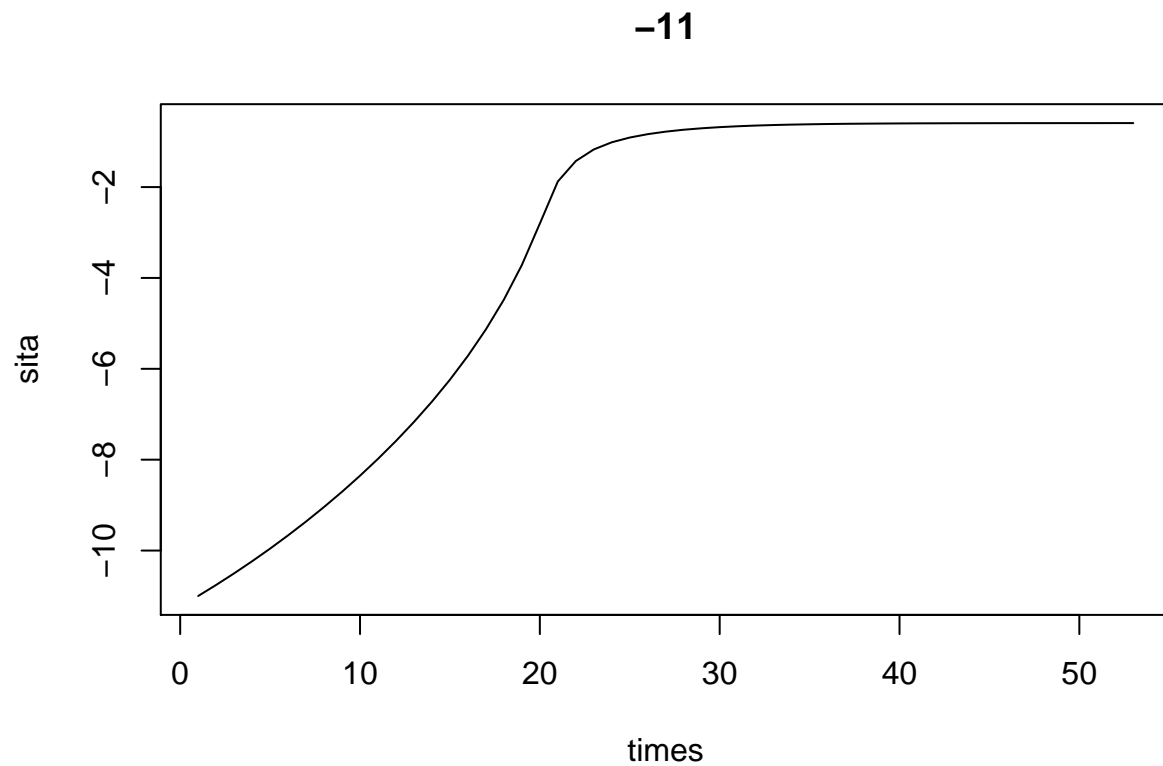
This section we use Fisher Scoring to find MLE, with $I(\theta)$ being constant of $n/2$

The functions we set up are similar with previous functions, and we compute I

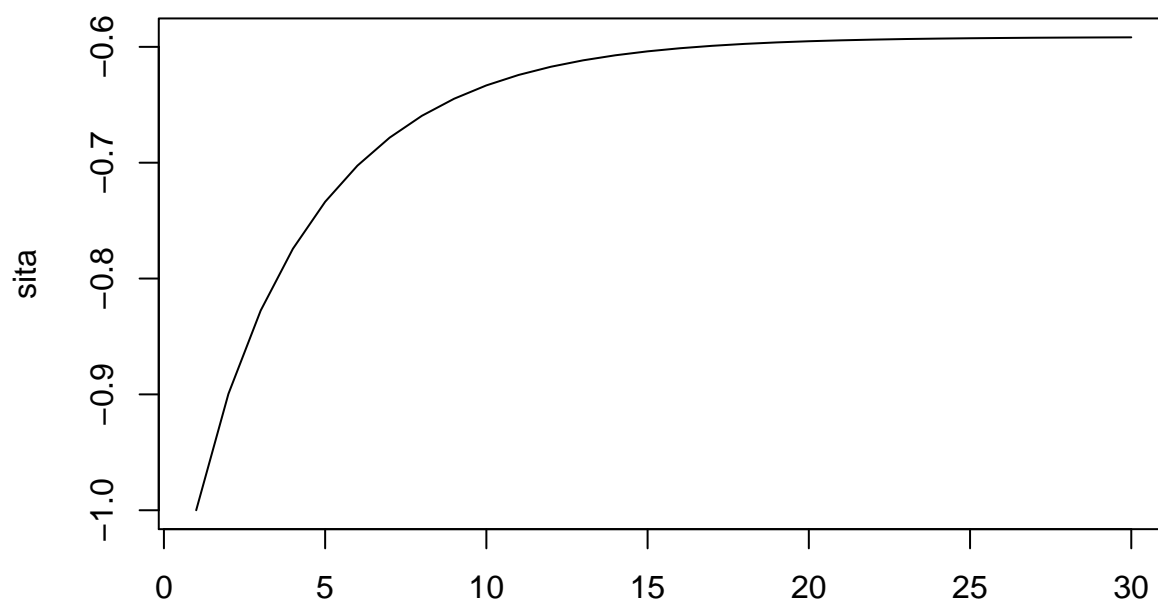
```
derivative1 <- function(x,sita){  
  value <- 0  
  for (i in 1:length(x)){  
    value <- value-2*(sita-x[i])/(1+(sita-x[i])^2)  
  }  
  return(value)  
}  
  
I <- length(x)/2
```

Plots1(d)

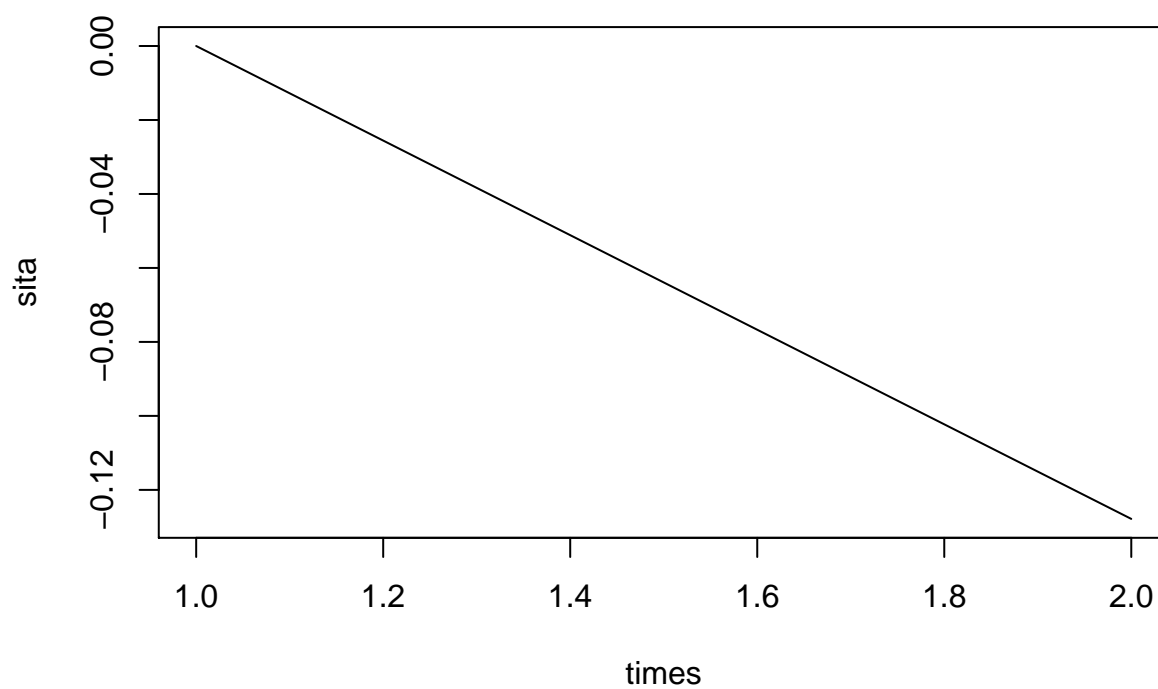
These are plots that I use multiple start points



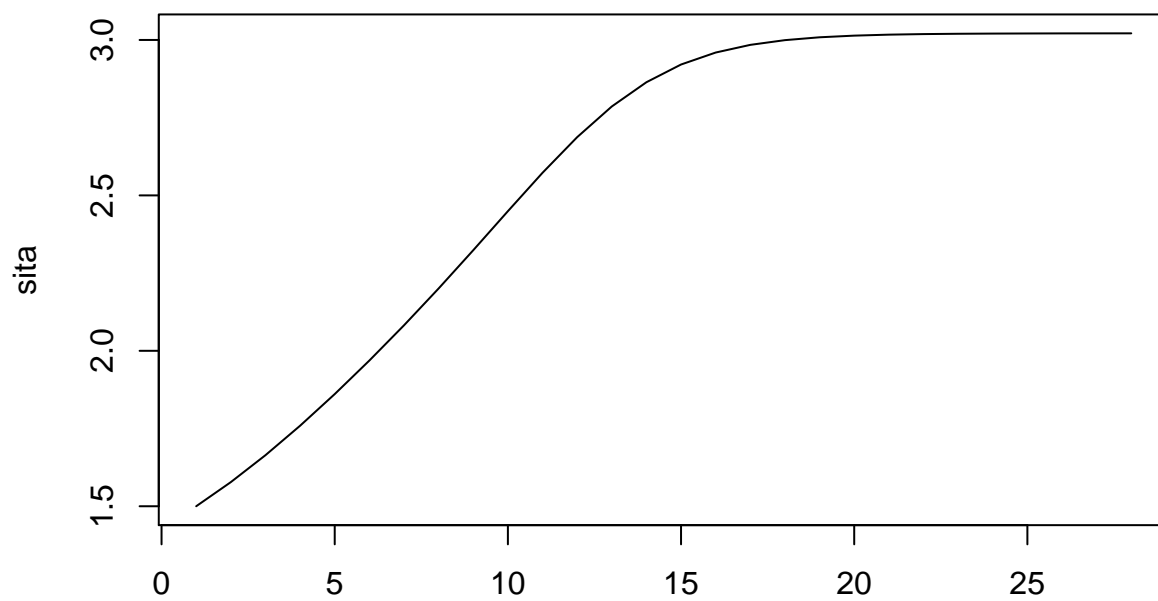
-1



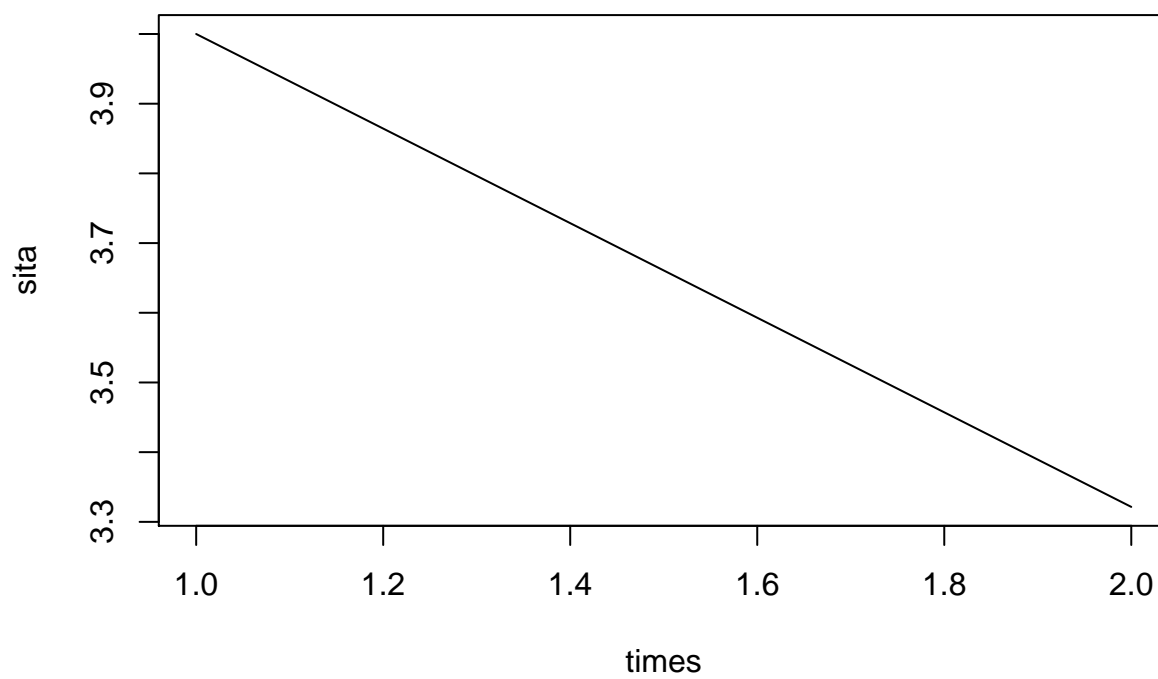
times
0



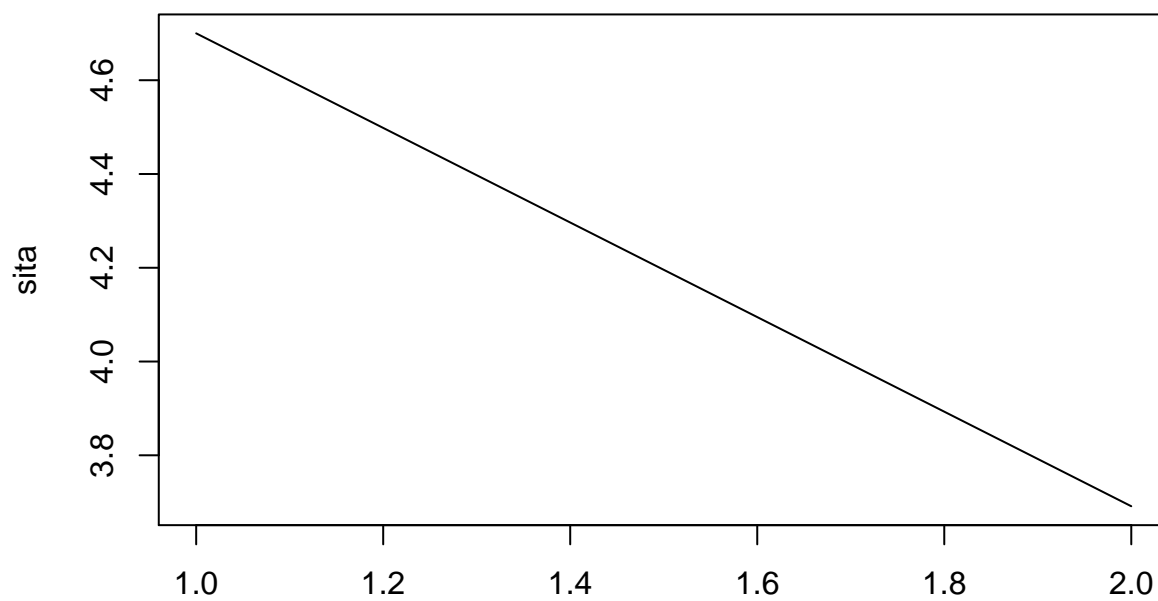
1.5



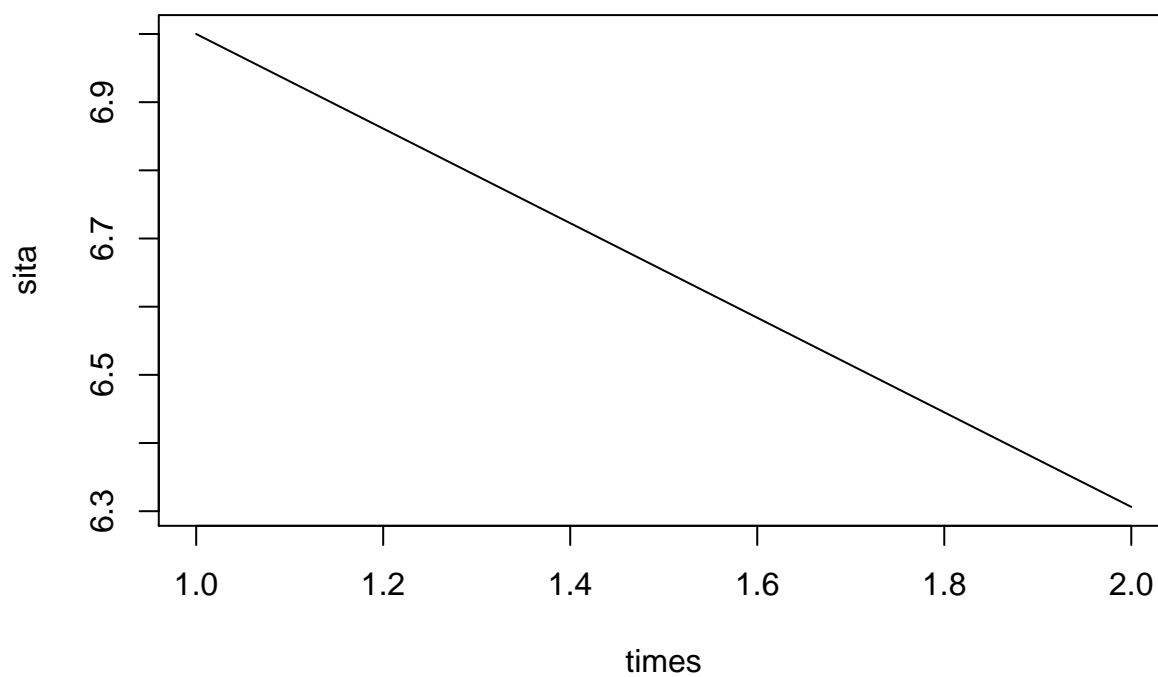
times
4



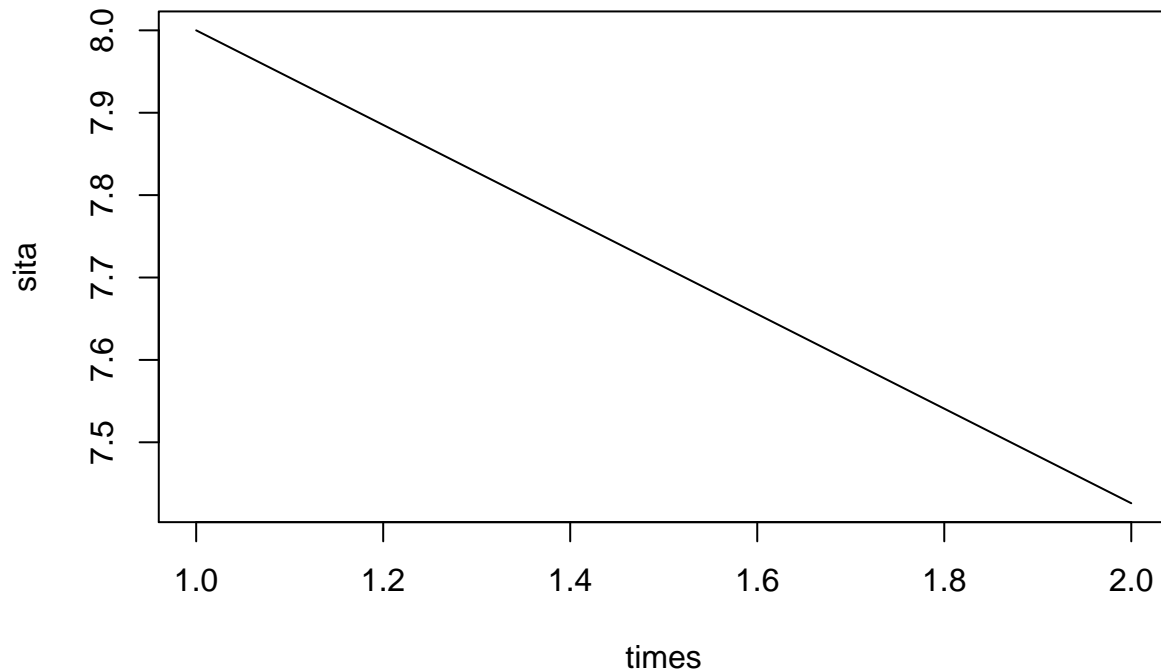
4.7



times
7



8



1(e)

With observation of the results and plots, we can see that Newton method has the highest speed and stability. For Fisher scoring, it has lower speed, but we can see from the plots, with alpha being some point the line is fluctuating up and down, so it has lowest stability. And for fixed point method, the speed of it is lowest but is relatively stable. But fixed-point has its disadvantage, not being able to utilize some points.

Qusetion 2

The likelihood function

$$E[X|\theta] = \pi + \sin(\theta) \quad (29)$$

two points

```
target <- asin(mm-pi)
print(target)

## [1] 0.09539407
target1 <- pi-target
print(target1)

## [1] 3.046199
```

The sequence of same converge start points

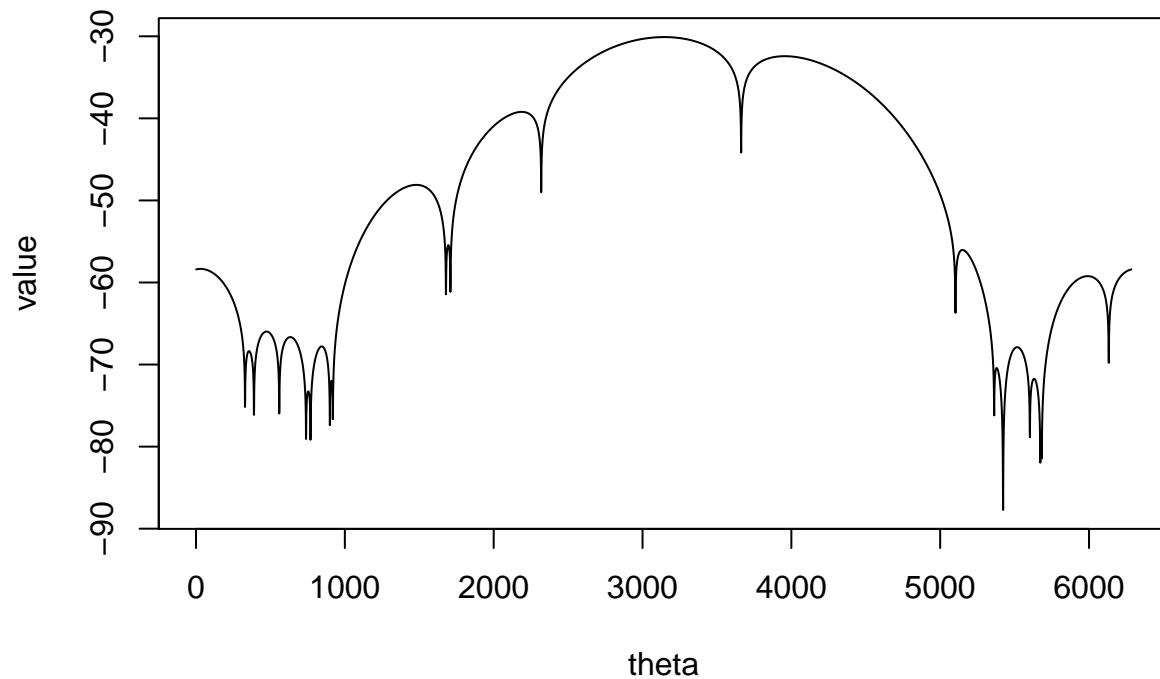
```
loglikelihood <- function(x,theta){  
  value <- 0  
  for (i in 1:length(x)){  
    value <- value+log((1-cos(x[i]-theta))/(2*pi))  
  }  
  return(value)  
}  
for (i in 1:length(result)){  
  if (abs(result[i]-result[j])>10^(-4)){  
    j <- i  
    num <- append(num,j-1)  
  }  
}  
num <- unique(num)  
print(unique(num[1:length(num)-1]))
```

```
## [[1]]  
## [1] 11  
##  
## [[2]]  
## [1] 13  
##  
## [[3]]  
## [1] 18  
##  
## [[4]]  
## [1] 24  
##  
## [[5]]  
## [1] 25  
##  
## [[6]]  
## [1] 29  
##  
## [[7]]  
## [1] 30  
##  
## [[8]]  
## [1] 54  
##  
## [[9]]  
## [1] 55  
##  
## [[10]]  
## [1] 74  
##  
## [[11]]  
## [1] 116  
##  
## [[12]]  
## [1] 162  
##
```

```
## [[13]]
## [1] 170
##
## [[14]]
## [1] 172
##
## [[15]]
## [1] 178
##
## [[16]]
## [1] 180
##
## [[17]]
## [1] 195
```

Plots2

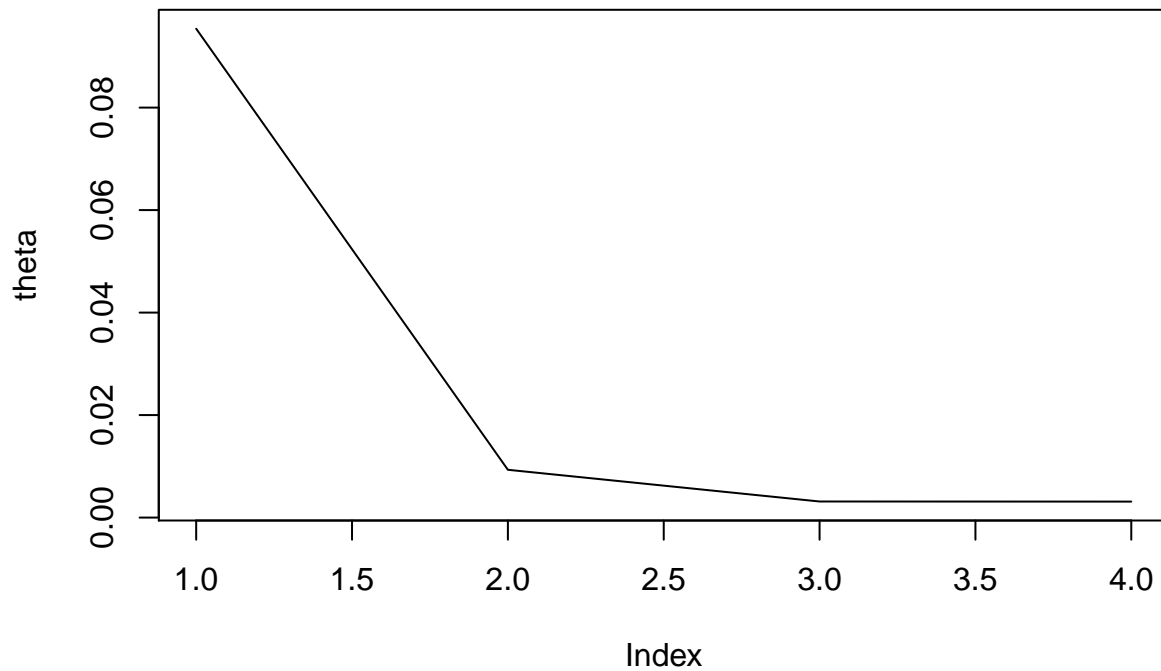
We plot the value of our target



we also plot the picture with strat point being 'target'

```
MLE <- function(theta){
  diff <- 1
  i <- 1
  while(abs(diff)>10-4){
    theta[i+1] <- theta[i]-derivative1(x,theta[i])/derivative2(x,theta[i])
    diff <- theta[i+1]-theta[i]
    i <- i+1
  }
  plot(theta,type='l')
  return(theta)
}
```

```
theta <- array()
theta[1] <- target
s <- MLE(theta)
```



Question 3(b)

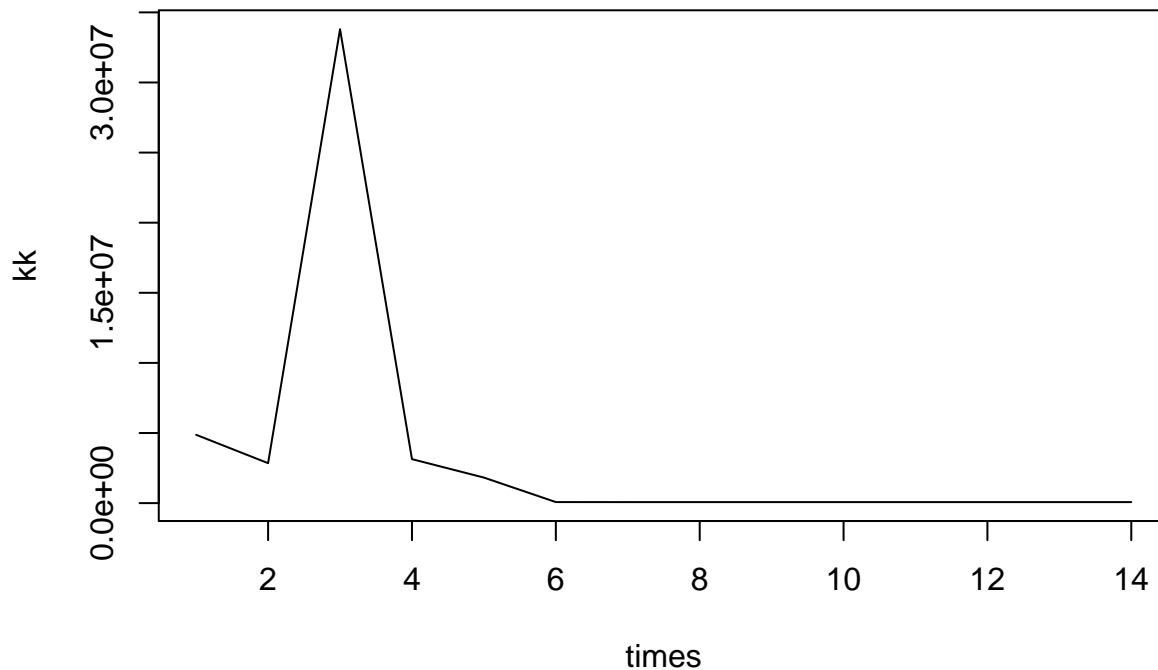
Functions

Here are matrix we need to establish to build our function

```
A_matrix <- function(r,k,times){
  A <- matrix(nrow=times,ncol=2)
  for (i in 1:times){
    A[i,1] <- (NO^2-NO^2*exp(-1*r*beetles$days[i]))/((NO+(k-NO)*exp(-1*r*beetles$days[i]))^2)
    A[i,2] <- beetles$days[i]*(k-NO)*exp(-1*r*beetles$days[i])*k*NO/((NO+(k-NO)*exp(-1*r*beetles$days[i]))^2)
  }
  A
}

Z_matrix <- function(r,k,times){
  z <- matrix(nrow=times,ncol=1)
  for (i in 1:times){
    z[i,1] <- beetles$beetles[i]-k^2/(2+(k-2)*exp(-r*beetles$days[i]))
  }
  z
}
```

Sum of squared errors



Question 3(c)

This time we need to optimize the value of r , K , σ

Partial Derivative

```
d_sigma <- as.expression(D(u, 'sigma'))
dd_sigma <- as.expression(D(d_sigma, 'sigma'))

d_k <- as.expression(D(u, 'k'))
dd_k <- as.expression(D(d_k, 'k'))

d_r <- as.expression(D(u, 'r'))
dd_r <- as.expression(D(d_r, 'r'))
```

3c

I use Newton method to optimize the r , K , and square of σ . These numbers are

Times we use

```
## [1] 37
```

The results

```
print(kF)
```

```
## [1] 820.38
```

```
print(rF)
```

```
## [1] 0.1926401
```

```
print(sigmaF)
```

```
## [1] 0.9108726
```