Review class of two-sample test:

Two groups, j = 1, 2, with hazards $\alpha_i(t)$, counting processes $N_j(t)$, no. at risk $Y_j(t)$ and Nelson-Aalen estimators $\hat{A}_i(t) = \int_0^t dN_i(s) / Y_i(s).$

Let L(t) be a general predictable weight function and define a general two-sample test by

$$Z_1 = \int_0^{t_0} L(s) [d\hat{A}_1(s) - d\hat{A}_1(s)] = \int_0^{t_0} L(s) [\frac{dN_1(s)}{Y_1(s)} - \frac{dN_2(s)}{Y_2(s)}]$$

Under $H_0: \alpha_1(t) = \alpha_2(t) = \alpha(t) Z_1$ has expectation 0 and variance

$$\mathbf{E}\left[\int_{0}^{t_{0}} L(s)^{2} \left(\frac{1}{Y_{1}(s)} + \frac{1}{Y_{2}(s)}\right) \alpha(s) ds\right]$$

which may be estimated $V_{11} = \int_0^{\tau_0} \frac{L(s)^2}{Y_1(s)Y_2(s)} dN_{\bullet}(s)$ General event histories - p. 1/10

Some weight functions

Let $L(t) = K(t) \frac{Y_1(s)Y_2(s)}{Y_{\bullet}(s)}$

Choices of K(t) up or down-weights early and late events:

- K(t) = 1 gives log-rank
- K(t) = Y(t) Gehan's generalisation of the Wilcoxon-test
- $K(t) = \hat{S}(t)$ Peto and Prentice generalization of Wilcoxon
- $K(t) = \hat{S}(t)^p (1 \hat{S}(t))^q$ Fleming and Harrington generalization of Prentice' test.
- $K(t) = \hat{S}(t)^p$ implementered in R

Ex. 3.9 Logrank Relapse Leukemia

- > tpl<-c(1,1,2,2,3,4,4,5,5,8,8,8,8,11,11,12,12,12,15,17,22,2</pre>
- > dpl<-rep(1,length(tpl))</pre>
- > t6MP<-c(6,6,6,6,7,9,10,10,11,13,16,17,19,20,22,23, 25,32,32,34,35)
- > times<-c(tpl,t6MP)</pre>
- > relapse<-c(dpl,d6MP)</pre>
- > group<-c(rep(1,length(tpl)),rep(2,length(t6MP)))</pre>
- >
- > #Log-rank
- > survdiff(Surv(times,relapse)~group)

N Observed Expected (O-E)^2/E (O-E)^2/V group=1 21 21 10.7 9.77 16.8 group=2 21 9 19.3 5.46 16.8

Chisq= 16.8 on 1 degrees of freedom, p= 4.17e-05 General event histories - p. 3/10

Ex. 3.9 Relapse Leukemia - two other tests

- > #Wilcoxon type,
- > survdiff(Surv(times,relapse)~group,rho=1)

N Observed Expected $(O-E)^2/E$ $(O-E)^2/V$ group=1 21 14.55 7.68 6.16 14.5 group=2 21 5.12 12.00 3.94 14.5 Chisq= 14.5 on 1 degrees of freedom, p= 0.000143> > #In between > survdiff(Surv(times,relapse)~group,rho=0.5) N Observed Expected $(O-E)^2/E$ $(O-E)^2/V$ group=1 21 17.22 8.98 7.57 15.7 group=2 21 6.68 14.92 4.56 15.7 Chisq= 15.7 on 1 degrees of freedom, p = 7.4e-0.5General event histories - p. 4/10

Ex. 3.10 Unbiased variance estimator

We will show that, see slide 2, $E[V_{11}] = Var(Z_1)$.

Since $N_{\bullet}(t) = N_1(t) + N_2(t)$ under H₀ has intensity process $Y_{\bullet}(t)\alpha(t) = Y_1(t)\alpha(t) + Y_2(t)\alpha(t)$, i.e. the sum of the intensity processes of the $N_j(t)$ we have

$$V_{11} = \int_0^{t_0} \frac{L(s)^2}{Y_1(s)Y_2(s)} dN_{\bullet}(s)$$

= $\int_0^{t_0} \frac{L(s)^2}{Y_1(s)Y_2(s)} Y_{\bullet}(s) \alpha(s) ds + \int_0^{t_0} \frac{L(s)^2}{Y_1(s)Y_2(s)} dM_{\bullet}(s)$

where $M_{\bullet}(t) = N_{\bullet}(t) - \int_{0}^{t} Y_{\bullet}(s)\alpha(s)ds$ is a martingale, thus the last term is an integral wrt martingale and has exp. 0. Thus

$$\begin{aligned} \mathsf{E}[V_{11}] &= \mathsf{E}[\int_0^{t_0} \frac{L(s)^2}{Y_1(s)Y_2(s)} Y_{\bullet}(s) \alpha(s) ds] \\ &= \mathsf{E}[\int_0^{t_0} L(s)^2 (\frac{1}{Y_1(s)} + \frac{1}{Y_2(s)}) \alpha(s) ds] = \mathsf{Var}(Z_1) \end{aligned}$$

Ex. 3.11

Want to show that under the null where $\alpha_1(t) = \alpha_2(t) = \alpha(t)$ we have $E[N_1(t_0)] = E[E_1(t_0)]$ where from eq. (3.60), ABG

$$E_1(t_0) = \int_0^{t_0} Y_1(s) \frac{dN_{\bullet}(s)}{Y_{\bullet}(s)} = \int_0^{t_0} Y_1(s)\alpha(s)ds + \int_0^{t_0} Y_1(s) \frac{dM_{\bullet}(s)}{Y_{\bullet}(s)}$$

where the last equality is added in here. The last term is a martingale with expectation 0 and we get

$$E[E_1(t_0)] = E[\int_0^{t_0} Y_1(s)\alpha(s)ds].$$

But we also have

$$\mathbf{E}[N_1(t_0)] = \mathbf{E}[\int_0^{t_0} Y_1(s)\alpha(s)ds + M_1(t_0)] = \mathbf{E}[\int_0^{t_0} Y_1(s)\alpha(s)ds],$$

thus equality (under the null).

General event histories -p. 6/10

About variance of Z_1

Under the null we may write, $M_j(t) = N_j(t) - \int Y_j(s)\alpha(s)ds$,

$$Z_1 = \int_0^{t_0} L(s) \frac{dM_1(s)}{Y_1(s)} - \int_0^{t_0} L(s) \frac{dM_2(s)}{Y_2(s)}$$

as the difference between two martingales and the variance result follows directly when they are uncorrelated.

In general $\text{Cov}(\sum_i U_i, \sum_j V_j) = \sum_i \sum_j \text{Cov}(U_i, V_j)$ and this will extend to integrals, thus

$$\operatorname{Cov}\left(\int_{0}^{t_{0}} L(s) \frac{dM_{1}(s)}{Y_{1}(s)}, \int_{0}^{t_{0}} L(s) \frac{dM_{2}(s)}{Y_{2}(s)}\right)$$
$$= \int_{0}^{t_{0}} \int_{0}^{t_{0}} \operatorname{Cov}(L(s_{1}) \frac{dM_{1}(s_{1})}{Y_{1}(s_{1})}, L(s_{2}) \frac{dM_{2}(s_{2})}{Y_{2}(s_{2})})$$

About variance of Z_1 , contd.

But the latter term simplifies to

$$\int_{0}^{t_{0}} \operatorname{Cov}(L(s) \frac{dM_{1}(s)}{Y_{1}(s)}, L(s) \frac{dM_{2}(s)}{Y_{2}(s)})$$

since for $s_1 \neq s_2$, say $s_1 < s_2$,

$$\operatorname{Cov}(L(s_1)\frac{dM_1(s_1)}{Y_1(s_1)}, L(s_2)\frac{dM_2(s_2)}{Y_2(s_2)}) =$$

$$E[E(L(s_1)\frac{dM_1(s_1)}{Y_1(s_1)}L(s_2)\frac{dM_2(s_2)}{Y_2(s_2)})|\mathcal{F}_{s_2-}]$$
$$E[L(s_1)\frac{dM_1(s_1)}{F_{s_2-}}E(L(s_2)\frac{dM_2(s_2)}{F_{s_2-}}|\mathcal{F}_{s_2-})] =$$

$$\mathbb{E}[L(s_1)\frac{dM_1(s_1)}{Y_1(s_1)}\mathbb{E}(L(s_2)\frac{dM_2(s_2)}{Y_2(s_2)}|\mathcal{F}_{s_2-})] = 0$$

About variance of Z_1 , **III**

Furthermore

$$\int_0^{t_0} \operatorname{Cov}(L(s) \frac{dM_1(s)}{Y_1(s)}, L(s) \frac{dM_2(s)}{Y_2(s)}) = 0$$

since

$$\operatorname{Cov}(L(s)\frac{dM_1(s)}{Y_1(s)}, L(s)\frac{dM_2(s)}{Y_2(s)}) = \operatorname{E}\left[\frac{L(s)^2}{Y_1(s)Y_2(s)}\operatorname{E}\left[dM_1(s)dM_2(s)|\mathcal{F}_{s-1}\right]\right]$$

which equal zero since $N_1(s) + N_2(s)$ has intensity process $(Y_1(s) + Y_2(s))\alpha(s)ds$, thus

 $\operatorname{Var}(dM_1(s) + dM_2(s)|\mathcal{F}_{s-}) = (Y_1(s) + Y_2(s))\alpha(s)ds$ $= \operatorname{Var}(dM_1(s)|\mathcal{F}_{s-}) + \operatorname{Var}(dM_2(s)|\mathcal{F}_{s-})$

giving $E[dM_1(s)dM_2(s)|\mathcal{F}_{s-}] = Cov[dM_1(s), dM_2(s)|\mathcal{F}_{s-}] = 0$

About variance of Z_1 , IV

A couple of the arguments on the previous page may need some more explanation: $N_j(t)$ has intensity process $Y_j(t)\alpha(t)$ and so for the martingale $M_j(t) = N_j(t) - \int_0^t Y_j(s)\alpha(s)ds$ we have

$$\operatorname{Var}(dM_j(t)|\mathcal{F}_{t-}) = Y_j(t)\alpha(t)dt$$

Furthermore $N_1(t) + N_2(t)$ has intensity process $(Y_1(t) + Y_2(t))\alpha(t)$ and martingale

$$M_{\bullet}(t) = (N_1(t) + N_2(t)) - \int_0^t (Y_1(s) + Y_2(s))\alpha(s)ds = M_1(t) + M_2(t)$$

and so $\operatorname{Var}(dM_{\bullet}(t)|\mathcal{F}_{t-}) = (Y_1(t) + Y_2(t))\alpha(t)dt$ = $\operatorname{Var}(dM_2(t)|\mathcal{F}_{t-}) + \operatorname{Var}(dM_2(t)|\mathcal{F}_{t-})$. Thus $M_1(t)$ and $M_2(t)$ have uncorrelated increments.