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C-statistics for Competing Risk

Previously we have Harrell C & Uno C, the only difference is the weight matrix:

$$Harrell~C: w_{i,j}(G,\tau_G) = \frac{\delta_i I(Y_i < Y_j, Y_i < \tau_G)}{\sum_{i=1}^n \sum_{j=1}^n \delta_i I(Y_i < Y_j, Y_i < \tau_G)}$$

$$Uno \; C: w_{i,j}(G,\tau_G) = \frac{\delta_i G\{Y_i\}^{-2} I(Y_i < Y_j, Y_i < \tau_G)}{\sum_{i=1}^n \sum_{j=1}^n \delta_i G\{Y_i\}^{-2} I(Y_i < Y_j, Y_i < \tau_G)}$$

For the Competing Risk, the paper "Concordance for prognostic models with competing risks (2014)" propose two methods:

The first one is a biased estimate:

$$w_{i,j}(G,\tau_G) = \frac{\{I(Y_i < Y_j) + I(Y_i \geq Y_j, \delta_i = 2)\}I(Y_i < \tau_G, \delta_i = 1)}{\sum_{i=1}^n \sum_{j=1}^n \{I(Y_i < Y_j) + I(Y_i \geq Y_j, \delta_i = 2)\}}$$

The second one is inverse probability of censoring weighted (IPCW) estimate:

$$\begin{split} w_{i,j}(G,\tau_G) &= \frac{\{\frac{I(Y_i < Y_j)}{\hat{G}(Y_i|X_i)\hat{G}(Y_i|X_j)} + \frac{I(Y_i \ge Y_j,,\delta_i = 2)}{\hat{G}(Y_i|X_i)\hat{G}(Y_j|X_j)}\}I(Y_i < \tau_G,\delta_i = 1)}{\sum_{i=1}^n \sum_{j=1}^n \{\frac{I(Y_i < Y_j)}{\hat{G}(Y_i|X_i)\hat{G}(Y_i|X_j)} + \frac{I(Y_i \ge Y_j,,\delta_i = 2)}{\hat{G}(Y_i|X_i)\hat{G}(Y_j|X_j)}\}I(Y_i < \tau_G,\delta_i = 1)}\\ &\hat{G}(t|X_i) = exp\{-\int_{t}^{t} exp(\hat{\gamma}^TX_i)\hat{\Gamma}_0(s)ds\} \end{split}$$

 $\hat{\Gamma}_0$ is the Breslow estimator of the baseline hazard function and $\hat{\gamma}$ is the maximum partial likelihood of the regression coefficients.

As an alternative, we could assume that the censoring is independent of the competing risks outcome and the predictors. And we can use KM estimate for the cenosring distribution.

```
# Estimating censoring distribution using KM
RiskC_Wmat2 <- function(Y,delta,tau,Cox_G=NULL){</pre>
    if (is.null(Cox_G)){
       # An index indicates whether the observation is censored
      censor = ifelse(delta==0,1,0)
       # Censoring Distribution Estimate using Kaplan-Meier Estimator
      KM_G = survfit(formula = Surv(Y ,censor) ~ 1)
      G_y = KM_G$surv[match(Y,KM_G$time)]
    }else{
      # Censoring Distribution Estimate using Kaplan-Meier Estimator
      G_y = Cox_G$surv[match(Y,Cox_G$time)]
    # Get G(Y) for each observation
    # (Since G(Y) in KM_G is ordered we want each G(Y) to match original Y)
    n <- length(Y)
    Wmat <- matrix(0, n, n)</pre>
    for(i in 1:n) {
       if(delta[i] != 0) {
          Wmat[i,] <-</pre>
            (delta[i] == 1) *
            ((Y[i] < Y)*G_y[i]^(-2)+
             (Y[i] \ge Y \& delta == 2)*G_y[i]^(-1)*
               ifelse(G_y!=0,G_y^{(-1)},G_y[max(which(G_y != 0))]^{(-1)})*
            (Y[i] < tau)
       }
    Wmat <- Wmat/sum(Wmat)</pre>
    return(Wmat)
```

Test the Code

Reference:

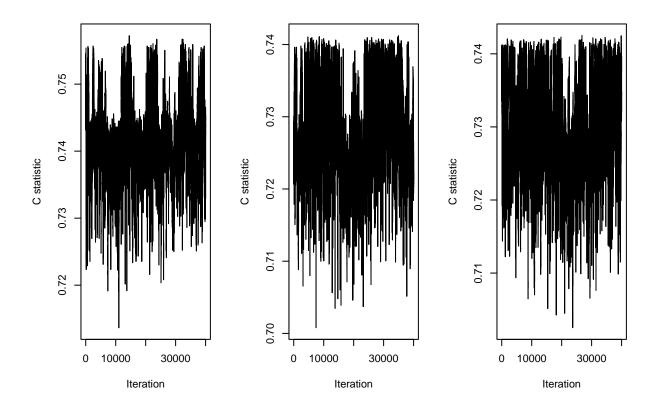
 $https://www.emilyzabor.com/tutorials/survival_analysis_in_r_tutorial.html\#Part_3:_Competing_Risks$

```
data(Melanoma, package = "MASS")
library(dplyr)
## Attaching package: 'dplyr'
## The following objects are masked from 'package:stats':
##
##
       filter, lag
## The following objects are masked from 'package:base':
##
##
       intersect, setdiff, setequal, union
library(gtsummary)
## #StandWithUkraine
Melanoma <-
  Melanoma %>%
  mutate(
    status = as.factor(recode(status, `2` = 0, `1` = 1, `3` = 2))
  )
```

status:

0=alive, 1=died from melanoma, 2=dead from other causes.

```
system.time({
result1 = MH_CR_Sampling(Y,delta,tau,
                      A,beta0,sigma0,var.prop,
                      m,B,eta,
                      Wmat_option=1)
result2 = MH_CR_Sampling(Y,delta,tau,
                      A,beta0,sigma0,var.prop,
                      m,B,eta,
                      Wmat_option=2)
censor = ifelse(delta==0,1,0)
Cox_G = survfit(coxph(Surv(Y ,censor) ~ age + sex + thickness + ulcer,
                  data=Melanoma))
result3 = MH_CR_Sampling(Y,delta,tau,
                    A,beta0,sigma0,var.prop,
                      m,B,eta,
                      Wmat_option=2,Cox_G)
})
##
      user system elapsed
           39.31 1168.06
## 731.37
par(mfrow=c(1,3))
plot(1:(m-B),result1$C_stat,type="l",xlab="Iteration",ylab="C statistic")
plot(1:(m-B),result2$C_stat,type="l",xlab="Iteration",ylab="C statistic")
plot(1:(m-B),result3$C_stat,type="l",xlab="Iteration",ylab="C statistic")
```



```
Wmat1 = RiskC_Wmat1(Y,delta,tau)
Wmat2 = RiskC_Wmat2(Y,delta,tau)
Wmat3 = RiskC_Wmat2(Y,delta,tau,Cox_G)
C_index(colMeans(result1$THETA),Wmat1)
```

[1] 0.7451304

C_index(colMeans(result2\$THETA),Wmat2)

[1] 0.7324692

C_index(colMeans(result3\$THETA),Wmat3)

[1] 0.7342648

${\it C-statistics}$ for time-dependent covariates

No need to consider?

My thinking: weight matrix for C-statistics only depends on three inputs: the follow-up time, event indicator and a truncation point (Y,delta,tau), covariates only affect the calculation of risk score.

Thus, C statistics can be directly applied to time-dependent covariates.

we only need to think about how to recode the time-dependent covariates or other methods.