

# Lecture twelve: Model Checking (III)

## Identification of influential observations

In the assessment of model adequacy it is important to check the influence of individual observations. Were hazard function, coefficients  $\hat{\beta}$  and other estimates substantially affected by any of the observations?

### 1. Checking for outliers following a Cox regression analysis

The optimal means is to refit the model by omitting one observation in the study and see the changes to the estimates.

- (a) similarity to Jackknife, cross evaluation (CV).
- (b) Huge task in terms of time and space when sample size is moderate or large.
- (c) More difficult in survival analysis than other linear models.
- (d) Must use some kind of approximation when sample size is not small.

### 2. Influence on a parameter estimate

Let  $(t_i, \delta_i, x_i)$  be the usual triple for the survival times,  $i = 1, 2, \dots, n$ . Define

$$a_{ji} = \frac{\sum_{l \in R(t_i)} x_{jl} \exp(\hat{\beta}' \mathbf{x}_l)}{\sum_{l \in R(t_i)} \exp(\hat{\beta}' \mathbf{x}_l)},$$

and let  $\mathbf{r}_{Si}, i = 1, 2, \dots, n$  be the  $i$ th score residual (a  $p \times 1$  vector) whose  $j$ th component is

$$r_{Sji} = \delta_i(x_{ji} - a_{ji}) + \exp(\hat{\beta}' \mathbf{x}_i) \sum_{t_r \leq t_i} \delta_r \frac{(a_{jr} - x_{ji})}{\sum_{l \in R(t_r)} \exp(\hat{\beta}' \mathbf{x}_l)},$$

for  $j = 1, 2, \dots, p$ .

- (a) It can be shown (ref. Biometrics, vol. 40: 493 - 499, 1984 by Cain and Lange) that an approximation to  $\hat{\beta}_j - \hat{\beta}_{j(i)}$ , the change in  $\hat{\beta}_j$  on omitting the  $i$ th observation, is the  $j$ th component of the vector (weighted transformation of score residual)

$$\mathbf{r}'_{Si} \mathbf{V}(\hat{\beta}),$$

where  $\mathbf{V}$  is the  $p \times p$  variance-covariance matrix of  $\hat{\beta}$ .

This quantity, which is called a *delta-beta*, will be denoted by  $\Delta_i \hat{\beta}_j$ , so that  $\Delta_i \hat{\beta}_j \approx \hat{\beta}_j - \hat{\beta}_{j(i)}$ .

- (b) *Standardized delta-beta*:  $\Delta_i \hat{\beta}_j$  divided by the standard error of  $\hat{\beta}_j$ .
- (c) Index plots of the *delta-beta*'s for each covariate: plots of the *delta-beta*'s for each covariate against the rank order of the survival times.
- (d) Standard?: Is the change less than one standard error?
- (e) Example 4.6: Infection in patients on dialysis (cont.)

**SAS output:**

Obs	DBAGE	DBSEX	LD	LMAX
1	0.001969	-0.19767	0.03285	0.16101
2	0.000406	0.54326	0.33875	0.30927
3	-0.001056	0.07414	0.00463	0.06766
4	-0.011880	0.59430	0.33785	0.62061
5	0.004903	0.01386	0.05001	0.10416
6	-0.000542	-0.11922	0.01938	0.05750
7	-0.009462	0.12695	0.13570	0.29117
8	-0.003241	-0.03455	0.02692	0.05397
9	-0.007271	-0.07335	0.13335	0.12352
10	0.003233	-0.20226	0.03532	0.19266
11	0.005979	-0.21584	0.06108	0.26352
12	0.004800	-0.19394	0.04318	0.22366
13	0.012162	-0.31568	0.21903	0.46368

**Figures generated from Splus:** Program is available at the course website (dial3.s)

**SAS program:**

```
options ls=80;
libname fu '.././sdata';
data work;
    set fu.dialysis;
proc phreg;
    model infectt*censor(0)=age sex;
```

```

        output out=outp dfbeta=dbage dbsex ld=ld lmax = lmax;
proc rank data=outp out=fu.infdiag;
        var infectt;
        ranks strank;
proc print;
        var dbage dbsex ld lmax;
filename gsasfile 'infdiag.gsf';
goptions reset=all gunit=pct border ftext=swissb htitle=6 htext=2.5
gaccess=gsasfile ROTATE=LANDSCAPE gsfmode=append device=ps;
proc gplot data=fu.infdiag;
        plot dbage*strank;
        plot dbsex*strank;
run;

```

### 3. Influence of observations on the set of parameter estimates

#### (a) Likelihood displacement (LD):

- i. The influence of each observation on the overall fit of the model can be measured by

$$2\{\log L(\hat{\beta}) - \log L(\hat{\beta}_{(i)})\}$$

- ii. Can we do it without refitting (n times) model? Pettitt and Bin Daud (Applied Statistics, vol. 38: 313-329, 1989) show

$$LD_i \approx \mathbf{r}'_{Si} \mathbf{V}(\hat{\beta}) \mathbf{r}_{Si},$$

- iii. plots of LD vs rank of survival time: Observations that have relatively large values of the diagnostic are influential.

#### (b) Eigenvector ( $l_{max}$ ) associated with the largest eigenvalue:

- i. The  $n \times n$  symmetric matrix

$$\mathbf{B} = \mathbf{\Theta}' \mathbf{V}(\hat{\beta}) \mathbf{\Theta},$$

where  $\mathbf{\Theta}'$  is the  $n \times p$  matrix whose  $i$ th row is  $\mathbf{r}'_{Si}$ .

- ii. Eigenvalues and eigenvectors of a square matrix

- iii. The absolute values of the elements of the standardized eigenvector corresponding to the largest eigenvalue of the matrix  $\mathbf{B}$ , is a measure of the sensitivity of the fit of the model to each of the  $n$  observations in the data set. denoting the eigenvector by  $l_{max}$ .
  - iv. index plots: Plot of  $|l_{max}|$  vs rank order of survival times, plots vs covariates can be used to assess influence of each observation.
  - v. plot  $|l_{max}|$  vs covariates will not have a deterministic pattern if the fitted model is correct.
- (c) Example 4.7: infection in patients on dialysis

The observations from patients 2, 4 and 13 affect the form of the hazard function to the greatest extent, the four models are

Omitting patient number 2:  $0.031Age_i - 3.530Sex_i$ ,

Omitting patient number 4:  $0.045Age_i - 3.529Sex_i$ ,

Omitting patient number 13:  $0.011Age_i - 2.234Sex_i$ ,

The model based on full data is

$$0.03Age_i - 2.711Sex_i.$$

Illustration: compare the hazard ratio for two age groups; male vs female.

- (d) example 4.8: survival of multiple myeloma patients

Figures generated from Splus: Influential obs. Patient 32, 38 (BUN). patient 32 had very short survival times and the second largest values of BUN. Patient 38 also had short survival. Patient 13 ( $l_{max}$ ) is an outlier.

Splus program:

```
ex48.s<-function(){
  tmpdf <- importData("../sdata/infmye.sas7bdat")
  motif()
  par(mfrow=c(2,3))
  attach(tmpdf)
  plot(strank, dbhb, xlab="Rank of survival time",
       ylab="Delta-beta for HB", xlim=c(0,50),
```

```

        ylim=c(-0.02,0.03))
    identify(strank, dbhb)
    plot(strank, dbbun, xlab="Rank of survival time",
         ylab="Delta-beta for BUN", xlim=c(0,50),
         ylim=c(-0.002,0.002))
    identify(strank, dbbun)
    plot(strank, lmax, xlab="Rank of survival time",
         ylab="Absolute value of Lmax", xlim=c(0,50), ylim=c(0,0.4))
    identify(strank, lmax)
    plot(hb, lmax, xlab="Value of HB",
         ylab="Absolute value of Lmax", xlim=c(4,15), ylim=c(0,0.4))
    plot(bun, lmax, xlab="Value of BUN",
         ylab="Absolute value of Lmax", xlim=c(5,176), ylim=c(0,0.4))
    detach()
}

```

SAS program:

```

options ls=80;
libname fu '..../sdata';
data work;
    set fu.myeloma;
proc phreg;
    model survt*censor(0)=hb bun;
        output out=outp dfbeta=dbhb dbbun ld=ld lmax = lmax;
proc rank data=outp out=fu.infmye;
    var survt;
    ranks strank;
filename gsasfile 'infmye.gsf';
goptions reset=all gunit=pct border ftext=swissb htitle=6 htext=2.5
gaccess=gsasfile ROTATE=LANDSCAPE gsfmode=append device=ps;
proc gplot data=fu.infmye;
    plot dbhb*strank;
    plot dbbun*strank;
    plot lmax*strank;
    plot lmax*hb;
    plot lmax*bun;
run;

```

#### 4. What to do about influential observations?

- (a) check the origin of influential observations (medical charts?), human error?
- (b) report the analysis with and without the influential values.
- (c) delete those observations if they are out of reasonable range.

**Assignment seven:** Assume the final Cox model for prostatic cancer patients study (Table 1.4, page 10) includes **SIZE, INDEX and TREAT** (see example 3.6 at page 73). Identify the influential observations if any. Write up your comments and interpretation. Provide tables as well as relevant plots to justify your answer.

Figure 1: Example 4.6

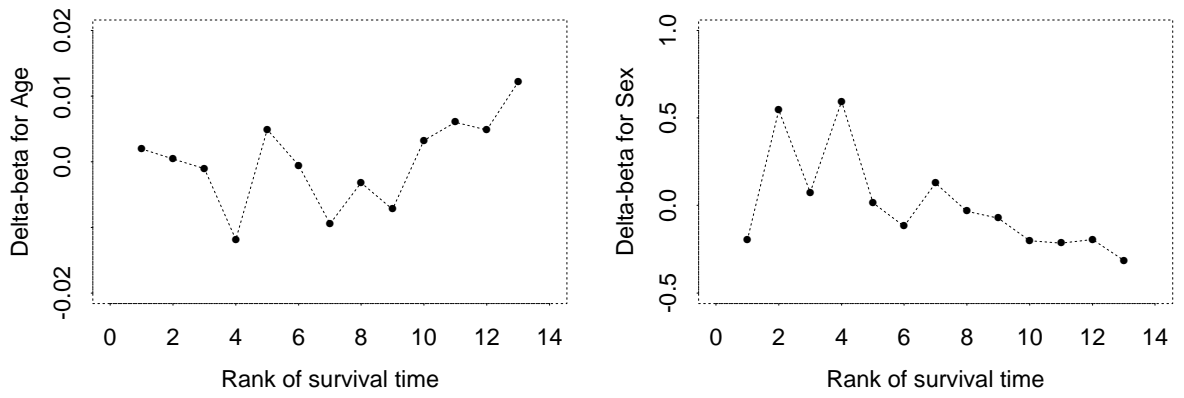


Figure 2: Example 4.8

