## Statistical Computing Homework 4, Chapter 3

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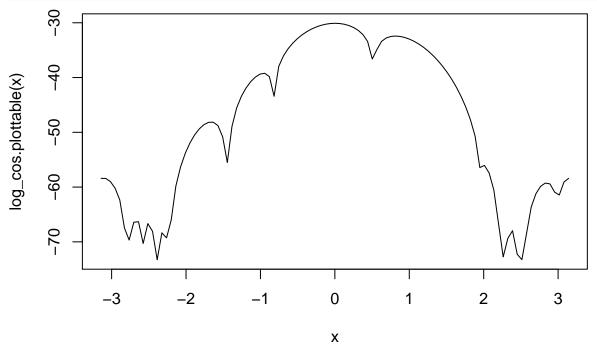
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## 3.3.2 Many local maxima

#### (a) log-likelihood



# (b) Methods of moment Let

$$\frac{1}{2\pi} \int_0^{2\pi} \left[ x - x \cos(x - \theta) \right] dx = \bar{X}$$

so evenually, we have  $\pi + \sin(\theta) = \bar{X}$ , so MOM  $\tilde{\theta}_n = \arcsin(\bar{X} - \pi) = 0.0953941$ 

#### (c) Find MLE using Newton-Raphson

```
log_cos_D1 <- function(theta) {</pre>
  sum(sin(theta-x)/(1-cos(x-theta)))
log_cos_D2 <- function(theta) {</pre>
  sum(1+cos(theta-x)/(1-cos(theta-x))^2)
para \leftarrow c(-2.7, 2.7); temp \leftarrow rep(0, length(para))
for (i in 1:length(para)) {
  iter <- 0; epsilon <- 0.001;
  temp[i] <- para[i] - 1
  while ((iter \leq 1000) (abs(para[i]-temp[i])/(abs(temp[i])) > epsilon)) {
    temp[i] <- para[i]</pre>
    para[i] <- para[i] - log_cos_D1(para[i])/log_cos_D2(para[i])</pre>
    if(abs(para[i]) == Inf) {break}
    iter <- iter + 1
    #print(para[i])
  }
}
print(para)
```

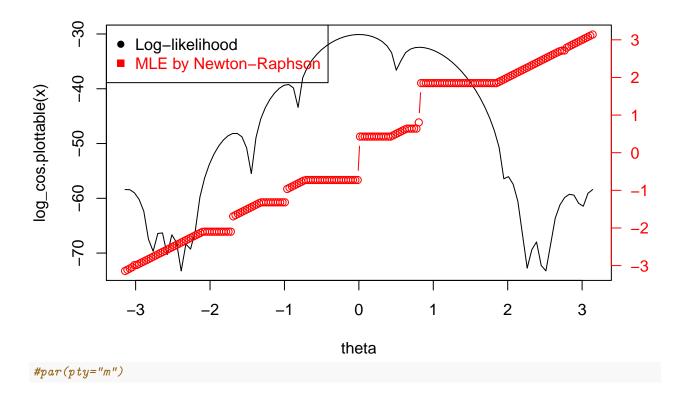
#### ## [1] -2.700049 2.697756

We can see that if we start from -2.7 and 2.7, the Newton\_Raphson algorithm will give us the similar result with the initial values.

#### (d)

```
## [1] -3.1421470 -3.1099375 -3.0769175 -3.0438883 -2.9862293 -2.9808953
## [7] -2.9503023 -2.9196235 -2.8886503 -2.8573610 -2.8258534 -2.7942822
## [13] -2.7627067 -2.7311387 -2.6996089 -2.6679818 -2.6363612 -2.6048332
## [19] -2.5732648 -2.5417143 -2.5101200 -2.4784189 -2.4469208 -2.4153942
## [25] -2.3838213 -2.3522535 -2.3207197 -2.2890875 -2.2575248 -2.2259526
## [31] -2.1944008 -2.1630228 -2.1320151 -2.1015594 -2.0984893 -2.0979572
## [37] -2.0983081 -2.0991544 -2.0993606 -2.0982989 -2.0995181 -2.0987066
## [43] -2.0994312 -2.0991218 -2.0985298 -2.0983966 -1.6903913 -1.6574795
## [49] -1.6254471 -1.5938975 -1.5625352 -1.5311748 -1.4997261 -1.4681814
## [55] -1.4366077 -1.4050512 -1.3736357 -1.3425156 -1.3186971 -1.3180609
```

```
[61] -1.3182941 -1.3185565 -1.3181618 -1.3186324 -1.3180132 -1.3181516
##
   [67] -1.3179187 -1.3183730 -1.3185563 -0.9631142 -0.9312931 -0.8997462
## [73] -0.8682469 -0.8367044 -0.8051350 -0.7736355 -0.7423622 -0.7254113
## [79] -0.7247663 -0.7247849 -0.7248769 -0.7249449 -0.7250450 -0.7248600
   [85] -0.7249321 -0.7251640 -0.7247881 -0.7251865 -0.7249138 -0.7253687
## [91] -0.7251252 -0.7248758 -0.7253206 -0.7250327 -0.7254081 -0.7250131
## [97] -0.7252162 -0.7252278 -0.7248338 -0.7252505 0.4283557 0.4280697
## [103] 0.4283589 0.4279754 0.4283668 0.4283586 0.4280268 0.4283044
## [109] 0.4280597 0.4283605 0.4283655 0.4281215 0.4281008 0.4279924
## [115] 0.4579482 0.4894087 0.5209676 0.5525251 0.5839990 0.6153368
## [121] 0.6397172 0.6396775 0.6394579 0.6395375 0.6395949 0.8046583
## [127] 1.8501991 1.8497966 1.8490294 1.8489455 1.8493700 1.8490720
## [133] 1.8501415 1.8492247 1.8498832 1.8503813 1.8491017 1.8495115
## [139] 1.8498470 1.8501305 1.8503907 1.8489066 1.8491647 1.8494102
## [145] 1.8496399 1.8498559 1.8500669 1.8502871 1.8487940 1.8491130
## [151] 1.8495217 1.8500669 1.8490903 1.8502084 1.8501620 1.8493903
## [157] 1.8488009 1.8488007 1.8489031 1.8792375 1.9103261 1.9417924
## [163] 1.9733613 2.0049335 2.0366779 2.0689210 2.1009061 2.1319497
## [169] 2.1630079 2.1943941 2.2259525 2.2575309 2.2890998 2.3206470
## [175] 2.3521779 2.3838648 2.4154385
                                         2.4469704 2.4785414 2.5101204
## [181] 2.5416905 2.5732348 2.6046310 2.6357777 2.6666448 2.6973277
## [187] 2.7140480 2.7145678 2.7922908 2.8252431 2.8575600 2.8892428
## [193] 2.9206980 2.9521743 2.9837238 3.0152893 3.0467834 3.0781594
## [199] 3.1094882 3.1410383
#par(pty="s")
curve(log_cos.plottable, from = -pi, to = pi, xlab="theta")
## Allow a second plot on the same graph
par(new=TRUE)
## Plot the second plot and put axis scale on right
plot(seq(-pi, pi, length.out = 200), para, pch=1, xlab="", ylab="",
   axes=FALSE, type="b", col="red")
## a little farther out (line=4) to make room for labels
mtext("MLE",side=3,col="red",line=4)
axis(4, ylim=c(-4,4), col="red",col.axis="red",las=1)
## Add Legend
legend("topleft",legend=c("Log-likelihood","MLE by Newton-Raphson"),
 text.col=c("black","red"),pch=c(16,15),col=c("black","red"))
```



## 3.3.3 Modeling beetle data

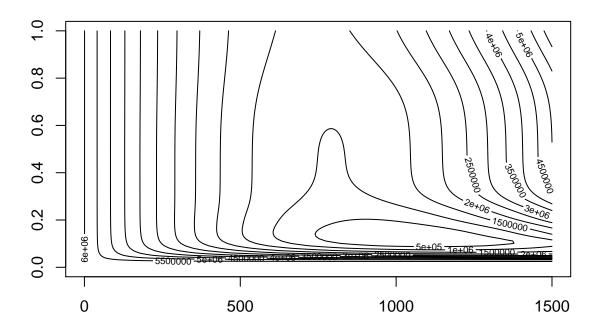
```
beet <- data.frame(
    days = c(0, 8, 28, 41, 63, 69, 97, 117, 135, 154),
    beetles = c(2, 47, 192, 256, 768, 896, 1120, 896, 1184, 1024))

growth <- function(x) {
    k <- x[1]; r <- x[2]
    k*beet$beetles[1]/(beet$beetles[1] + (k-beet$beetles[1])*exp(-r*beet$days))
}

growth.contour <- function(k,r) {
    k*beet$beetles[1]/(beet$beetles[1] + (k-beet$beetles[1])*exp(-r*beet$days))
}

growth.error <- function(k, r) {
    sum( (beet$beetles - growth.contour(k, r))^2 )
}</pre>
```

Plot the contour plot to visually check:



#### Gauss-Newton method

Multivariate method based on log-normal model MLE

- (a) Use self method: Steepest Descent(Gradient Descent)
- (b) Validate using R function optim: use L-BFGS-B method

```
growth.error.optim <- function(x) {</pre>
  sum( (beet$beetles - growth(x))^2 )
optim(c(1, 1), growth.error.optim, lower=c(0,0), upper=c(Inf, 1), method = "L-BFGS-B")
## $par
## [1] 1049.3480876
                        0.1182881
##
## $value
## [1] 73419.77
##
## $counts
## function gradient
         54
##
##
## $convergence
## [1] 0
##
## $message
## [1] "CONVERGENCE: REL_REDUCTION_OF_F <= FACTR*EPSMCH"
```