

Survival Analysis I HW4

Example 7.1.1 of Lawless's book (2003)

➤ Data.frame

time	event	X	time	event	X	time	event	X
1	1	1	8	1	0	22	1	1
1	1	0	9	1	0	26	1	1
1	1	0	10	1	1	27	0	0
2	1	0	11	1	0	28	0	1
2	1	0	12	1	1	29	1	1
3	1	1	12	1	0	31	1	0
3	1	1	14	1	1	34	1	1
3	1	0	14	1	0	38	0	0
4	1	0	15	1	1	40	1	1
5	1	0	16	1	0	44	1	0
6	1	1	18	1	1	48	0	1
7	1	1	18	1	0	49	0	1
7	1	1	19	1	1			
8	1	0	21	1	0			

Where, $\text{time}(t_i)$ is remission time, $\text{event}(\delta_i)$ is actually happened not censoring and

$X(x_i)$ denote which treatment data come from.

Notation:

$$N = \text{the number of samples}, \quad d_i = \delta_i, \quad d_{1i} = \delta_i x_i$$

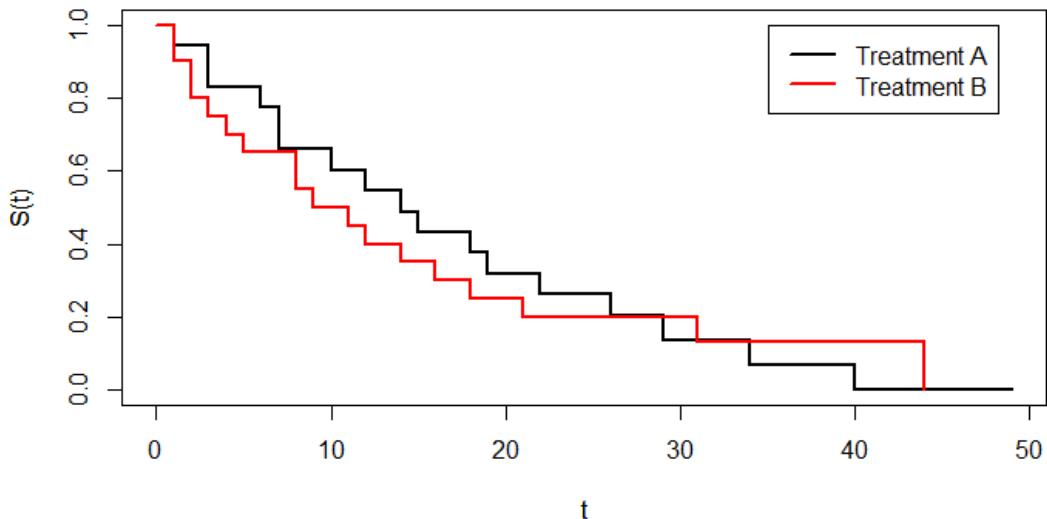
$$R_i = \{j : t_j \geq t_{(i)}\}, \quad t_{(i)} \text{ is ordered times}$$

$$n_{1i} = \sum_{\ell \in R_i} x_i, \quad n_{2i} = \sum_{\ell \in R_i} (1 - x_i), \quad n_i = n_{1i} + n_{2i}$$

➤ Survival t^* ordered time at death $\hat{S}(t) = \prod_{t_j^* < t} \left(1 - \frac{d_j}{n_j}\right)$

where $d_j = \sum_{i=1}^n I(t_i = t_j^*, \delta_i = 1)$ $n_j = \sum_{i=1}^n I(t_i \geq t_j^*)$

Kaplan-Meier



The Kaplan-Meier estimates for two treatments show the correctness of the proportional hazard assumption.

➤ Score test

$$U(0) = \sum_{i=1}^N \left(d_{1i} - \frac{d_i n_{1i}}{n_i} \right) \quad I(0) = \sum_{i=1}^N \frac{d_i n_{1i} n_{2i}}{n_i^2}$$

$$Z = \frac{U(0)}{I(0)^{\frac{1}{2}}} \sim N(0,1) \Rightarrow Z^2 \equiv \chi^2_{df=1} \text{ and } \chi^2_1(0.05) = 3.841459$$

We find $U(0) = -3.323137$ $I(0) = 8.408741$

$$\Rightarrow Z^2 = 1.313305 < 3.841459 \text{ and } p\text{-value} = 0.2517972$$

All conclude that have no evidence prove $S_1(t) \neq S_2(t)$

➤ Score test 2

$$\text{Improve } I(0) = \sum_{i=1}^k \frac{d_i(n_i - d_i)n_{1i}n_{2i}}{n_i^2(n_i - 1)}$$

Where i indexes the k distinct times at which failures occur, and d_i is the total number of failures at the i_{th} time $t_{(i)}$

time	di	ni	n1	n2	time	di	ni	n1	n2
1	3	40	20	20	15	1	18	11	7
2	2	37	19	18	16	1	17	10	7
3	3	35	19	16	18	2	16	10	6
4	1	32	17	15	19	1	14	9	5
5	1	31	17	14	21	1	13	8	5
6	1	30	17	13	22	1	12	8	4
7	2	29	16	13	26	1	11	7	4
8	2	27	14	13	29	1	8	5	3
9	1	25	14	11	31	1	7	4	3
10	1	24	14	10	34	1	6	4	2
11	1	23	13	10	40	1	4	3	1
12	2	22	13	9	44	1	3	2	1
14	2	20	12	8					

We find $U(0) = -3.323137$ $I(0) = 8.196201$

$$\Rightarrow Z^2 = 1.347361 < 3.841459 \text{ and } p\text{-value} = 0.2457401$$

Both conclude that have no evidence prove $S_1(t) \neq S_2(t)$

➤ Iteration for β

Fix-point algorithm:

Step1: β_0

$$\text{Step2: } e^{\beta_j} = \frac{\sum_{i=1}^N d_i}{\sum_{i=1}^N \frac{d_i n_i}{n_1 i e^{\beta_{j-1}} + n_2 i}} \quad j = 1, 2, \dots$$

Step3: $\hat{\beta} \equiv \beta_j$ if $|\beta_j - \beta_{j-1}| < 10^{-5}$

$$\text{Where } U(\theta) = \frac{\partial \ell(\theta)}{\partial (\theta)} \quad H(\theta) = \frac{\partial^2 \ell(\theta)}{\partial (\theta)^2}$$

Newton-Raphson algorithm:

Step1: β_0

$$\text{Step2: } \beta_j = \beta_{j-1} - H(\beta_{j-1})^{-1} U(\beta_{j-1}) \quad j = 1, 2, \dots$$

Step3: $\hat{\beta} \equiv \beta_j$ if $|\beta_j - \beta_{j-1}| < 10^{-5}$

$$\text{Where } U(\beta) = \frac{\partial \ell(\beta)}{\partial (\beta)} \quad H(\beta) = \frac{\partial^2 \ell(\beta)}{\partial (\beta)^2}$$

From Fix-point algorithm within 10^{-5} error

$$\hat{\beta} = -0.387997 \text{ by 18 iterations and 0.056566 secs}$$

From Newton-Raphson algorithm within 10^{-5} error

$$\hat{\beta} = -0.3880057 \text{ by 4 iterations and 0.06106305 secs}$$

We can see the each iteration for beta in the below “Output”.

Therefore, we found the Newton-Raphson algorithm which has less iterations than Fix-point algorithm. And the passing time are almost same between two method. But we know the Newton-Raphson algorithm is more complicated to estimate the parameters.

➤ Wald test

$$U(\beta) = \sum_{i=1}^N \left(d_{1i} - \frac{d_i n_{1i} e^\beta}{n_{1i} + n_{2i} e^\beta} \right) \quad I(\beta) = \sum_{i=1}^N \frac{d_i n_{1i} n_{2i} e^\beta}{(n_{1i} e^\beta + n_{2i})^2}$$

$$Z = \frac{\hat{\beta}}{se(\hat{\beta})^2} \sim N(0,1) \Rightarrow Z^2 \equiv \chi^2_{df=1} \text{ and } se(\hat{\beta})^2 = I(\beta)^{-\frac{1}{2}}$$

We find $\hat{\beta} = -0.387997$ $I(\hat{\beta}) = 8.619081$

$$\Rightarrow Z^2 = 1.297531 < 3.841459 \text{ and } p-value = 0.2546647$$

Both conclude that have no evidence prove $S_1(t) \neq S_2(t)$

➤ Likelihood ratio test

$$\ell(\beta) = \sum_{i=1}^N d_i \left[\beta x_i - \log \left\{ \sum_{\ell \in R_i} (1 - x_\ell) \right\} \right]$$

$$\Lambda = 2\{\ell(\hat{\beta}) - \ell(0)\} \sim \chi^2_{df=1} \quad \text{and } \chi^2_1(0.05) = 3.841459$$

We find $\hat{\beta} = -0.387997$ $\ell(\hat{\beta}) = -103.2979$ $\ell(0) = -103.9453$

$$\Rightarrow \Lambda = 1.294698 < 3.841459 \text{ and } p-value = 0.255184$$

Both conclude that have no evidence prove $S_1(t) \neq S_2(t)$

- Output

```
> #scorce test
[1] 3.841459
> u0
[1] -3.323137
> I0
[1] 8.408741
> chi
[1] 1.313305
> p_value
[1] 0.2517972
> qchisq(0.95,1)
[1] 3.841459
```

```
> #scorce test2
[1] 3.841459
> u0
[1] -3.323137
> I0
[1] 8.196201
> chi
[1] 1.347361
> p_value
[1] 0.2457401
> qchisq(0.95,1)
[1] 3.841459
```

```
> # Fixed point iteration
> beta
[1] -0.38799702
> time1
Time difference of 0.056566 secs

> # Newton-Raphson iteration
> nbeta
[1] -0.3880057
> time2
Time difference of 0.06106305 secs
```

```
> #wald test
> #beta from Fixed point iteration
> I
[1] 8.619081
> chi
[1] 1.297531
> p_value
[1] 0.2546647
```

```
> #LR test
> #beta from Fixed point iteration
> l1b
[1] -103.2979
> l0
[1] -103.9453
> lambda
[1] 1.294698
> p_value
[1] 0.2546647
```

```
> Newton_bata
[1] -0.8281464 -0.3713842 -0.3880024 -0.3880057
```

```
> Fixedpoint_bata
[1] 0.51581373 0.15407233 -0.08544973 -0.22777721 -0.30590401 -0.34671324
-0.36744213 -0.37781673
[9] -0.38297001 -0.38552006 -0.38677954 -0.38740103 -0.38770756 -0.38785871
-0.38793323 -0.38796998
[17] -0.38798809 -0.38799702
```

● R-code

```

n1[idx]=sum(data[i:nrow(data),"X"])

}

n2=rep(1,nrow(data))

X2=1-data[, "X"]

n2[1]=sum(X2)

for(idx in 2:nrow(data)){

  i=idx

  while(data[i,"time"]==data[i-1,"time"]){

    i=i-1

    if(i==1){break}

  }

  n2[idx]=sum(X2[i:nrow(data)])

}

ni=n1+n2


#Kaplan-Meier

kplan=cbind(data[, "time"],d1i,d2i,n1,n2)

colnames(kplan)[1]="time"

kplan=as.data.frame(kplan)

k=kplan%>%group_by(time)%>%summarise(d1i=sum(d1i),d2i=sum(d2i),n
1=max(n1),n2=max(n2))

Ax=as.matrix(k["time"])

Ay=as.matrix(cumprod(1-(k[, "d1i"]/k[, "n1"])))

Ax=c(0,Ax)

Ay=c(1,Ay)

```

```

plot(Ax,Ay,type="s",xlab="t",ylab="S(t)",main="Kaplan-Meier",xaxt="n",y
axt="n",lwd=2)

Bx=as.matrix(k["time"])

By=as.matrix(cumprod(1-(k[, "d2i"]/k[, "n2"])))

Bx=c(0,Bx)

By=c(1,By)

par(new=T)

plot(Bx,By,type="s",xlab="t",ylab="S(t)",col="red",xaxt="n",yaxt="n",lwd
=2)

axis(1,seq(0,50,10))

axis(2,seq(0,1,0.2))

#scorce test

U0=sum(d1i-di*n1/ni)

I0=sum(di*n1*n2/(ni)^2)

Z=U0/(I0)^(1/2)

Chi=Z^2

p_value=1-pchisq(Chi,1)

qchisq(0.95,1)

#ties data

XX=cbind(data[, "time"],di,ni,n1,n2)

XX=subset(XX,di>0)

colnames(XX)[1]="time"

XX=as.data.frame(XX)

```

```

xx=XX%>%group_by(time)%>%summarise(di=
  sum(di),ni=max(ni),n1=max(n1),n2=max(n2))

I00=sum(xx[,"di"]*(xx[,"ni"]-xx[,"di"])*xx[,"n1"]*xx[,"n2"]/(xx[,"ni"]^2*(
  xx[,"ni"]-1)))

write.csv(xx,"ties.data.csv")

#scorce test2

Z=U0/(I00)^(1/2)

Chi=Z^2

p_value=1-pchisq(Chi,1)

# Fixed point iteration

start=Sys.time()

d=1

beta0=1

ebeta0=exp(beta0)

itern=0

Fixedpoint_bata=c()

while(d>10^-5){

  ebata=sum(d1i)/sum(di*n1/(n1*ebeta0+n2))

  d=abs(log(ebata)-log(ebeta0))

  ebata0=ebata

  Fixedpoint_bata=c(Fixedpoint_bata,log(ebata))

  itern=itern+1

}

```

```

beta=log(ebeta)

end=Sys.time()

time1=end-start

# Newton-Raphson iteration

start=Sys.time()

d=1

nbeta0=1

itern=0

Newton_bata=c()

while(d>10^-5){

  U=sum(d1i-di*n1*exp(nbeta0)/(n1*exp(nbeta0)+n2))

  I=sum(di*(n1*n2*exp(nbeta0)/(n1*exp(nbeta0)+n2)^2))

  nbeta=nbeta0+I^(-1)*U

  d=abs(nbeta-nbeta0)

  nbeta0=nbeta

  Newton_bata=c(Newton_bata,nbeta)

  itern=itern+1

}

beta=nbeta

end=Sys.time()

time2=end-start

#wald test

I=sum(di*(n1*n2*exp(beta)/(n1*exp(beta)+n2)^2))

```

```
Z=beta/(I)^(-1/2)

Chi=Z^2

p_value=1-pchisq(Chi,1)

#LR test

lb=sum(di*(beta*data[, "X"]-log(n1*exp(beta)+n2)))

l0=sum(di*(0*data[, "X"]-log(n1*exp(0)+n2)))

lambda=2*(lb-l0)

p_value=1-pchisq(lambda,1)
```