Data Analysis

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```r
knitr::opts_chunk$set(message=FALSE, warning=FALSE, fig.height=3, fig.width=5, fig.align="center")
library(tidyverse)
library(broom)
library(plyr)
library(survival)
library(survminer)
aids <- read.csv( "http://pages.pomona.edu/~jsh04747/courses/math150/AIDSdata.csv")
dim(aids)
```

```
## [1] 851  16
```

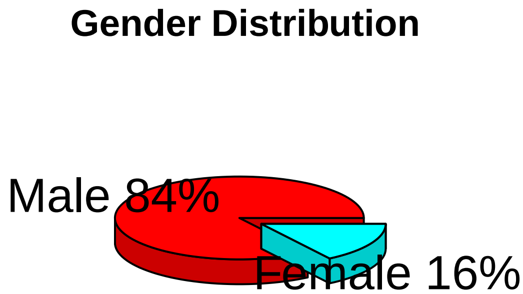
```r
summary(aids)
```

```
##        id              time           censor            time_d
##  Min.   :   1.0   Min.   :  1.0   Min.   :0.00000   Min.   :  1.0
##  1st Qu.: 287.5   1st Qu.:179.5   1st Qu.:0.00000   1st Qu.:199.5
##  Median : 581.0   Median :257.0   Median :0.00000   Median :266.0
##  Mean   : 579.5   Mean   :231.8   Mean   :0.08108   Mean   :243.4
##  3rd Qu.: 873.0   3rd Qu.:300.0   3rd Qu.:0.00000   3rd Qu.:306.0
##  Max.   :1156.0   Max.   :362.0   Max.   :1.00000   Max.   :362.0
##     censor_d            tx             txgrp           strat2
##  Min.   :0.0000   Min.   :0.0000   Min.   :1.000   Min.   :0.0000
##  1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:1.000   1st Qu.:0.0000
##  Median :0.0000   Median :1.0000   Median :2.000   Median :1.0000
##  Mean   :0.0235   Mean   :0.5041   Mean   :1.504   Mean   :0.6157
##  3rd Qu.:0.0000   3rd Qu.:1.0000   3rd Qu.:2.000   3rd Qu.:1.0000
##  Max.   :1.0000   Max.   :1.0000   Max.   :2.000   Max.   :1.0000
##       sex            raceth          ivdrug         hemophil
##  Min.   :1.000   Min.   :1.000   Min.   :1.000   Min.   :0.00000
##  1st Qu.:1.000   1st Qu.:1.000   1st Qu.:1.000   1st Qu.:0.00000
##  Median :1.000   Median :1.000   Median :1.000   Median :0.00000
##  Mean   :1.157   Mean   :1.706   Mean   :1.317   Mean   :0.03408
##  3rd Qu.:1.000   3rd Qu.:2.000   3rd Qu.:1.000   3rd Qu.:0.00000
##  Max.   :2.000   Max.   :5.000   Max.   :3.000   Max.   :1.00000
##      karnof            cd4            priorzdv            age
##  Min.   : 70.00   Min.   :  0.00   Min.   :  3.00   Min.   :15.00
##  1st Qu.: 90.00   1st Qu.: 22.25   1st Qu.: 11.00   1st Qu.:33.00
##  Median : 90.00   Median : 75.00   Median : 21.00   Median :38.00
##  Mean   : 91.34   Mean   : 86.45   Mean   : 30.63   Mean   :38.81
##  3rd Qu.:100.00   3rd Qu.:135.75   3rd Qu.: 44.00   3rd Qu.:44.00
##  Max.   :100.00   Max.   :348.00   Max.   :288.00   Max.   :73.00
```

The data set contains a sample size equal to 851 participants and 16 different variables.

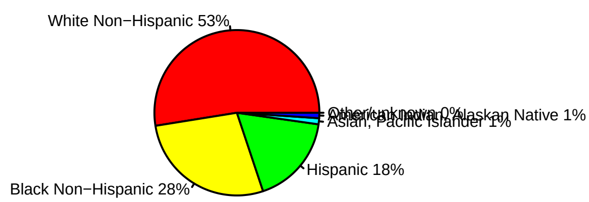
```r
library(plotrix)
male<-sum(aids$sex==1)
female<-sum(aids$sex==2)
slices <- c(male, female)
lbls <- c("Male", "Female")
pct <- round(slices/sum(slices)*100)
lbls <- paste(lbls, pct)
```

```
lbls <- paste(lbls,"%",sep="")
pie3D(slices,labels=lbls,explode=0.1,
   main="Gender Distribution ", cex.lab=0.1)
```



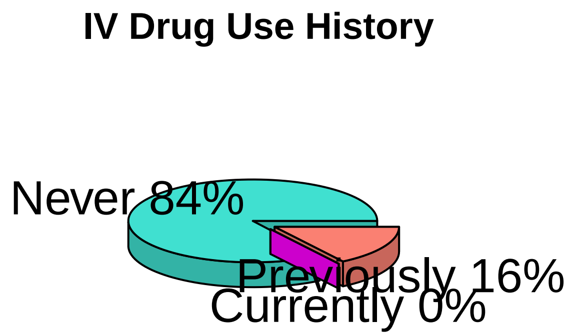
The Pie Chart represents the gender distribution in the sample, with 84% male and 16% female. This shows the potential for the data to not be able to correctly represent the difference of the data variance by gender, if there were to be one. Therefore, gender is something to look into in future data analysis.

```
wnh<-sum(aids$raceth==1)
bnh<-sum(aids$raceth==2)
h<-sum(aids$raceth==3)
api<-sum(aids$raceth==4)
aian<-sum(aids$raceth==5)
oth<-sum(aids$raceth==6)
slices <- c(wnh,bnh,h,api,aian,oth)
lbls <- c("White Non-Hispanic", "Black Non-Hispanic", "Hispanic","Asian, Pacific Islander", "American I
pct <- round(slices/sum(slices)*100)
lbls <- paste(lbls, pct)
lbls <- paste(lbls,"%",sep="")
pie(slices,lbls,col = rainbow(length(lbls)), cex=0.5 )
```



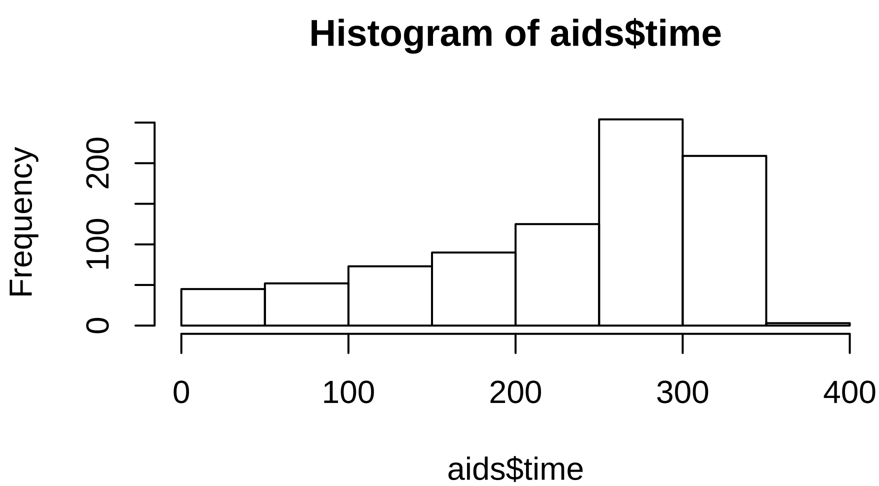
The distribution od race/ethnicity shows that the greatest number of participants consists of white non-hispanic identifying indicidual, with black non-hispanic following and hispanic as the 3rd largest represented group.

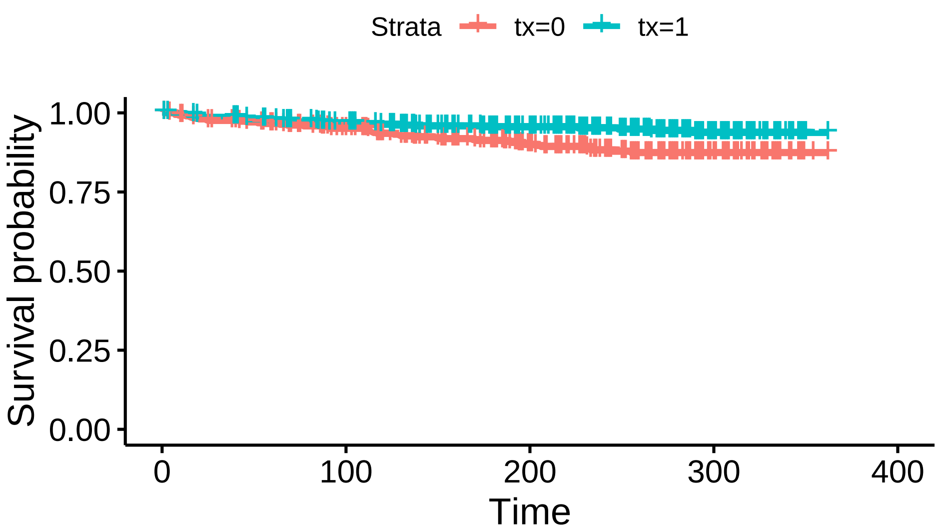
```
never<-sum(aids$ivdrug==1)
cur<-sum(aids$ivdrug==2)
prev<-sum(aids$ivdrug==3)
slices <- c(never,cur,prev)
lbls <- c("Never", "Currently", "Previously")
pct <- round(slices/sum(slices)*100)
lbls <- paste(lbls, pct)
lbls <- paste(lbls,"%",sep="")
pie3D(slices,labels=lbls,explode=0.1,col=c("turquoise","magenta","salmon"),cex.sub=0.5,
   main="IV Drug Use History ")
```



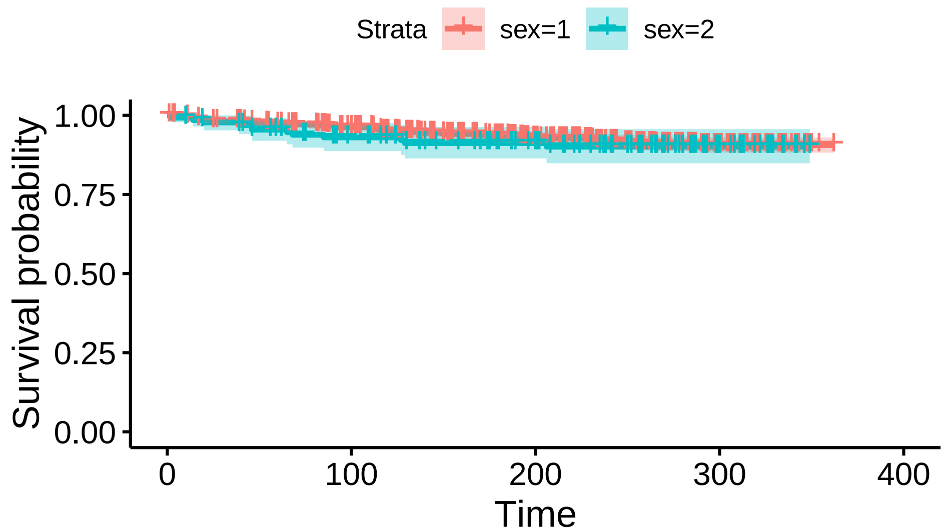
From this chart we see that most of the participants (84%) have never used IV drugs, whereas 16% of participants have some type of history of usage and none of the participants reported to be currently using the drugs.

```r
hist(aids$time)

###Data Plots

fit <- survfit(Surv(time,censor)~tx, data = aids)
ggsurvplot(fit,data = aids,conf.int = FALSE)
```

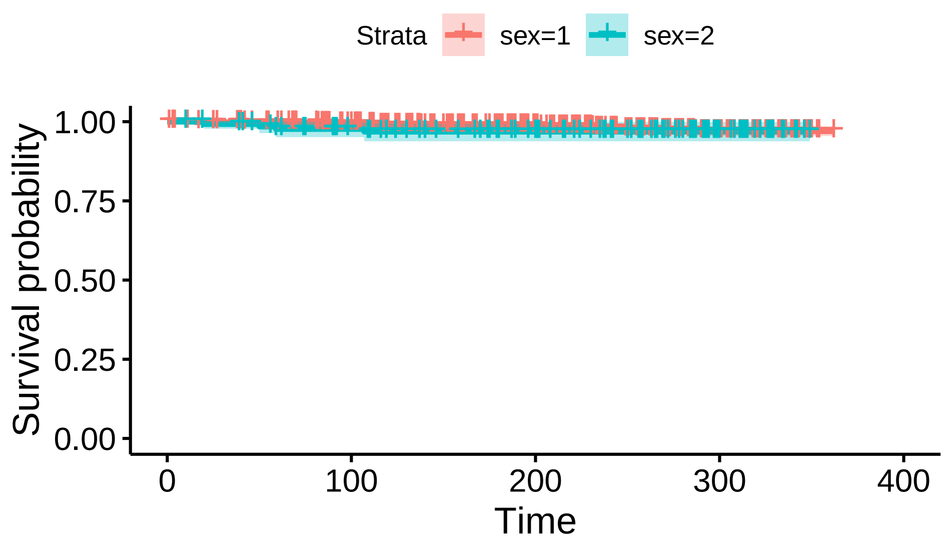




```r
aids_fit_time <- survfit(Surv(time, censor) ~ sex, data=aids)
ggsurvplot(aids_fit_time, data=aids,  conf.int = TRUE)
```




```r
aids_fit_time.d <- survfit(Surv(time_d, censor_d) ~ sex, data=aids)
ggsurvplot(aids_fit_time.d, data=aids,  conf.int = TRUE)
```



Survival Analysis

```r
#mutation of age
aids <- read.csv( "http://pages.pomona.edu/~jsh04747/courses/math150/AIDSdata.csv")
aids <- aids %>%
  mutate(age = ifelse(age <= 20, "under20",
                           ifelse(age <=30, "20-30",
                                  ifelse(age <= 40, "30-40",
                                         ifelse(age <=50, "40-50",
                                                ifelse(age <=60, "50-60",
                                                       ifelse(age <=70, "60-70", "over70"))))))) %>%
```

```r
  mutate(age = factor(age,
                      levels = c("under20", "20-30", "30-40","40-50", "50-60","60-70","over70")),  sex
```

```r
library(survival)
library (survminer)
library(ggplot2)
library(broom)

coxph(Surv(time_d,censor_d) ~ sex , data=aids)  %>% tidy()
```

```
## # A tibble: 1 x 7
##   term    estimate std.error statistic p.value conf.low conf.high
##   <chr>      <dbl>     <dbl>     <dbl>   <dbl>    <dbl>     <dbl>
## 1 sexmale    0.390     0.559     0.697   0.486   -0.706      1.49
```

```r
coxph(Surv(time,censor) ~ sex, data=aids) %>% tidy()
```

```
## # A tibble: 1 x 7
##   term    estimate std.error statistic p.value conf.low conf.high
##   <chr>      <dbl>     <dbl>     <dbl>   <dbl>    <dbl>     <dbl>
## 1 sexmale    0.199     0.318     0.625   0.532   -0.424     0.821
```

```r
coxph(Surv(time,censor) ~ age+ txgrp+ karnof, data=aids) %>% tidy()
```

```
## # A tibble: 8 x 7
##   term      estimate std.error statistic       p.value conf.low conf.high
##   <chr>        <dbl>     <dbl>     <dbl>         <dbl>    <dbl>     <dbl>
## 1 age20-30   -0.438      1.07    -0.409   0.682           -2.53     1.66
## 2 age30-40   -0.442      1.02    -0.434   0.665           -2.44     1.55
## 3 age40-50   -0.361      1.03    -0.352   0.725           -2.37     1.65
## 4 age50-60    0.460      1.04     0.442   0.659           -1.58     2.50
## 5 age60-70   -0.780      1.42    -0.551   0.582           -3.55     2.00
## 6 ageover70 -14.1     2688.      -0.00525 0.996         -Inf       Inf
## 7 txgrp      -0.844      0.257   -3.28    0.00103         -1.35    -0.340
## 8 karnof     -0.0814     0.0138  -5.89    0.00000000385   -0.109   -0.0543
```

```r
cox.zph(coxph(Surv(time,censor) ~ age + txgrp+karnof, data=aids))
```

```
##                rho    chisq     p
## age20-30   0.09054 5.70e-01 0.450
## age30-40   0.19294 2.53e+00 0.112
## age40-50   0.14871 1.50e+00 0.220
## age50-60   0.19861 2.69e+00 0.101
## age60-70   0.16251 1.81e+00 0.179
## ageover70  0.16355 2.57e-07 1.000
## txgrp     -0.10779 8.34e-01 0.361
## karnof     0.00121 1.03e-04 0.992
## GLOBAL          NA 7.98e+00 0.435
```

```r
coxph(Surv(time,censor) ~ age *txgrp*karnof, data=aids) %>% tidy()
```

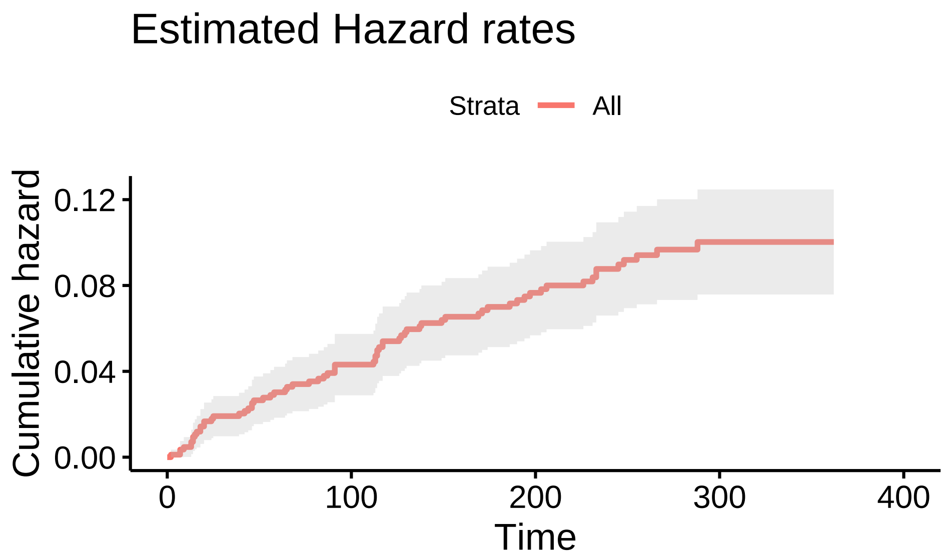
```
## # A tibble: 27 x 7
##    term             estimate std.error  statistic p.value conf.low conf.high
##    <chr>               <dbl>     <dbl>      <dbl>   <dbl>    <dbl>     <dbl>
##  1 age20-30             307.    138277.  0.00222     0.998     -Inf       Inf
##  2 age30-40             319.    138277.  0.00231     0.998     -Inf       Inf
##  3 age40-50             327.    138277.  0.00237     0.998     -Inf       Inf
```

```
## 4 age50-60         343.     138277.  0.00248     0.998     -Inf       Inf
## 5 age60-70         287.     176491.  0.00163     0.999     -Inf       Inf
## 6 ageover70         -1.66    29414. -0.0000565   1.000     -Inf       Inf
## 7 txgrp            150.      92392.  0.00163     0.999     -Inf       Inf
## 8 karnof             3.36     1424.  0.00236     0.998     -Inf       Inf
## 9 age20-30:txgrp  -144.      92392. -0.00156     0.999     -Inf       Inf
## 10 age30-40:txgrp  -146.      92392. -0.00158     0.999     -Inf       Inf
## # ... with 17 more rows
```

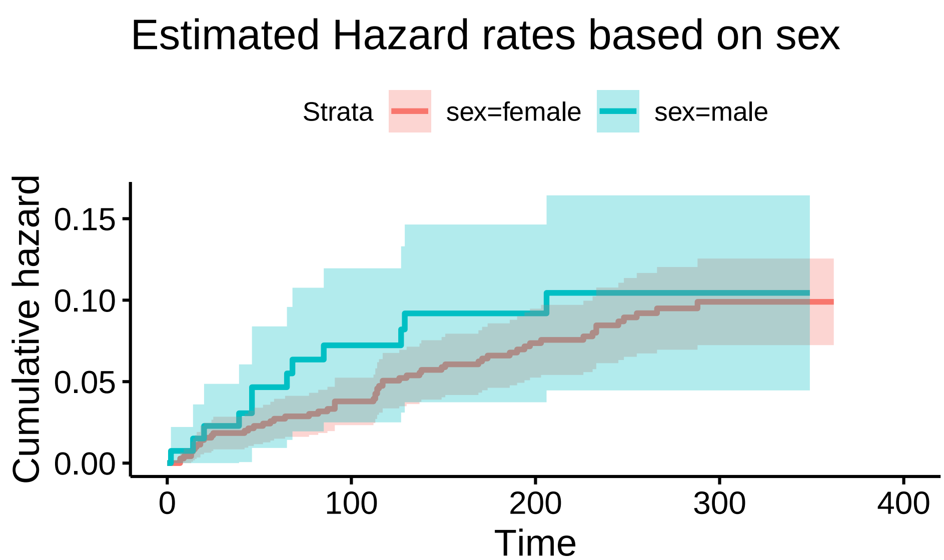
```r
cox.zph(coxph(Surv(time,censor) ~ age *txgrp*karnof, data=aids))
```

```
##                              rho    chisq     p
## age20-30                 -0.1008 4.31e-08 1.000
## age30-40                 -0.1583 3.15e-08 1.000
## age40-50                 -0.0965 1.25e-08 1.000
## age50-60                 -0.2071 6.53e-08 1.000
## age60-70                 -0.2062 3.04e-08 1.000
## ageover70                -0.2493 7.81e-11 1.000
## txgrp                    -0.2032 2.68e-08 1.000
## karnof                   -0.1974 5.24e-08 1.000
## age20-30:txgrp            0.0921 2.14e-08 1.000
## age30-40:txgrp            0.1142 1.08e-08 1.000
## age40-50:txgrp            0.0826 5.64e-09 1.000
## age50-60:txgrp            0.1851 3.47e-08 1.000
## age60-70:txgrp            0.2102 2.15e-08 1.000
## ageover70:txgrp           0.1967 3.96e-11 1.000
## age20-30:karnof           0.0984 4.53e-08 1.000
## age30-40:karnof           0.1524 3.44e-08 1.000
## age40-50:karnof           0.0938 1.40e-08 1.000
## age50-60:karnof           0.2053 7.78e-08 1.000
## age60-70:karnof           0.1978 3.00e-08 1.000
## ageover70:karnof              NA      NaN   NaN
## txgrp:karnof              0.1996 2.81e-08 1.000
## age20-30:txgrp:karnof    -0.0910 2.15e-08 1.000
## age30-40:txgrp:karnof    -0.1020 9.71e-09 1.000
## age40-50:txgrp:karnof    -0.0823 6.23e-09 1.000
## age50-60:txgrp:karnof    -0.1796 3.72e-08 1.000
## age60-70:txgrp:karnof    -0.1981 1.98e-08 1.000
## ageover70:txgrp:karnof        NA      NaN   NaN
## GLOBAL                        NA 1.84e+01 0.891
```

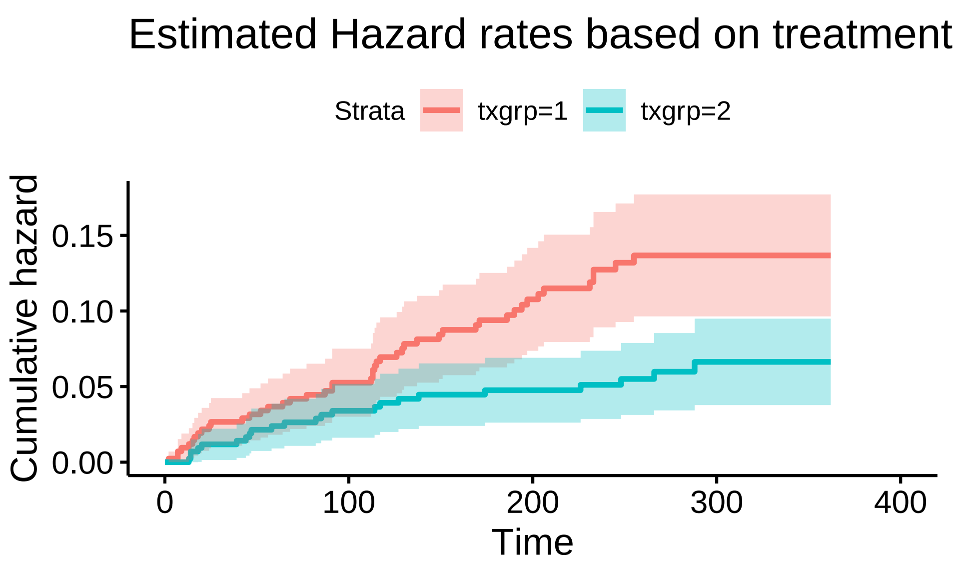
```r
ggsurvplot(survfit(Surv(time,censor) ~ 1, data=aids),
           censor=F, conf.int=T, fun="cumhaz") + ggtitle("Estimated Hazard rates")
```



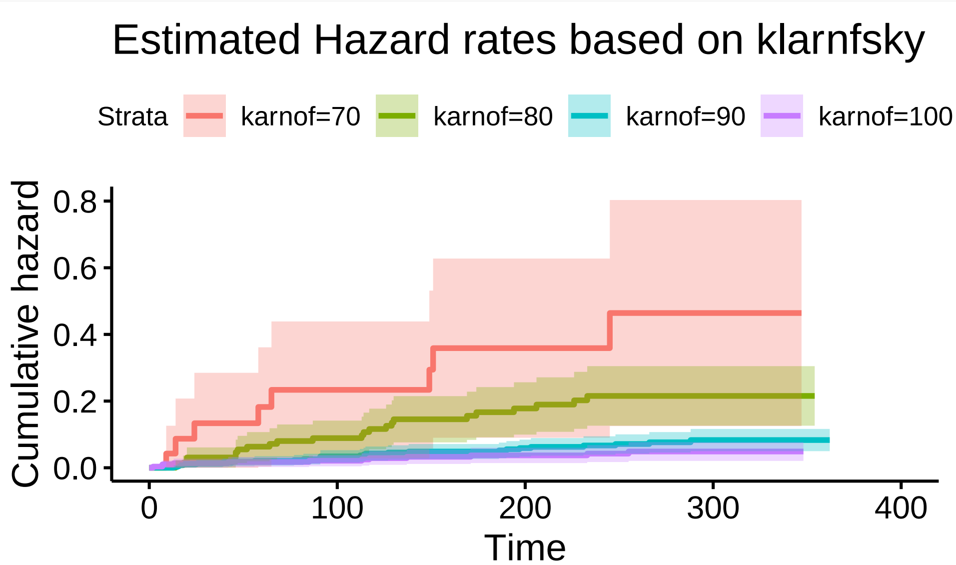

```
ggsurvplot(survfit(Surv(time,censor) ~ sex, data=aids),
           censor=F, conf.int=T, fun="cumhaz") + ggtitle("Estimated Hazard rates based on sex")
```



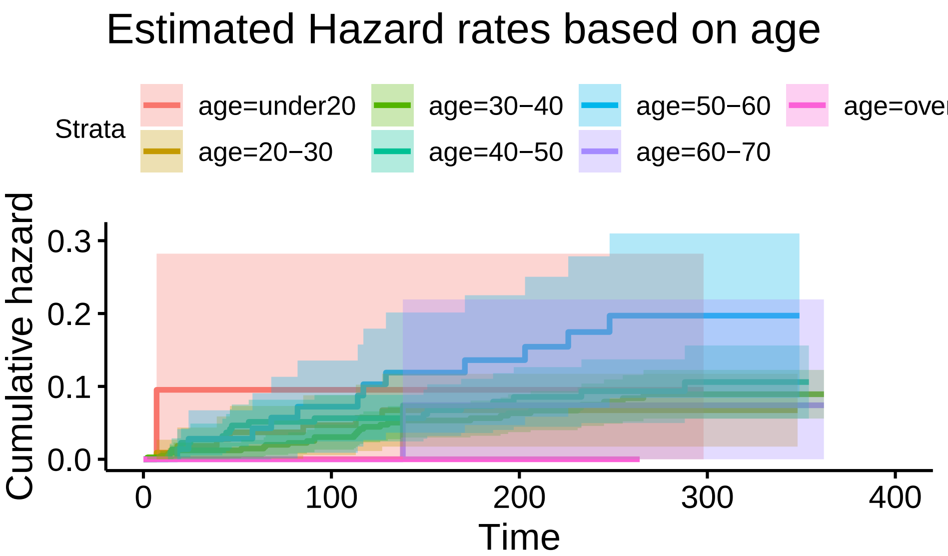

```
ggsurvplot(survfit(Surv(time,censor) ~ txgrp, data=aids),
           censor=F, conf.int=T, fun="cumhaz") + ggtitle("Estimated Hazard rates based on treatment grou
```




```r
ggsurvplot(survfit(Surv(time,censor) ~ karnof, data=aids),
           censor=F, conf.int=T, fun="cumhaz") + ggtitle("Estimated Hazard rates based on klarnfsky")
```




```r
ggsurvplot(survfit(Surv(time,censor) ~ age, data=aids),
           censor=F, conf.int=T, fun="cumhaz") + ggtitle("Estimated Hazard rates based on age")
```



Juste's "Something New"

I will be analyzing the Weibull PH regression (parametric survival model).

1. What is goign on? What is the topic?

Weibull model is a parametric model,which provides a flexible way for the inclusion of covariates of the survival times. It has been previously determined that when the shape of parameter is known, the Weibull model shows better results than the Cox proportional hazards model, but when the shape parameter is unknown, the Cox proportional hazards model and the Weibull model give comparable results. ### 2. How it is relevant? How it relates to survival analysis/analysis at hand?

Fully parametric models have many advantages in analyzing survival data, they can be more convenient for representing complex data structures and processes. Studies have indicated that under certain situations when the shape of the survival time is determined, the parametric models are more powerful and efficient than Cox's regression model (ex. Kleinbaum D, Klein M. Survival analysis: a self-learning text. New York: Springer; 2005). Furthermore, if the only basic assumption of this model (proportional hazards) is not met, parametric models are suitable alternative models to be used instead of Cox's regression analysis.

3. Resources to learn about the topic.

I have been researching articles and scientific journals that provide insights into this model and comparisons between the Cox PH and teh parametric model. Sources include: a) https://krex.k-state.edu/dspace/bitstream/handle/2097/8787/AngelaCrumer2011.pdf b) http://nematilab.info/bmijc/assets/weibull_cox.pdf c) https://www.jstatsoft.org/article/view/v070i08

4. What will be challenging about learning something new?

Taking a completely new model of analyzing survival data is particulalrly difficult since the mathematical derivations and notations are also very varied from what we have seen in class. Although, I do remember some of the ideas behind parametric functions, their applications to statistical models are much more challenging than I have expected. Therefore, it will require me a lot of time and extensive research to be able to understand and learn how to apply this model to our data and other instances of survival analysis.

```r
### some trials of applications of parametric functions in r
library(flexsurv)

flexsurvreg(Surv(time, censor) ~ age, data = aids,  dist = "weibull")
```

```
## Call:
## flexsurvreg(formula = Surv(time, censor) ~ age, data = aids,
##     dist = "weibull")
##
## Estimates:
##             data mean  est        L95%       U95%       se
## shape              NA   7.90e-01   6.30e-01   9.90e-01   9.10e-02
## scale              NA   4.17e+03   3.20e+02   5.43e+04   5.46e+03
## age20-30     1.30e-01   5.91e-01  -2.06e+00   3.25e+00   1.36e+00
## age30-40     4.89e-01   4.53e-01  -2.07e+00   2.98e+00   1.29e+00
## age40-50     2.64e-01   2.08e-01  -2.34e+00   2.75e+00   1.30e+00
## age50-60     8.46e-02  -5.81e-01  -3.17e+00   2.01e+00   1.32e+00
## age60-70     1.65e-02   6.27e-01  -2.88e+00   4.14e+00   1.79e+00
## ageover70    2.35e-03   1.88e+01  -8.97e+03   9.01e+03   4.59e+03
##             exp(est)   L95%       U95%
## shape              NA         NA         NA
## scale              NA         NA         NA
## age20-30     1.81e+00   1.27e-01   2.57e+01
## age30-40     1.57e+00   1.26e-01   1.97e+01
## age40-50     1.23e+00   9.65e-02   1.57e+01
## age50-60     5.60e-01   4.21e-02   7.45e+00
## age60-70     1.87e+00   5.59e-02   6.27e+01
## ageover70    1.51e+08   0.00e+00        Inf
##
## N = 851,  Events: 69,  Censored: 782
## Total time at risk: 197290
## Log-likelihood = -612.8653, df = 8
## AIC = 1241.731
```

More about the Weibull Model

The Weibull model is very similar to the Cox PH model we have explored in class. The Weibull Model usually used when the exponential distribution is not suffiecient to come up with a model. The exponential desnity function is $f(t) = \lambda exp(-\lambda(t))$, for $\lambda > 0$ and $t > 0$ With a constant hazard function of $h(t) = \lambda$

```r
letters
```

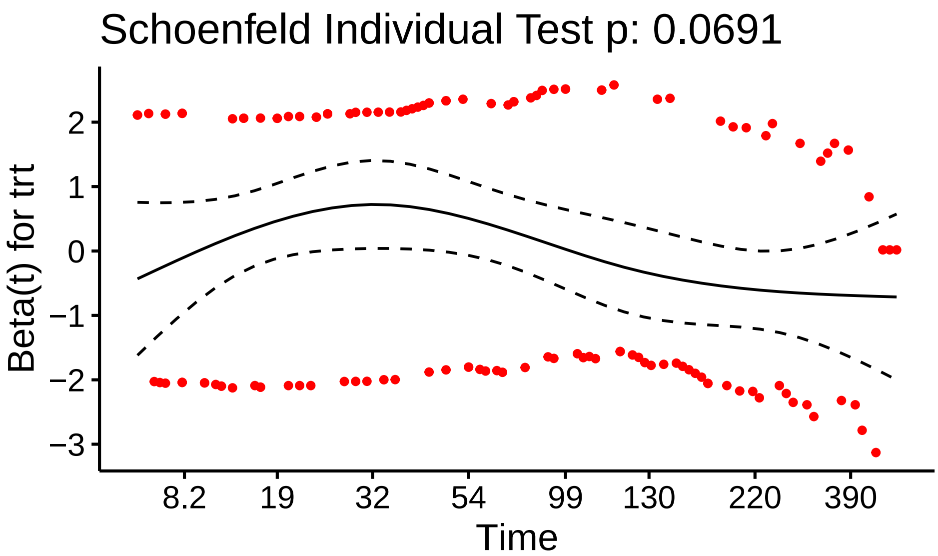
```
##  [1] "a" "b" "c" "d" "e" "f" "g" "h" "i" "j" "k" "l" "m" "n" "o" "p" "q"
## [18] "r" "s" "t" "u" "v" "w" "x" "y" "z"
```

SHoenfeld:

```r
veteran.ph <- coxph(Surv(time,status) ~ trt, data=veteran)
cox.veteran <- cox.zph(veteran.ph)
cox.veteran
```

```
##       rho chisq      p
## trt -0.16   3.3 0.0691
```

```r
ggcoxzph(cox.veteran)
```




```r
ggcoxdiagnostics(veteran.ph, type="schoenfeld")
```