

Homework #3
#1

(i) In this case, assume that the brake pad life time T follows log-normal distribution with

unknown parameters μ and σ . The likelihood function is $L(\mu, \sigma) = \prod_{i=1}^n \frac{f(t_i, \mu, \sigma)}{S(u_i, \mu, \sigma)}$ and log-

likelihood function is $\ell(\mu, \sigma) = \sum_{i=1}^n \log(f(t_i, \mu, \sigma)) - \log(S(u_i, \mu, \sigma))$, where

$$f(t_i, \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma t_i} \phi\left(\frac{\log t_i - \mu}{\sigma}\right) \text{ and } S(u_i, \mu, \sigma) = 1 - \Phi\left(\frac{\log u_i - \mu}{\sigma}\right). \text{ Therefore,}$$

$$\ell(\mu, \sigma) = -\frac{n}{2} \log(2\pi) - \frac{n}{2} \log(\sigma^2) - \sum_{i=1}^n \log(t_i) - \sum_{i=1}^n \frac{(\log(t_i) - \mu)^2}{2\sigma^2} - \log(1 - \Phi(\frac{\log u_i - \mu}{\sigma})).$$

To apply the Newton-Raphson Algorithm, we should derive the score function

$$U(\mu, \sigma) = \begin{bmatrix} \frac{\partial}{\partial \mu} \ell(\mu, \sigma) \\ \frac{\partial}{\partial \sigma} \ell(\mu, \sigma) \end{bmatrix} \text{ and Hessian matrix } H(\mu, \sigma) = \begin{bmatrix} \frac{\partial^2}{\partial \mu^2} \ell(\mu, \sigma) & \frac{\partial^2}{\partial \sigma \partial \mu} \ell(\mu, \sigma) \\ \frac{\partial^2}{\partial \mu \partial \sigma} \ell(\mu, \sigma) & \frac{\partial^2}{\partial \sigma^2} \ell(\mu, \sigma) \end{bmatrix}.$$

$$\frac{\partial}{\partial \mu} \ell(\mu, \sigma) = \sum_{i=1}^n \frac{(\log t_i - \mu)}{\sigma^2} - \frac{1}{\sigma} \sum_{i=1}^n \frac{\phi(\frac{\log u_i - \mu}{\sigma})}{1 - \Phi(\frac{\log u_i - \mu}{\sigma})}$$

$$\frac{\partial}{\partial \sigma} \ell(\mu, \sigma) = -\frac{n}{\sigma} + \sum_{i=1}^n \frac{(\log t_i - \mu)^2}{\sigma^3} - \sum_{i=1}^n \frac{(\frac{\log u_i - \mu}{\sigma^2}) \phi(\frac{\log u_i - \mu}{\sigma})}{1 - \Phi(\frac{\log u_i - \mu}{\sigma})}$$

$$\frac{\partial^2}{\partial \mu^2} \ell(\mu, \sigma) = -\frac{n}{\sigma^2} - \frac{1}{\sigma^2} \sum_{i=1}^n \frac{(\log u_i - \mu) \phi(\frac{\log u_i - \mu}{\sigma}) (1 - \Phi(\frac{\log u_i - \mu}{\sigma})) - (\phi(\frac{\log u_i - \mu}{\sigma}))^2}{(1 - \Phi(\frac{\log u_i - \mu}{\sigma}))^2}$$

$$\frac{\partial^2}{\partial \sigma^2} \ell(\mu, \sigma) = \frac{n}{\sigma^2} - \frac{3 \sum_{i=1}^n (\log t_i - \mu)^2}{\sigma^4} + \frac{2}{\sigma^3} \sum_{i=1}^n \frac{(\log u_i - \mu) \phi(\frac{\log u_i - \mu}{\sigma})}{1 - \Phi(\frac{\log u_i - \mu}{\sigma})}$$

$$-\sum_{i=1}^n \frac{(\log u_i - \mu)^2}{\sigma^4} \left(\frac{(\log u_i - \mu) \phi(\frac{\log u_i - \mu}{\sigma}) (1 - \Phi(\frac{\log u_i - \mu}{\sigma})) - (\phi(\frac{\log u_i - \mu}{\sigma}))^2}{(1 - \Phi(\frac{\log u_i - \mu}{\sigma}))^2} \right)$$

$$\begin{aligned} \frac{\partial^2}{\partial \mu \partial \sigma} \ell(\mu, \sigma) = & -\frac{2}{\sigma^3} \sum_{i=1}^n (\log t_i - \mu) + \frac{1}{\sigma^2} \sum_{i=1}^n \frac{\phi\left(\frac{\log u_i - \mu}{\sigma}\right)}{1 - \Phi\left(\frac{\log u_i - \mu}{\sigma}\right)} \\ & - \sum_{i=1}^n \frac{(\log u_i - \mu)}{\sigma^3} \frac{\left(\frac{\log u_i - \mu}{\sigma}\right) \phi\left(\frac{\log u_i - \mu}{\sigma}\right) (1 - \Phi\left(\frac{\log u_i - \mu}{\sigma}\right)) - (\phi\left(\frac{\log u_i - \mu}{\sigma}\right))^2}{(1 - \Phi\left(\frac{\log u_i - \mu}{\sigma}\right))^2} \end{aligned}$$

Hence we could apply the following algorithm to obtain the MLE. The following table shows the result if the Newton-Raphson algorithm. The MLE of μ is about 4.109 and σ is about 0.421.

$\varepsilon = \theta_j - \theta_{j-1} < 10^{-10}$				
STEP	μ	$ \mu_j - \mu_{j-1} $	σ	$ \sigma_j - \sigma_{j-1} $
0	4.00000	-	0.3000000	-
1	4.080210	8.021027e-02	0.3488822	4.888225e-02
2	4.104229	2.401824e-02	0.3942647	4.538244e-02
3	4.109126	4.897348e-03	0.4169719	2.270719e-02
4	4.109192	6.598783e-05	0.4211433	4.171405e-03
5	4.109176	1.588903e-05	0.4212609	1.176354e-04
6	4.109176	2.331113e-08	0.4212610	9.084697e-08
7	4.109176	1.865175e-14	0.421261	5.484502e-14

『Newton-Raphson Algorithm』

STEP 1. Given an initial value θ_0 .

STEP 2. $\theta_j = \theta_{j-1} - H(\theta_{j-1})^{-1} U(\theta_{j-1}), j = 1, 2, \dots$

STEP 3. If $\theta_j - \theta_{j-1} \approx 0$, $\hat{\theta} = \theta_j$ and STOP. Otherwise, go back to STEP 2.

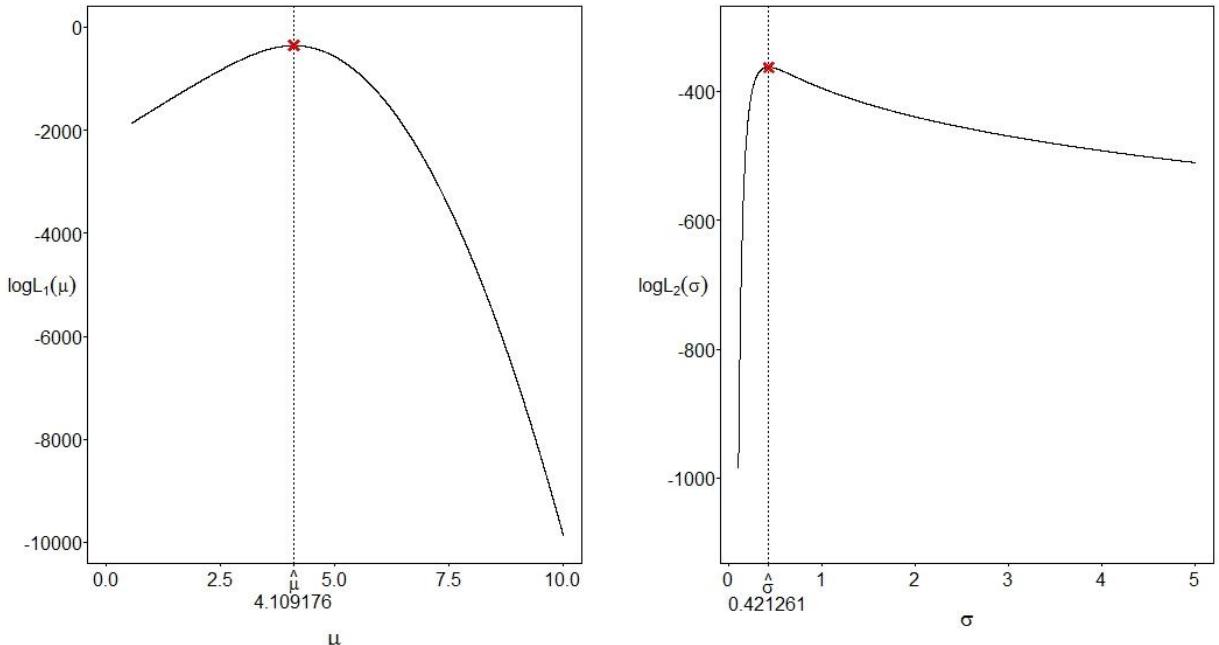
(ii) The profile likelihood of μ and σ are

$$\ell_1(\mu) = \ell(\mu, \hat{\sigma}) = -49 \log(2\pi) - 49 \log(\hat{\sigma}^2) - \sum_{i=1}^{98} \log(t_i) - \sum_{i=1}^{98} \frac{(\log(t_i) - \mu)^2}{2\hat{\sigma}^2} - \log(1 - \Phi(\frac{\log u_i - \mu}{\hat{\sigma}}))$$

$$\ell_2(\sigma) = \ell(\hat{\mu}, \sigma) = -49 \log(2\pi) - 49 \log(\sigma^2) - \sum_{i=1}^{98} \log(t_i) - \sum_{i=1}^{98} \frac{(\log(t_i) - \hat{\mu})^2}{2\sigma^2} - \log(1 - \Phi(\frac{\log u_i - \hat{\mu}}{\sigma}))$$

, where $\hat{\sigma} = 0.421$ and $\hat{\mu} = 4.109$, respectively. Also the following plots show that

$$\hat{\mu} = \max_{\mu} \ell_1(\mu) = 4.10976 \text{ and } \hat{\sigma} = \max_{\sigma} \ell_2(\sigma) = 0.421261.$$



《CODE》

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rm(list=ls(all=TRUE))

u = c(22.2, 23.0, 24.0, 28.6, 21.8, 17.0, 26.0, 23.2, 18.9, 21.9, 27.3, 13.8, 24.0, 20.1, 15.7, 26.8,
27.9, 15.3, 28.8, 16.0, 23.6, 53.8, 21.7, 28.8, 17.0, 16.5, 15.7, 28.0, 13.3, 16.5, 24.2, 17.6, 27.8,
18.3, 17.7, 20.0, 13.2, 16.9, 14.9, 15.5, 7.0, 15.8, 15.0, 38.3, 11.2, 38.2, 26.7, 17.1, 29.0, 18.3, 18.4,
18.2, 15.9, 16.4, 23.6, 19.2, 23.3, 20.4, 20.9, 28.5, 23.2, 17.9, 46.1, 39.3, 11.8, 17.7, 30.9, 22.4,
45.0, 18.2, 30.2, 21.8, 18.2, 23.0, 27.2, 10.9, 25.5, 12.4, 39.9, 17.7, 26.3, 14.1, 21.0, 11.2, 10.8, 25.7,
32.4, 13.6, 19.1, 16.1, 53.3, 57.3, 36.5, 19.7, 20.8, 30.8, 20.0, 39.6)

t = c(38.7, 49.2, 42.4, 73.8, 46.7, 44.1, 61.9, 39.3, 49.8, 46.3, 56.2, 50.5, 54.9, 54.0, 49.2, 44.8,
72.2, 107.8, 81.6, 45.2, 124.6, 64.0, 83.0, 143.6, 43.4, 69.6, 74.8, 32.9, 51.5, 31.8, 77.6, 63.7, 83.0,
24.8, 68.8, 68.8, 89.1, 65.0, 65.1, 59.3, 53.9, 79.4, 47.4, 61.4, 72.8, 54.0, 37.2, 44.2, 50.8, 65.5, 86.7,
43.8, 100.6, 67.6, 89.5, 60.3, 103.6, 82.6, 88.0, 42.4, 68.9, 95.7, 78.1, 83.6, 18.6, 92.6, 42.4,
34.3, 105.6, 20.8, 52.0, 77.2, 68.9, 78.7, 165.5, 79.5, 55.0, 46.8, 124.5, 92.5, 110.0, 101.2, 59.4, 27.8,
33.6, 69.0, 75.2, 58.4, 105.6, 56.2, 55.9, 83.8, 123.5, 69.0, 101.9, 87.6, 38.8, 74.7)

lu = log(u)
lt = log(t)

##### Score Function #####
U_fun = function(theta){
  n = length(t)
}
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mu = theta[1]
sigma = theta[2]
a11 = (sum(lt-theta[1])/theta[2]^2)-(sum(dnorm((lu-mu)/sigma)/(1-pnorm((lu-
mu)/sigma)))/theta[2])
a21 = (-n/theta[2])+sum((lt-theta[1])^2/theta[2]^3)-sum(((lu-
theta[1])/theta[2]^2)*dnorm((lu-mu)/sigma)/(1-pnorm((lu-mu)/sigma)))
c(a11,a21)
}

##### Hessian Matrix #####
H_fun = function(theta){
  n = length(t)
  mu = theta[1]
  sigma = theta[2]
  a11 = -n/theta[2]^2-(1/theta[2]^2)*sum(((lu-theta[1])/theta[2])*dnorm((lu-mu)/sigma)*(1-
  pnorm((lu-mu)/sigma))-(dnorm((lu-mu)/sigma))^2)/(1-pnorm((lu-mu)/sigma))^2
  a12 = (-2*sum(lt-theta[1])/theta[2]^3)+(1/theta[2]^2)*sum(dnorm((lu-mu)/sigma)/(1-
  pnorm((lu-mu)/sigma)))-sum(((lu-theta[1])/theta[2]^3)*((lu-theta[1])/theta[2])*dnorm((lu-
  mu)/sigma)*(1-pnorm((lu-mu)/sigma))-(dnorm((lu-mu)/sigma))^2)/(1-pnorm((lu-mu)/sigma))^2
  a22 = (n/theta[2]^2)-(3*sum((lt-theta[1])^2)/theta[2]^4)+sum((2*(lu-
  theta[1])/theta[2]^3)*dnorm((lu-mu)/sigma)/(1-pnorm((lu-mu)/sigma)))-sum(((lu-
  theta[1])/theta[2]^2)^2)*((lu-theta[1])/theta[2])*dnorm((lu-mu)/sigma)*(1-pnorm((lu-
  mu)/sigma))-(dnorm((lu-mu)/sigma))^2)/(1-pnorm((lu-mu)/sigma))^2
  matrix(c(a11,a12,a12,a22),2,2)
}

##### Newton-Raphson Algorithm #####
theta1 = c(4,0.3)
theta2 = theta1 - solve(H_fun(theta1))%*%U_fun(theta1)
mu1 = theta1[1]
mu2 = theta2[1]
sigma1 = theta1[2]
sigma2 = theta2[2]
s = 1
M = c()
S = c()
M[s] = mu1
S[s] = sigma1
while(abs(mu1-mu2)>10^(-10) || abs(sigma1-sigma2)>10^(-10)){
  theta1 = theta2
  mu1 = theta1[1]
  sigma1 = theta1[2]
  s = s + 1
  M[s] = mu1
  S[s] = sigma1
  theta2 = theta1 - (solve(H_fun(theta1)))%*%U_fun(theta1)
  mu2 = theta2[1]
  sigma2 = theta2[2]
}

##### Profile likelihood of mu #####
L1_fun = function(t1){
  n = length(t)

```

```

sigma = sigma2
zz = c()
for(i in 1:length(t1)){
  zz[i] = (-n/2)*log(sigma^2)-sum(lt)-(1/(2*sigma^2))*sum((lt-t1[i])^2)-sum(log(1-
pnorm((lu-t1[i])/sigma)))
}
zz
}

##### Profile likelihood of sigma #####
L2_fun = function(t2){
  n = length(t)
  mu = mu2
  zz = c()
  for(i in 1:length(t2)){
    zz[i] = (-n/2)*log(t2[i]^2)-sum(lt)-(1/(2*t2[i]^2))*sum((lt-mu)^2)-sum(log(1-
pnorm((lu-mu)/t2[i])))
  }
  zz
}
##### Plot Profile likelihood of mu#####
plot(seq(0,10,0.001),L1_fun(seq(0,10,0.001)),type="l",xlab="",ylab="",ylim=c(-
10000,0),axes=FALSE)
points(theta2[1],L1_fun(theta2[1]),pch=4)
axis(1,at=c(seq(0,10,2.5)),mgp=c(3,0.2,0),tcl=-0.15)
axis(1,at=theta2[1],labels=expression(hat(mu)),mgp=c(3,0.5,0),tcl=-0.15)
axis(1,at=theta2[1],mgp=c(3,1.2,0),tcl=-0.15)
axis(2,las=1,font.axis=1,at=c(seq(-10000,0,2000)),mgp=c(3,0.2,0),tcl=-0.15)
box()
mtext(side=1,line=3,expression(mu),cex=1.2)
mtext(side=2,las=1,line=0.5,expression(logL[1](mu)),cex=1)
abline(v=theta2[1],lty=3)
##### Plot Profile likelihood of sigma#####
plot(seq(0.1,5,0.001),L2_fun(seq(0.1,5,0.001)),type="l",xlab="",ylab="",ylim=c(-1100,-
300),axes=FALSE)
points(theta2[2],L2_fun(theta2[2]),pch=4)
axis(1,at=c(seq(0.5,1)),mgp=c(3,0.2,0),tcl=-0.15)
axis(1,at=theta2[2],labels=expression(hat(sigma)),mgp=c(3,0.5,0),tcl=-0.15)
axis(1,at=theta2[2],mgp=c(3,1.3,0),tcl=-0.15)
axis(2,las=1,font.axis=1,at=c(seq(-1000,-400,200)),mgp=c(3,0.2,0),tcl=-0.15)
box()
mtext(side=1,line=2,expression(sigma),cex=1.2)
mtext(side=2,las=1,line=0.5,expression(logL[2](sigma)),cex=1)
abline(v=theta2[2],lty=3)

```

《OUTPUT》

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> mu2
[1] 4.109176
> sigma2
[1] 0.421261

```