The stratified Cox Procedure

1 The stratified Cox Model (SC)

Introducing the variables

- Denote by $X_1, ..., X_p$ for $p \in \mathbb{N}$ the variables satisfying the PH assumption.
- Denote by $Z_1, ..., Z_k$ for $k \in \mathbb{N}$ the variables not satisfying the PH assumption.
- We assume no interaction between the Z_j 's and the X_i 's for all i, j.
- Define a single new variable Z^*
 - 1. Categorize each Z_i
 - 2. Form combinations of categories (strata)
 - 3. The strata are the categories of Z^\ast
- k^* denotes the number of combinations, i.e. Z^* has k^* categories.

The general SC model

The general Cox model is given by

$$h_{q}(t,X) = h_{0q} \exp[\beta_{1}X_{1} + \dots + \beta_{p}X_{p}]$$
(1)

with $g = 1, ..., k^*$ strata defined from Z^*

A few observations

- The same coefficients: for each stratum $\beta_1, ..., \beta_p$.
- BUT: the baseline hazard functions $h_{0g}(t)$ may be different for each stratum.
- $X_1, ..., X_p$ directly included in the model, but Z^* appears only through the different baseline hazard functions.

In R:

The estimation procedure

1. We calculate the likelihood function for each strata

Strata:	$1, \ldots, k^*$
Likelihood:	L_1,\ldots,L_{k^*}
Hazard:	h_1, \ldots, h_{k^*}

2. We multiply all the likelihood function we have obtained this way.

$$L = L_1 \times \ldots \times L_{k^*}$$

3. We obtain the estimates for coefficients β_1, \ldots, β_p by maximizing the log likelihood function L.

2 No interaction assumption

The interaction model is given by:

$$h_{q}(t) = h_{0q}(t) \exp[\beta_{1q}X_{1} + \dots + \beta_{pq}X_{p}]$$

The difference to the no-interaction model is that the coefficients β depend on the strata.

An alternative formulation:

$$h_g(t) = h_{g0}(t) [\beta_1^* X_1 + \ldots + \beta_p^* X_p + \sum_{j=1}^{k^*-1} \sum_{i=1}^p \beta_{ij}^* X_i Z_j^*]$$

where the β^* do not involve g.

In R:

```
cox_2 <- coxph(Surv(time,status) ~ X_1 * strata(Z_1,Z_2,Z_3) +
X_2 * strata(Z_1,Z_2,Z_3), data=yourdataname, method="breslow")
```

3 Comparing: Likelihood, Wald & score test

Fisher's score vector $U(\theta)$.

The first derivative of the log-likelihood function is called (Fisher's) score vector,

$$U(\theta) = \frac{\partial}{\partial \theta} \ln L(\theta, X)$$

Remeber, that the derivative wrt a vector is a vector, with entires:

$$U_i(\theta) = \frac{\partial}{\partial \theta_i} \ln(L(\theta, X)).$$

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- Still a function in θ .
- If the log-likelihood is concave we have:

$$U(\hat{\theta}) = (0, \dots, 0)$$

The Fischer information matrix $i(\theta)$.

The Fischer information matrix is a $p \times p$ matrix defined by:

$$i(\theta) = E_{\theta} \left[U(\theta)^T U(\theta) \right] = \left\{ -E_{\theta} \left[\frac{\delta^2}{\delta \theta_i \theta_j} \ln L(\theta, X) \right] \right\}_{\substack{i=1,\dots,p\\j=1,\dots,p}}$$

Mostly this is to hard to compute, thus we estimate i with:

$$\hat{i}(\theta) =: I_{i,j}(\theta) := -\frac{\delta^2}{\delta \theta_i \delta \theta_j} \ln L(\theta, X), \quad i = 1, \dots, p, j = 1, \dots, p$$

Definition of the different tests

We already know the *likelihood ratio test* statistic:

$$LR := -2\left(\ln L(\theta_0, X) - \ln L(\hat{\theta}, X)\right) \to \chi_p^2$$

The *Wald test* statistic is defined as:

$$W := (\hat{\theta} - \theta_0)^T I(\hat{\theta})(\hat{\theta} - \theta_0) \to \chi_p^2$$

And the *score test* uses the efficient score vector:

$$S := U(\theta_0)^T I^{-1}(\theta_0) U(\theta_0) \to \chi_p^2$$

Note: Score test does not depend of $\hat{\theta}$.

4 Graphical Comparison of the tests so far

Overview of the examples

