

Lab 9 Part 1 - Survival analysis

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Survival Analysis

This notebook walks through the analysis of the lung data from the survival library.

```
library(survival)
```

The lung data has many columns

```
help("lung")
```

In order to focus I subset the data into a smaller set of columns:

```
lung.analysis<-subset(lung, select = c("time", "status", "sex"))
```

To estimate the survival curve using KM

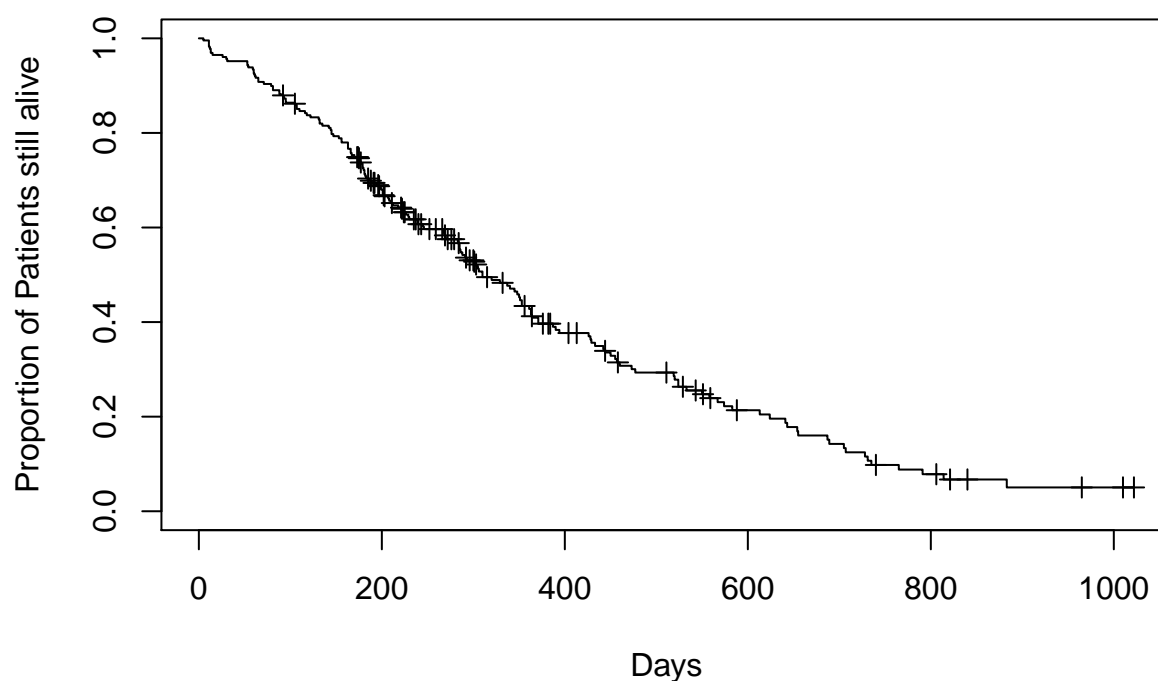
```
s.survfit <- survfit(Surv(lung.analysis$time, lung.analysis$status) ~ 1, data=lung.analysis )
s.survfit
```

```
## Call: survfit(formula = Surv(lung.analysis$time, lung.analysis$status) ~
##      1, data = lung.analysis)
##
##      n  events  median 0.95LCL 0.95UCL
##    228     165     310     285     363
```

and to plot it:

```
plot(s.survfit, mark.time = TRUE, conf.int = FALSE)
title(main="Survival Curve for Lung data", xlab="Days", ylab = "Proportion of Patients still alive")
```

Survival Curve for Lung data



Research Question: Does Gender affect survival?

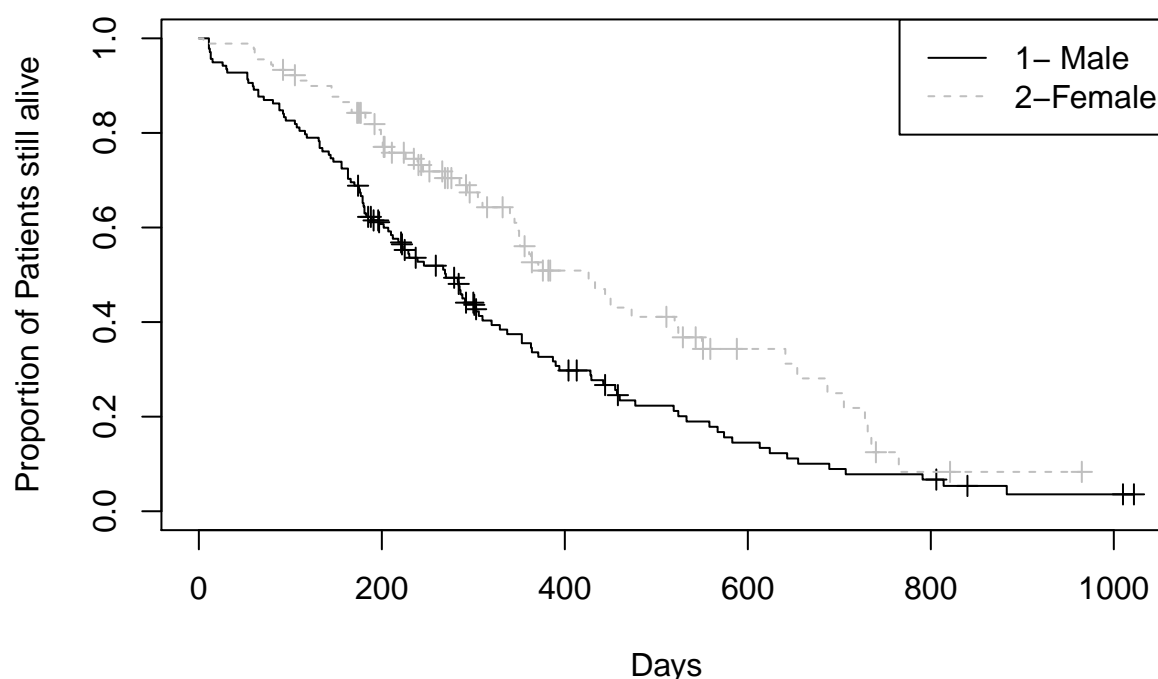
Here we use `survdif` to see if there is a difference.

```
lung.gender.survfit<-survfit(Surv(lung.analysis$time, lung.analysis$status)~ lung.analysis$sex, data=lung)
lung.gender.survdif<-survdif(Surv(lung.analysis$time, lung.analysis$status)~ lung.analysis$sex, data=lung)
lung.gender.survdif
```

```
## Call:
## survdiff(formula = Surv(lung.analysis$time, lung.analysis$status) ~
##   lung.analysis$sex, data = lung.analysis)
##
##               N Observed Expected (O-E)^2/E (O-E)^2/V
## lung.analysis$sex=1 138      112      91.6      4.55      10.3
## lung.analysis$sex=2  90       53      73.4      5.68      10.3
##
## Chisq= 10.3  on 1 degrees of freedom, p= 0.001
```

```
plot(lung.gender.survfit, mark.time = TRUE, col=c("black", "grey75"), lty=1:2)
title(main="Survival Curve by Gender", xlab="Days", ylab = "Proportion of Patients still alive")
legend("topright", c("1- Male", "2-Female"), lty=1:2, col=c("black", "grey75"))
```

Survival Curve by Gender



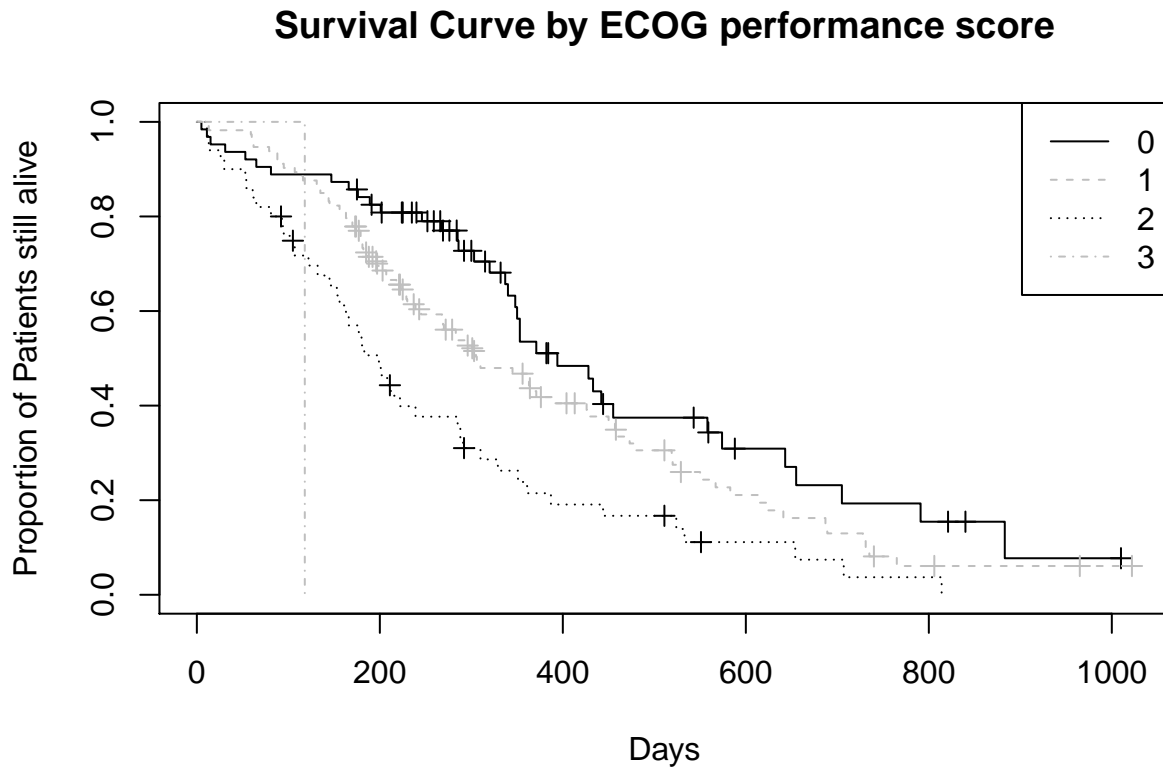
The p-value is significant and this supports what we see in the survival curves. There is a difference in survival curves between Male and Female patients.

Another possible research question

```
lung.perf.survfit<-survfit(Surv(lung$time, lung$status)~ lung$ph.ecog, data=lung)
lung.perf.survdif<-survdif(Surv(lung$time, lung$status)~ lung$ph.ecog, data=lung)
lung.perf.survdif
```

```
## Call:
## survdiff(formula = Surv(lung$time, lung$status) ~ lung$ph.ecog,
##           data = lung)
##
## n=227, 1 observation deleted due to missingness.
##
##               N Observed Expected (O-E)^2/E (O-E)^2/V
## lung$ph.ecog=0  63      37    54.153    5.4331    8.2119
## lung$ph.ecog=1 113      82    83.528    0.0279    0.0573
## lung$ph.ecog=2  50      44    26.147   12.1893   14.6491
## lung$ph.ecog=3   1       1     0.172    3.9733    4.0040
##
## Chisq= 22  on 3 degrees of freedom, p= 7e-05
```

```
plot(lung.perf.survfit, mark.time = TRUE, col=c("black", "grey75"), lty=1:4)
title(main="Survival Curve by ECOG performance score", xlab="Days", ylab = "Proportion of Patients still alive")
legend("topright", c("0", "1", "2", "3"), lty=1:4, col=c("black", "grey75"))
```



We can see that there is one category with only one case. Perhaps this can be removed or grouped with group `ecog=2`?

Cox Proportional Hazards (OPTIONAL)

```
lung.gender.ph<-coxph(Surv(lung.analysis$time, lung.analysis$status)~ lung.analysis$sex, data=lung.analysis)
summary(lung.gender.ph)
```

```
## Call:
## coxph(formula = Surv(lung.analysis$time, lung.analysis$status) ~
##       lung.analysis$sex, data = lung.analysis)
##
## n= 228, number of events= 165
##
##               coef exp(coef) se(coef)      z Pr(>|z|)
## lung.analysis$sex -0.5310    0.5880  0.1672 -3.176  0.00149 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
##               exp(coef) exp(-coef) lower .95 upper .95
## lung.analysis$ssex    0.588    1.701    0.4237    0.816
##
## Concordance= 0.579 (se = 0.021 )
## Likelihood ratio test= 10.63 on 1 df,  p=0.001
## Wald test              = 10.09 on 1 df,  p=0.001
## Score (logrank) test = 10.33 on 1 df,  p=0.001
```

The $\exp(\text{coef})$ column contains $\exp(\beta_1)$. This is the hazard ratio – the multiplicative effect of that variable on the hazard rate (for each unit increase in that variable). So, for a categorical variable like gender (in this case), going from male (baseline) to female results in approximately ~40% reduction in hazard. Recall that the CoxPH model is a linear model of the natural log of the hazard at time t , denoted $h(t)$, as a function of the baseline hazard ($h_0(t)$)

$$\log(h(t)) = \log(h_0(t)) + \beta_1 x_1 + \cdots + \beta_p x_p$$

if both sides are exponentiated:

$$h_1(t) = h_0(t) \times \exp(\beta_1 x_1)$$

Rearranging makes it possible to estimate the hazard ratio:

$$HR(t) = \frac{h_1(t)}{h_0(t)} = \exp^{\beta_1}$$