

# The stratified Cox Procedure

## 1 The stratified Cox Model (SC)

### Introducing the variables

- Denote by  $X_1, \dots, X_p$  for  $p \in \mathbb{N}$  the variables satisfying the PH assumption.
- Denote by  $Z_1, \dots, Z_k$  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  $Z^*$
- $k^*$  denotes the number of combinations, i.e.  $Z^*$  has  $k^*$  categories.

### The general SC model

The general Cox model is given by

$$h_g(t, X) = h_{0g} \exp[\beta_1 X_1 + \dots + \beta_p X_p] \quad (1)$$

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

### A few observations

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

### In R:

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

## The estimation procedure

1. We calculate the likelihood function for each strata

$$\begin{array}{ll} \text{Strata:} & 1, \dots, k^* \\ \text{Likelihood:} & L_1, \dots, L_{k^*} \\ \text{Hazard:} & h_1, \dots, h_{k^*} \end{array}$$

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

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

3. We obtain the estimates for coefficients  $\beta_1, \dots, \beta_p$  by maximizing the log likelihood function  $L$ .

## 2 No interaction assumption

The interaction model is given by:

$$h_g(t) = h_{0g}(t) \exp[\beta_{1g}X_1 + \dots + \beta_{pg}X_p]$$

The difference to the no-interaction model is that the coefficients  $\beta$  depend on the strata.

An alternative formulation:

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

where the  $\beta^*$  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*,

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

Remember, that the derivative wrt a vector is a vector, with entries:

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

- Still a function in  $\theta$ .
- 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:

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

Mostly this is too 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:

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

The *Wald test* statistic is defined as:

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

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

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

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

## 4 Graphical Comparison of the tests so far

### Overview of the examples

