



Variables

> head(LOS)

	ID	AGE	FUNC	PT	ОТ	ST	FIM_F	FIM_S	BAR_F	BAR_S	sex	ht	dm	in_date	out_date
1	1	21	神外	1	1	0	48	50	10	15	0	0	0	2000/11/1	2000/12/19
2	2	21	神外	1	1	0	67	81	30	65	1	0	0	2000/10/25	2000/11/30
3	3	21	骨疫	1	0	0	125	125	95	100	1	0	0	2002/5/3	2002/5/6
4	4	28	骨疫	1	1	0	83	89	35	50	1	0	0	2001/8/13	2001/9/20
5	5	29	神外	1	0	0	18	18	0	0	0	0	0	2000/11/15	2001/1/9
6	6	30	內疫	1	1	0	87	99	20	60	0	0	0	2003/9/17	2003/10/25

共544個樣本

ID:患者編號 AGE:年齡

FUNC: 經由該門診辦理住院

PT: 物理治療 OT: 職能治療 ST: 語言治療

FIM_F: 入院時功能獨立量表分數 FIM S: 出院時功能獨立量表分數

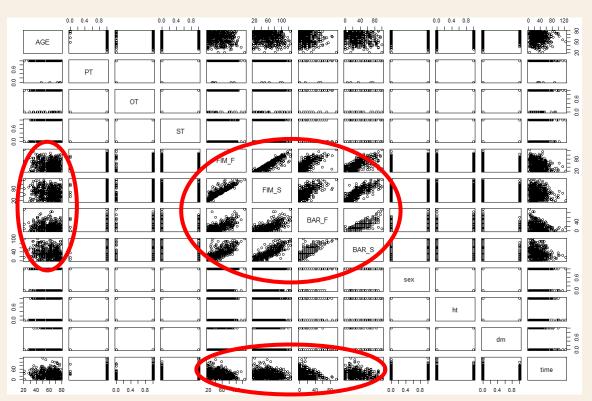
BAR_F: 入院時巴氏量表分數 (35以下可申請外籍看護)

BAR_S: 出院時巴氏量表分數

sex : 性別 ht : 高血壓 dm : 糖尿病

in_date : 入院日期 out_date : 出院日期

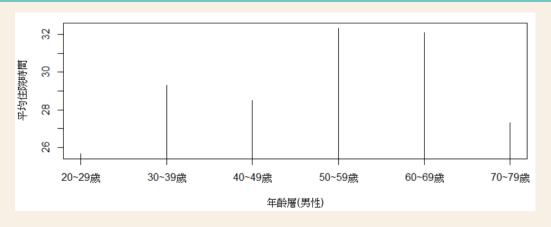
Correlation

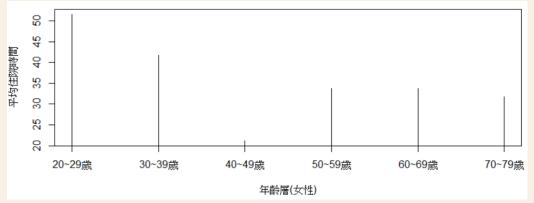


- [1] -0.1647077
 > cor(Los\$AGE,Los\$BAR_F)
 [1] -0.1348637
 > cor(Los\$AGE,Los\$FIM_S)
 [1] -0.1756479
 > cor(Los\$AGE,Los\$BAR_S)
 [1] -0.1651406
- > cor(LOS\$AGE,as.numeric(time))
 [1] -0.0004152204
 > cor(LOS\$AGE,LOS\$FIM_S-LOS\$FIM_F)
 [1] -0.06202067
 > cor(as.numeric(time),LOS\$FIM_F)
 [1] -0.2496124
 > cor(as.numeric(time),LOS\$BAR_F)
 [1] -0.2706034

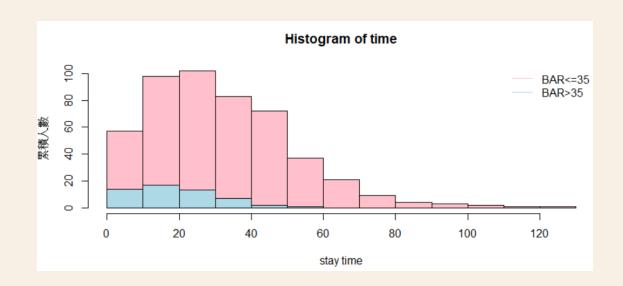
按年齡做分組

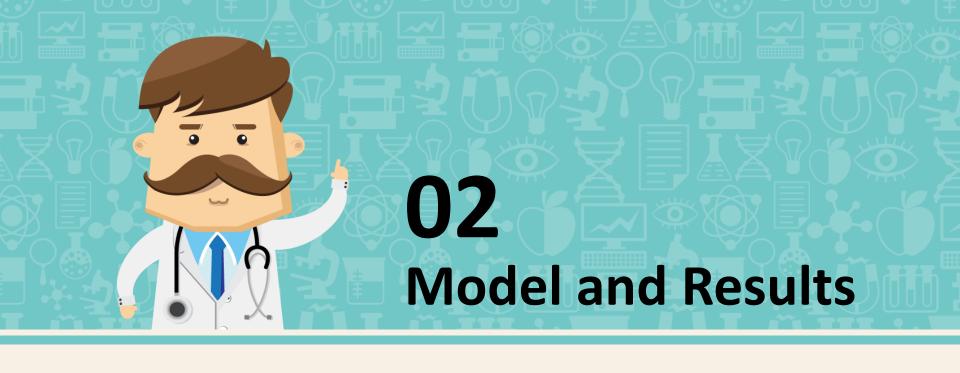
20~29歲 30~39歲 40~49歲 50~59歲 60~69歲 70~79歲





FIM分數若為35分以下,則可以申請外籍看護 有490人在入院時分數已達可申請看護標準





Survival Analysis

研究或分析樣本所觀察到的某一段時間長度之分配,一段時間長度通常是從一特定事件起始之時間原點(起始時間點)直到某一特定事件發生的時間點

- 時間長度時間原點到事件發生時間點
- 事件: 死亡、患病、復發、提早退出試驗

在此次LOS中是分析影響住院時間長短的變數

Survival Analysis

survival function

某特定時間點下,個案可以活過此特定時間點的機率

$$S(t) = P(T > t) = \int_{t}^{\infty} f(u) \ du$$

CDF :
$$F(t) = P(T \le t) = 1 - S(t)$$

hazard function

下一個瞬間事件發生的機率

$$h(t) = \lim_{\delta \to 0} \frac{1}{\delta} P(t \le T < t + \delta | T \ge t)$$

累積風險: $H(t) = \int_0^t h(u) \ du$

$$h(t) = \frac{-\frac{d[S(t)]}{dt}}{S(t)} = \frac{f(t)}{S(t)} = -\frac{d}{dt} \log[S(t)]$$

$$S(t) = \exp(-\int_0^t h(u) \ du)$$

假設解釋變數對風險的作用是成比例,則hazard function和基線風險度(baseline hazard)的關係可表示為

$$h(t|x) = h_0(t)e^{\beta^T x}$$

比例風險假設:解釋變量對與風險的作用所帶來的風險比是不隨時間改變

$$h(t) = \lambda$$

$$S(t) = \exp\left(-\int_0^t h(u) \ du\right) = \exp(-\lambda t) = e^{-\lambda t}$$

$$f(t) = h(t) * S(t) = \lambda * e^{-\lambda t}$$

因 λ 為一定值,故可以推出 Cox Regression 為

$$\log(HR(x)) = \log \frac{h(t|x)}{h_0(t)} = \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \varepsilon$$

Cox 比例風險模型下的概似函數為

$$L = \prod_{i=1}^{n} \{h_0(t)e^{\beta^T x_i} \exp\left(-\int_0^{t_i} h_0(u)e^{\beta^T x_i} du\right)\}^{\delta_i} \{\exp\left(-\int_0^{t_i} h_0(u)e^{\beta^T x_i} du\right)\}^{1-\delta_i}$$

無法估計,所以使用partial likelihood,它漸進一致(asymptotically the same)完整的likelihood

時間點發生事件的條件機率為

$$\frac{h_0(t_j)\exp(\beta^T x_{i_j})}{\sum_{k \in R_j} h_0(t_j)\exp(\beta^T x_k)} = \frac{\exp(\beta^T x_{i_j})}{\sum_{k \in R_j} \exp(\beta^T x_k)}$$

其中 i_j 為實驗對象, x_{i_j} 為解釋變數, t_j 為生存時間

用這個性質忽略 $h_0(t)$,使用MLE去估計 β 把所有發生事件時的條件機率相乘,得到偏概似函數

$$L_p = \prod_j \frac{\exp(\beta^T x_{i_j})}{\sum_{k \in R_j} \exp(\beta^T x_k)}$$

$$l_p = \sum_j \beta^T x_{i_j} - \sum_j \log(\sum_{k \in R_j} \exp(\beta^T x_k))$$
 透過 $\frac{dl_p}{d\beta} = \sum_j x_{i_j} - \sum_j \frac{\sum_{k \in R_j} x_k \exp(\beta x_k)}{\sum_{k \in R_i} \exp(\beta x_k)} = 0$,求解 $\hat{\beta}_{MLE}$

使用不同變數建立模型

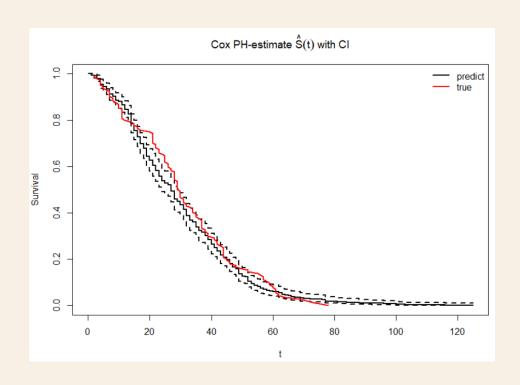
```
> model1 = coxph(time~FIM F+FIM S+BAR F.data = LOS.train)
> summarv(model1)
Call:
coxph(formula = time \sim FIM F + FIM S + BAR F. data = LOS.train)
 n= 400. number of events= 400
           coef exp(coef) se(coef)
                                         z Pr(>|z|)
FIM F 0.023328 1.023602 0.006639 3.514 0.000441 ***
FIM S -0.019380 0.980806 0.005724 -3.386 0.000710 ***
BAR_F 0.020419 1.020629 0.005177 3.944 8.02e-05 ***
signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
      exp(coef) exp(-coef) lower .95 upper .95
        1.0236
                   0.9769
                             1.0104
                                        1.0370
FIM_F
         0.9808
                   1.0196
                              0.9699
                                        0.9919
FIM_S
         1.0206
                    0.9798
                              1.0103
BAR F
                                        1.0310
Concordance= 0.62 (se = 0.016)
Likelihood ratio test= 56.6 on 3 df,
                                        p = 3e - 12
                    = 61.45 on 3 df,
wald test
                                         p = 3e - 13
Score (logrank) test = 61.19 on 3 df.
                                         p = 3e - 13
```

```
> model = coxph(time~AGE+FIM_F+FIM_S+BAR_F+BAR_S+PT+OT+ST+sex+ht+dm.data =
 LOS.train)
> summary(model)
Call:
coxph(formula = time ~ AGE + FIM_F + FIM_S + BAR_F + BAR_S +
    PT + OT + ST + sex + ht + dm. data = LOS.train)
  n= 400. number of events= 400
           coef exp(coef) se(coef)
                                        z Pr(>|z|)
       0.005324 1.005339 0.004577 1.163 0.24472
FIM F 0.021578 1.021812 0.006697 3.222 0.00127 **
FIM_S -0.015450 0.984669 0.006644 -2.326 0.02004
BAR F 0.026119 1.026463 0.006590 3.963 7.39e-05 ***
BAR_S -0.007466 0.992562 0.005637 -1.324 0.18536
       0.480933 1.617583 0.755881 0.636 0.52461
      -0.064365 0.937663 0.252897 -0.255 0.79910
      -0.198766 0.819742 0.111114 -1.789 0.07364
       0.141240 1.151701 0.111742 1.264 0.20624
       0.205265 1.227851 0.105399 1.948 0.05147 .
      -0.041958 0.958910 0.142005 -0.295 0.76763
signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
     exp(coef) exp(-coef) lower .95 upper .95
        1.0053
                   0.9947
                             0.9964
                                      1.0144
        1.0218
                   0.9787
FIM_F
                             1.0085
                                      1.0353
FTM S
        0.9847
                   1.0156
                             0.9719
                                      0.9976
        1.0265
                   0.9742
                             1.0133
                                      1.0398
BAR F
        0.9926
                   1.0075
                             0.9817
                                      1.0036
BAR S
                                      7.1166
        1.6176
                   0.6182
                             0.3677
        0.9377
                   1.0665
                             0.5712
                                      1.5393
        0.8197
                   1.2199
                             0.6593
                                      1.0192
        1.1517
                   0.8683
                             0.9252
                                      1.4337
        1.2279
                   0.8144
                             0.9987
                                      1.5096
        0.9589
                   1.0429
                             0.7259
                                      1.2666
Concordance = 0.621 (se = 0.016)
Likelihood ratio test= 66.27 on 11 df.
                                        p = 6e - 10
wald test
                    = 71.01 on 11 df.
                                        p=8e-11
Score (logrank) test = 71.28 on 11 df,
                                         p = 7e - 11
```

模型比較

```
> anova(model1,model)
Analysis of Deviance Table
Cox model: response is time
Model 1: ~ FIM_F + FIM_S + BAR_F
Model 2: ~ AGE + FIM_F + FIM_S + BAR_F + BAR_S + PT + OT + ST + sex + ht +
dm
    loglik Chisq Df P(>|Chi|)
1 -1972.2
2 -1967.4 9.6724 8
0.2888
```

Estimated Survival Function





Thank you for your attention