MLE Project

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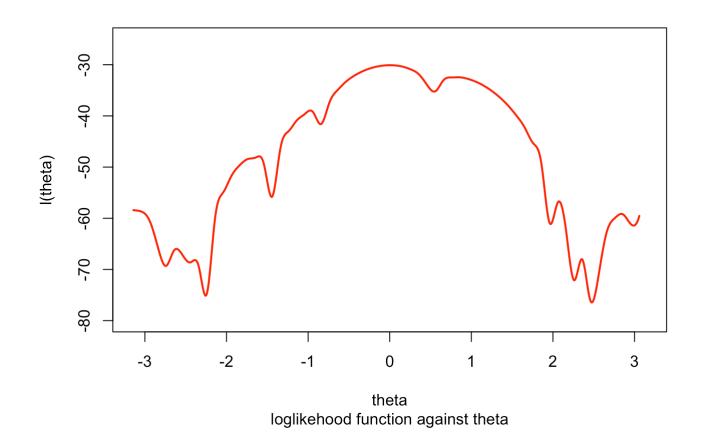
3.3.2 Many Local Maxima

Find the log-likelihood and plot

Equation:

$$L(\theta; x) = \prod_{i=1}^{n} f(x_i; \theta) = (2\pi)^{-n} \prod_{i=1}^{n} [1 - \cos(x_i - \theta)]$$

$$l(\theta) = \ln L(\theta; X) = -n \ln(2\pi) + \sum_{i=1}^{n} \ln[1 - \cos(x_i - \theta)]$$



Find Method of moments estimator of theta

$$E[X|\theta] = \int_0^{2\pi} \frac{x(1 - \cos(x - \theta))}{2\pi} dx = \frac{1}{2\pi} (2\pi^2 + 2\pi \sin(\theta)) = \sin(\theta) + \pi$$
$$\tilde{\theta}_n = \arcsin(\bar{X}_n - \pi)$$

Find the MLE by Newton-Raphson method

$$l'(\theta) = \sum_{i=1}^{n} \frac{-sin(x_i - \theta)}{1 - cos(x_i - \theta)}$$

$$l''(\theta) = \sum_{i=1}^{n} \frac{1}{\cos(x_i - \theta) - 1}$$

```
11 <- function(sample, theta){
    sum((-sin(sample-theta))/(1 -cos(sample-theta)))
}
12 <- function(sample, theta){
    sum((1)/(cos(sample-theta)-1))
}
Newton.Method <- function(y,f,f1){
    y0 <- y
    for(i in 1:100){
        y1 <- y0 - f(sample,y0)/f1(sample,y0)
        if(abs(y1-y0)<0.0001)
            break
        y0 <- y1
    }
    return(data.frame(init=y,root=y0,iter=i))
}
Newton.Method(pi - asin(mean(sample) - pi),11,12)</pre>
```

```
## init root iter
## 1 3.046199 3.170713 5
```

```
Newton.Method(asin(mean(sample) - pi),11,12)
```

```
## init root iter
## 1 0.09539407 0.003136419 3
```

solutions

```
Newton.Method(-2.7,11,12)
```

```
## init root iter
## 1 -2.7 -2.668857 4
```

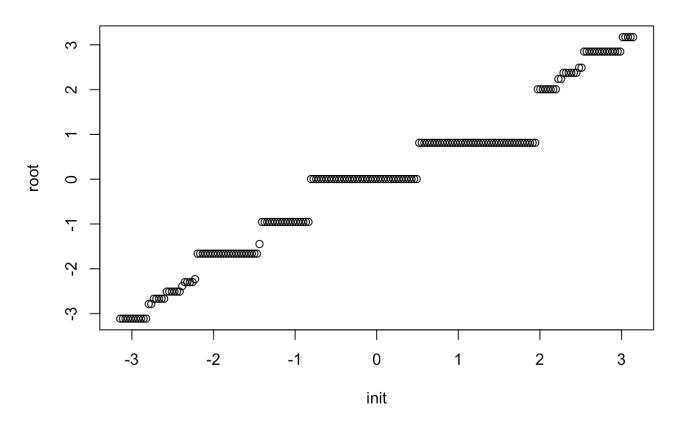
```
Newton.Method(2.7,11,12)
```

```
## init root iter
## 1 2.7 2.848423 4
```

repoeat 200 times

```
init <- seq(-pi,pi,length=200)
root <- numeric(length(init))
for(i in 1:length(init)){
  root[i] <- Newton.Method(init[i],l1,l2)[1,2]
}
plot(init,root,main = "Roots VS. Initial Values")</pre>
```

Roots VS. Initial Values



3.3.3 Modeling beetle data

Fit the population growth model to the beetles data using the Gauss-Newton approach, to minimize the sum of squared errors between model predictions and observed counts. From data frame, assues initial N is 2.

$$F = \sum_{i=1}^{n} \left[N_i - \frac{2K}{2 + (K-2)e^{-rt_i}} \right]^2$$

```
beetles <- data.frame(
    days = c(0, 8, 28, 41, 63, 69, 97, 117, 135, 154),
    beetles = c(2, 47, 192, 256, 768, 896, 1120, 896, 1184, 1024))
N0 <- 2  ## initial value by beetles.

func <- function(x){
    beetles$beetles-(2*x[1])/(2+(x[1]-2)*exp(-x[2]*beetles$days))
}
library(pracma)
gaussNewton(c(100,1),func)</pre>
```

Show the contour plot of the sum of squared errors

```
func1 <- function(a,b){
   sum((beetles$beetles-(2*a)/(2+(a-2)*exp(-b*beetles$days)))^2)
}
library(plotly)</pre>
```

```
## Loading required package: ggplot2
```

```
##
## Attaching package: 'plotly'
```

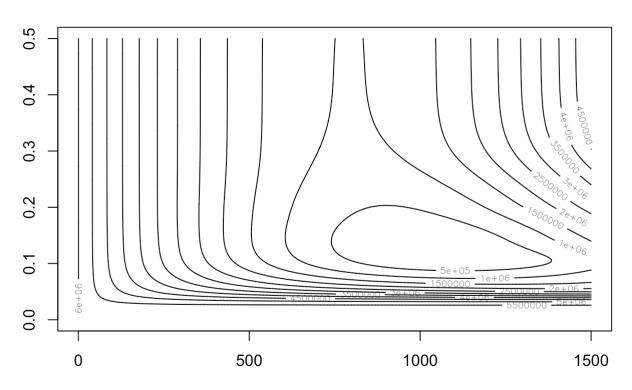
```
## The following object is masked from 'package:ggplot2':
##
## last_plot
```

```
## The following object is masked from 'package:stats':
##
## filter
```

```
## The following object is masked from 'package:graphics':
##
## layout

k <- seq(0,1500,0.1)
r <- seq(0,0.5,0.001)
y <-outer(k,r,Vectorize(func1))
contour(k,r,y,main="Contour plot of the sume of Squared Errors")</pre>
```

Contour plot of the sume of Squared Errors



Find the maximum likelihood estimators & Estimate the variance your parameter estimates.

```
Inday <- log(beetles$beetles)
# by previous result, set:
k1 <- 1049.4072453
r1 <- 0.1182684

Infunc <- function(x){
    k <- x[1]
    r <- x[2]
    sigma <- x[3]
    -sum(-(log(2 * pi * (sigma)) / 2 )- (log(beetles$beetles) - log((2*k)/(2 + (k - 2) * e xp(-r * beetles$days)))) ^ 2 / (2 * (sigma)))
}

x <- c(k1,r1,1)
Infunc(x)</pre>
```

```
## [1] 12.53528
```

```
MLEfunc <- optim(x, lnfunc, method = "BFGS", hessian = TRUE)
```

```
## Warning in log(2 * pi * (sigma)): NaNs produced
## Warning in log(2 * pi * (sigma)): NaNs produced
```

MLEfunc

```
## $par
## [1] 1038.8791759 0.1719385
                                 0.4386654
##
## $value
## [1] 10.09091
##
## $counts
## function gradient
##
        80
                  37
##
## $convergence
## [1] 0
##
## $message
## NULL
##
## $hessian
##
                 [,1]
                             [,2]
## [1,] 1.091616e-05
                      0.05120572 -0.005480509
## [2,] 5.120572e-02 795.90868517 0.012541935
## [3,] -5.480509e-03 0.01254193 26.209272440
```