# Lab1 - Group 6

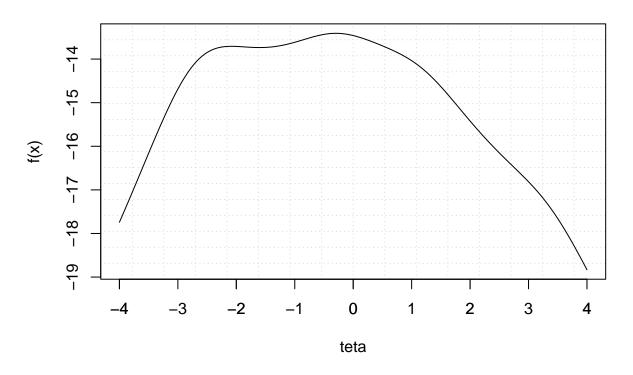
Ayesha Gamage - ayega<br/>981, N ${\it Muditha}$ Cherangani-mudch 175

### Question 1:

The log likelihood function,

$$f(x) = -nlog(\pi) - \sum_{i=1}^{n} log(1 + (x_i - \theta)^2)$$

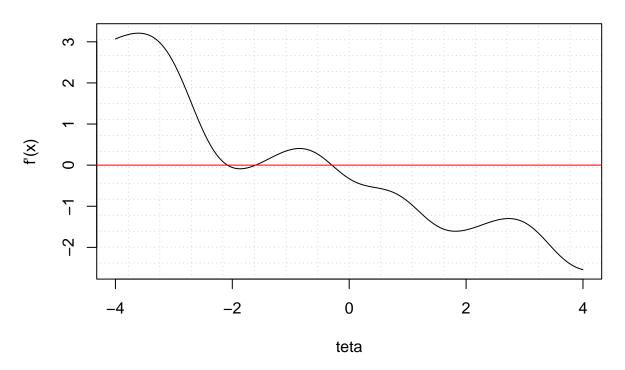
# **Log Likelihood Function**



f(x) derivative with respect to  $\theta$  is,

$$f'(x) = \sum_{i=1}^{n} \frac{2(x_i - \theta)}{1 + (x_i - \theta)^2}$$

# **Derivative of Log Likelihood Function**

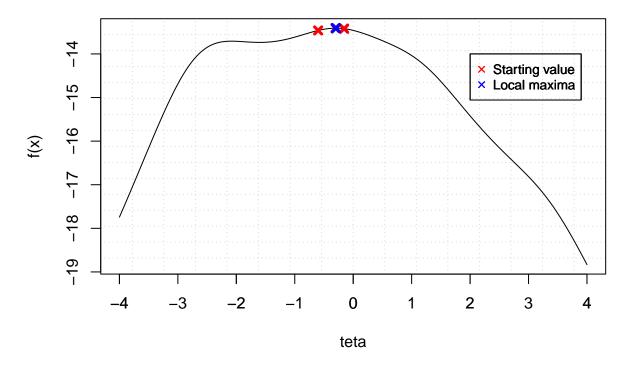


A derivative of zero given when y=0.In this graph shown 3 points which derivative is 0.

### b). Newton-Raphson Method,

In the question has first derivative of log likelihood function, using the "Deriv" r library got second derivative by derivative function. In the following r code, "d2fx" function return the second derivative.

### **Log Likelihood Function**



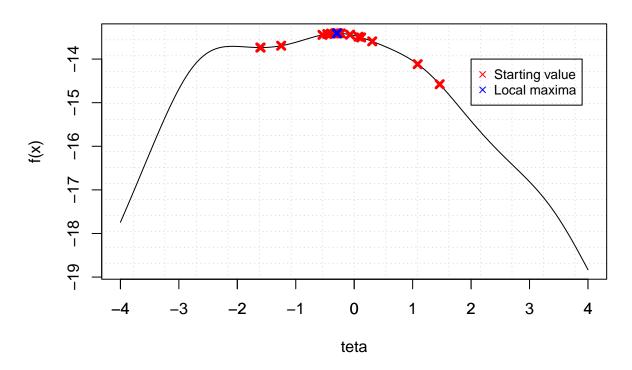
## [1] -0.2952455

c).

Two local maxima identified by using log likelihood and derivative log likelihood plots. Using the following example for newton functions found suitable starting values to lead local maxima based on the plots. The starting values between -0.6 to 0.1 lead one local maxima and values between -3 and -1.9 lead other local maxima. In here identify staring values which not lead local maxima such as ,-3.5,-3.7,-3.8,-3.9,-4 and starting values between 4 and 2. I got two local maxima values from the program. Those are -2.082124 and -0.2952455. When consider the log likelihood function plot i get the -0.2952455 as global maxima.

d).

## Log Likelihood Function



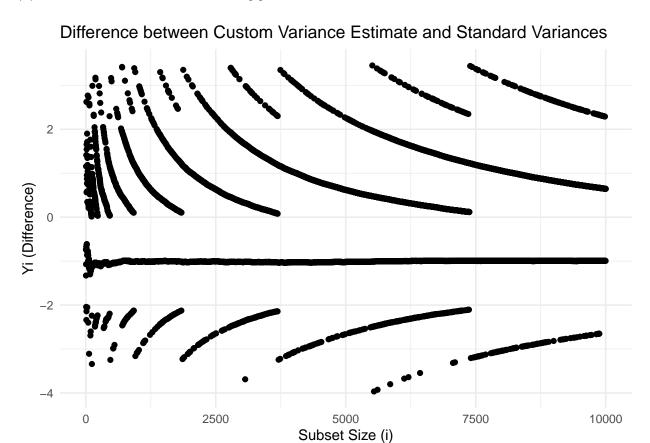
## [1] -0.2952455

### Question 2

#### (a).R function, myvar

### (b). Generate a vector $\mathbf{x} = (\mathbf{x}1, \dots, \mathbf{x}10000)$ with 10000 random numbers

### (c). Plot the dependence Y\_{i} on i.



With an increasing sample size, variance different should be close to 0.But, here variance difference is fluctuate between -4 and 4. The plot shows that. When consider function given variance values, there is a Precision error when divided by n and n-1.

(d).

To implement a better variance estimator, can use the sample variance formula, which is more numerically stable and equivalent to standard variances. In here used following formula for better variance,

$$bettervar = \sum_{i=1}^{n} (X - meanx)^{2} / (n-1)$$

```
stop("Sample size must be greater than 1.")
}

mean_x <- mean(X)
better_var_x <- sum((X - mean_x)^2) / (n - 1)

return(better_var_x)
}

# i <- 2:10000

# Y<-sapply(i, function(i){better_var(x[1:i])-var(x[1:i])})

# data <- data.frame(i, Y)

# ggplot(data, aes(x = i, y = Y)) +

# geom_point() +

# labs(x = "Subset Size (i)", y = "Yi (Difference)") +

# ggtitle("Difference between Better Variance Estimate and Standard Variances") +

# theme_minimal()</pre>
```

### Appendix: All r code for this report

```
knitr::opts chunk$set(echo = TRUE)
library("Deriv")
n < -5
x \leftarrow c(-2.8, 3.4, 1.2, -0.3, -2.6)
teta \leftarrow seq(-4,4,by=0.01)
#log function
fx <- function(teta,x){</pre>
 return( -n*log(pi) - sum(log(1+((x-teta)^2))))
\#print(fx(0.2,x))
#plot the log function
log_plot <- function(){</pre>
 points <- (sapply(teta, fx,x))</pre>
 plot(teta ,points,type = "l", xlab="teta",ylab = "f(x)",xlim =c(-4,4),panel.first = grid(nx=16),main =
 axis(side=1, at=c(-4:4))
}
log_plot()
#derivative function
dfx <- function(teta,x){</pre>
 return(sum((2*(x-teta))/(1+(x-teta)^2)))
#plot the derivative function
```

```
derivative_plot <- function(){</pre>
  points <- (sapply(teta, dfx,x))</pre>
  plot(teta ,points,type = "l", xlab="teta",ylab = "f'(x)",xlim =c(-4,4),panel.first = grid(nx=16),main
  abline(h=0,col="red")
}
derivative_plot()
#second derivative
d2fx <- function(teta,x){</pre>
  f \leftarrow expression(sum((2*(x-teta))/(1+(x-teta)^2)))
 d2val <- Deriv(f,'teta')</pre>
 return(eval({teta; d2val}))
}
# Newton function
newton \leftarrow function(x0, eps=0.0001){
  xt <- x0
  xt1 \leftarrow x0 + 2 # xt1 is x(t-1); starting value
  log_plot()
  while(abs(xt-xt1)>eps)
   xt1 <- xt
    dfx_v \leftarrow dfx(xt1,x)
    d2fx_v \leftarrow d2fx(xt1,x)
    xt <- xt1 - (dfx_v/d2fx_v)
    points(xt1, fx(xt1,x), col="red", pch=4, lwd=3) # starting value in plot
    points(xt, fx(xt,x), col="blue", pch=4, lwd=3) # result in plot
    legend(2,-14,legend=c("Starting value","Local maxima"), col =c("red","blue"),ncol = 1,pch=4, cex=0.
   }
  xt
}
newton(-0.6)
get_stating <- function(min_range,max_range,N,eps=0.0001){</pre>
  log_plot()
  rand_points <- runif(N,min_range,max_range)</pre>
  global_max<- rand_points[1]</pre>
  for(i in rand_points){
   x0<- i
    xt <- x0
    xt1 < - x0 + 2
    found<-TRUE
    while(abs(xt-xt1)>eps)
      prev_dif <- xt1-xt</pre>
      xt1 <- xt
      dfx_v \leftarrow dfx(xt1,x)
      d2fx_v \leftarrow d2fx(xt1,x)
      xt \leftarrow xt1 - (dfx_v/d2fx_v)
      current_dif <-xt1-xt</pre>
```

```
#check weather value in given range
     if((abs(xt)>4) && abs(prev_dif) < abs(current_dif)){</pre>
       found<-FALSE
       break
      points(xt1, fx(xt1,x), col="red", pch=4, lwd=3) # starting value in plot
   if(found && fx(xt,x)>fx(global_max,x)){
       local_max <- xt</pre>
   }
  }
   points(local_max, fx(local_max,x), col="blue", pch=4, lwd=3) # result in plot
   legend(2,-14,legend=c("Starting value","Local maxima"), col =c("red","blue"),ncol = 1,pch=4, cex=0..
 local_max
}
get_stating(-4,4,5)
library(ggplot2)
myvar <- function(X) {</pre>
 n <- length(X)
  if (n <= 1) {
   stop("Sample size must be greater than 1.")
  sum_xi_squared <- sum((X^2))</pre>
  sum_xi <- sum(X)</pre>
 myvar_x \leftarrow (sum_xi_squared - ((sum_xi^2)/n))/(n - 1)
 return(myvar_x)
x \leftarrow rnorm(10000, mean = 10^8, sd = 1)
options(digits = 22)
i <- 2:10000
Y<-sapply(i, function(i){myvar(x[1:i])-var(x[1:i])})
data <- data.frame(i, Y)</pre>
ggplot(data, aes(x = i, y = Y)) +
  geom_point() +
 labs(x = "Subset Size (i)", y = "Yi (Difference)") +
 ggtitle("Difference between Custom Variance Estimate and Standard Variances") +
 theme_minimal()
better_var <- function(X) {</pre>
 n <- length(X)
  if (n <= 1) {
   stop("Sample size must be greater than 1.")
  }
 mean_x <- mean(X)</pre>
```

```
better_var_x <- sum((X - mean_x)^2) / (n - 1)

return(better_var_x)
}
# i <- 2:10000
# Y<-sapply(i, function(i){better_var(x[1:i])-var(x[1:i])})
# data <- data.frame(i, Y)

# ggplot(data, aes(x = i, y = Y)) +
# geom_point() +
# labs(x = "Subset Size (i)", y = "Yi (Difference)") +
# ggtitle("Difference between Better Variance Estimate and Standard Variances") +
# theme_minimal()</pre>
```