Parametric Analysis

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Data Prep

```
lung_df = lung %>%
  mutate_at(c(1, 3, 5, 6), .funs = ~as.factor(.))
lung_df2 = lung_df %>% na.omit()
```

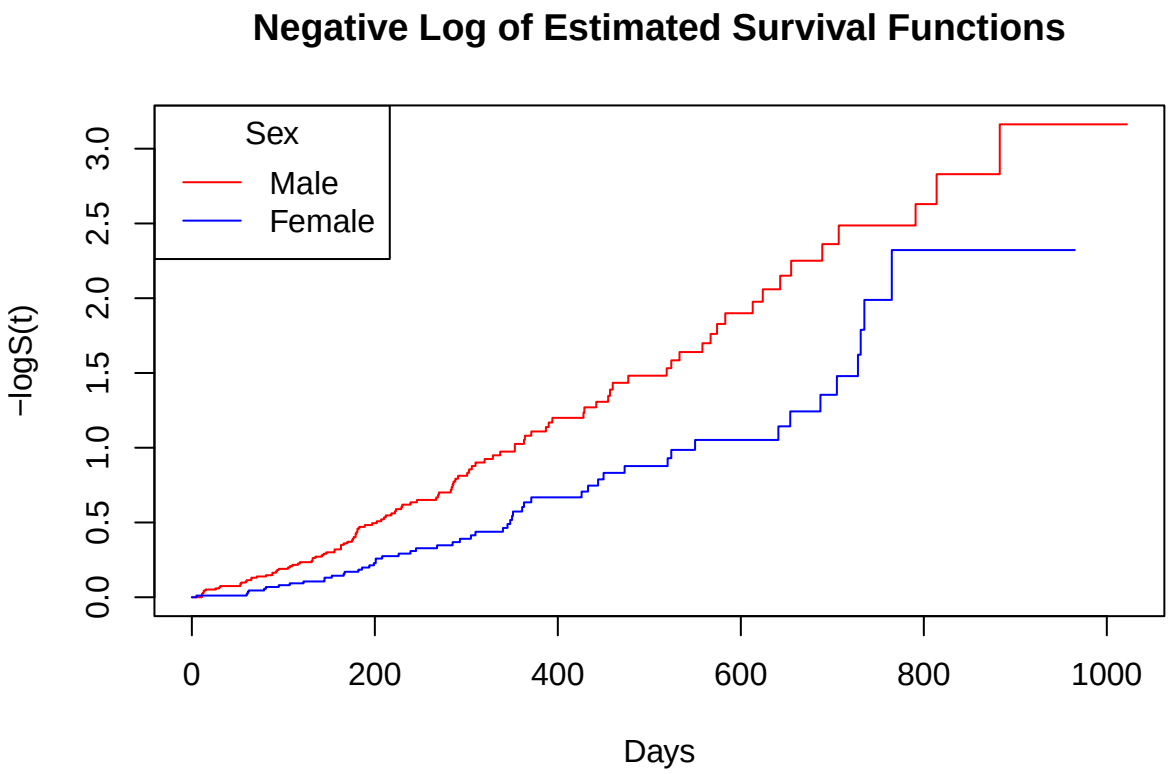
Model Checking

From the KM plot, we assume the survival data follow the Weibull distribution, with non-constant hazard rate.

Use plots to check if the lung data, by sex, follows the exponential distribution or the Weibull distribution.

Plot $-log\hat{S}(t)$

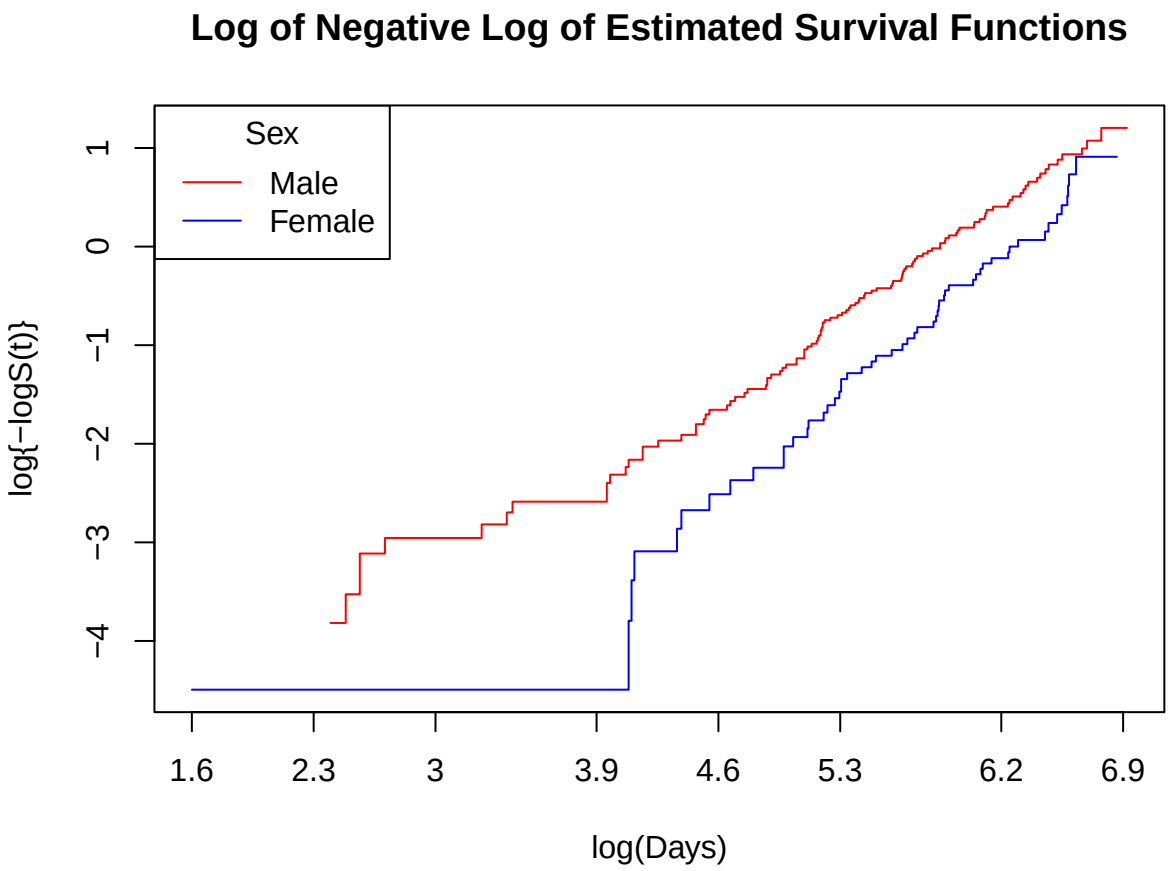
```
lung_fit = survfit(Surv(time, status == 2) ~ sex,
                   data = lung_df)

plot(lung_fit, col = c("red", "blue"),
     fun = "cumhaz", xlab = "Days", ylab = "-logS(t)",
     main = "Negative Log of Estimated Survival Functions")
legend("topleft", legend = c("Male", "Female"),
       title = "Sex", col = c("red", "blue"), lty = 1)
```



The curve for males is close to a straight line, while the curve for females is obviously non-linear, indicating a better choice of the Weibull distribution.

Plot $log(-logS(t))$

```
x_tick = c(5, 10, 20, 50, 100, 200, 500, 1000)
log_x = round(log(x_tick), 1)

plot(lung_fit, col = c("red", "blue"), fun = "cloglog",
     xlab = "log(Days)", ylab = "log{-logS(t)}",
     xaxt = "n", main = "Log of Negative Log of Estimated Survival Functions")
axis(1, at = x_tick, labels = log_x)
legend("topleft", legend = c("Male", "Female"),
       title = "Sex", col = c("red", "blue"), lty = 1)
```

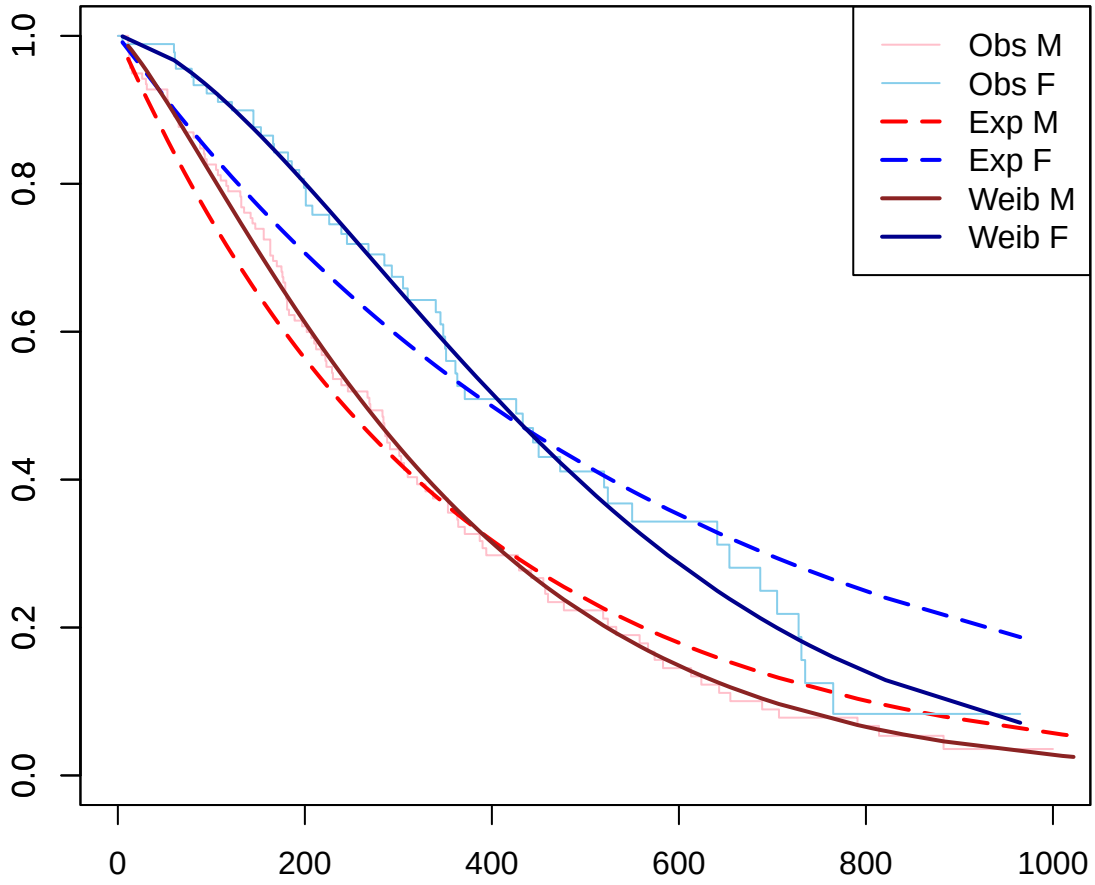


The slope of the male curve is close to 1, while the slope of the female curve is larger than 1, also indicating a Weibull distribution.

Fit exponential and Weilbull distributions

```
#parametric survival function
fit_exp_m = flexsurvreg(Surv(time, status == 2) ~ 1,
                        data = subset(lung_df, sex == 1), dist = "exp")
fit_exp_f = flexsurvreg(Surv(time, status == 2) ~ 1,
                        data = subset(lung_df, sex == 2), dist = "exp")
fit_weib_m = flexsurvreg(Surv(time, status == 2) ~ 1,
                         data = subset(lung_df, sex == 1), dist = "weibull")
fit_weib_f = flexsurvreg(Surv(time, status == 2) ~ 1,
                         data = subset(lung_df, sex == 2), dist = "weibull")

#plot km, exp fitted and weib fitted
plot(fit_exp_m, conf.int = FALSE, ci = FALSE, col = "red", col.obs = "pink", lty = "longdash", xlim = c
par(new = TRUE)
plot(fit_exp_f, conf.int = FALSE, ci = FALSE, col = "blue", col.obs = "skyblue", lty = "longdash", xlim
plot(fit_weib_m, add = TRUE, ci = FALSE, col = "brown4")
plot(fit_weib_f, add = TRUE, ci = FALSE, col = "blue4")
legend("topright", legend = c("Obs M", "Obs F", "Exp M", "Exp F", "Weib M", "Weib F"),
```

```
       col = c("pink", "skyblue", "red", "blue", "brown4", "blue4"),
       lty = c("solid", "solid", "longdash", "longdash", "solid", "solid"),
       lwd = c(1,1,2,2,2,2))
```



From the plot we can see that fitting a Weibull distribution is actually more precise than an exponential distribution.

Parametric Regression Models

Parametric PH Models

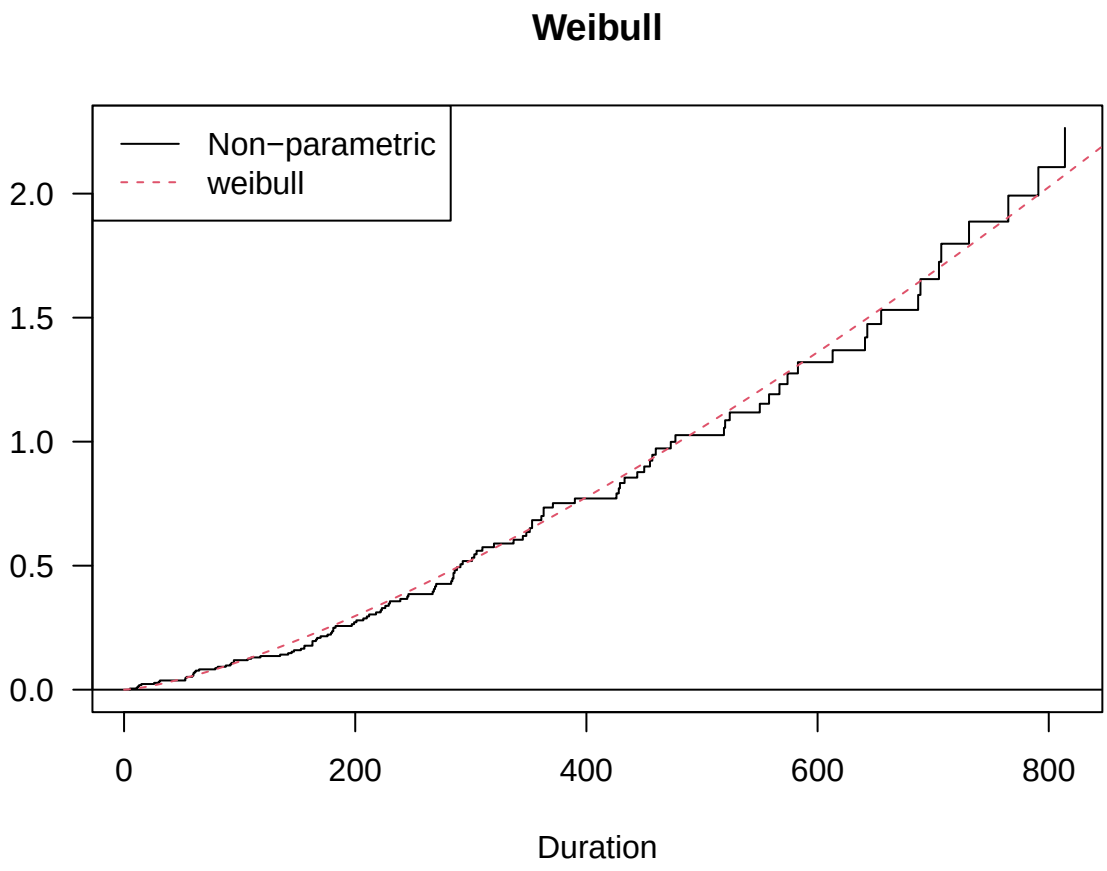
```
#backward selection, significance level = 0.05
fit_ph1 = phreg(Surv(time, status == 2) ~ age + sex + ph.ecog + ph.karno +
                  pat.karno + meal.cal + wt.loss,
```

```
                data = lung_df2, dist = "weibull")
summary(fit_ph1)
#remove meal.cal

fit_ph2 = phreg(Surv(time, status == 2) ~ age + sex + ph.ecog + ph.karno + pat.karno + wt.loss,
                data = lung_df2, dist = "weibull")
summary(fit_ph2)
#remove age

fit_ph3 = phreg(Surv(time, status == 2) ~ sex + ph.ecog + ph.karno + pat.karno + wt.loss,
                data = lung_df2, dist = "weibull")
summary(fit_ph3)
#remove pat.karno

fit_ph4 = phreg(Surv(time, status == 2) ~ sex + ph.ecog + ph.karno + wt.loss,
                data = lung_df2, dist = "weibull")
summary(fit_ph4)
#remove wt.loss

fit_ph5 = phreg(Surv(time, status == 2) ~ sex + ph.ecog + ph.karno,
                data = lung_df2, dist = "weibull")
summary(fit_ph5)
#remove ph.karno
```

```
#final model
fit_ph6 = phreg(Surv(time, status == 2) ~ sex + ph.ecog,
                data = lung_df2, dist = "weibull")
summary(fit_ph6)
```

```
## Covariate             Mean       Coef     Rel.Risk   S.E.    LR p
## sex                                                            0.0087
##                1      0.579     0         1 (reference)
##                2      0.421    -0.504     0.604     0.197
## ph.ecog                                                        0.0023
##                0      0.309     0         1 (reference)
##                1      0.520     0.290     1.337     0.233
##                2      0.169     0.925     2.523     0.260
##                3      0.002     1.944     6.986     1.028
##
## Events                    120
## Total time at risk         51759
## Max. log. likelihood      -830.69
## LR test statistic         20.75
## Degrees of freedom        4
## Overall p-value           0.000354567
```

```
#compare the estimated baseline hazards with a non-parametric ph model
fit_cox = coxreg(Surv(time, status == 2) ~ sex + ph.ecog, data = lung_df2)
check.dist(fit_ph6, fit_cox)
```



The fit of the Weibull baseline function is very close to the non-parametric one.

For a Weibull distribution, the AFT model is also a PH model.