

Survival Analysis Project: HIV Clinical Trial

Juste Simanauskaite & Patricia Rivera

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```
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)
library(coxed)
```

```
aids <- read.csv( "http://pages.pomona.edu/~jsh04747/courses/math150/AIDSdata.csv")
dim(aids)
```

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

```
summary(aids)
```

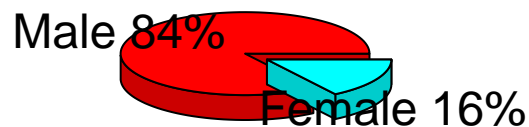
```
##      id      time      censor      time_d
## Min.   : 1.0   Min.   : 1.0   Min.   :0.00000   Min.   : 1.0
## 1st Qu.:287.5  1st Qu.:179.5  1st Qu.:0.00000   1st Qu.:199.5
## Median :581.0  Median :257.0  Median :0.00000   Median :266.0
## Mean   :579.5  Mean   :231.8  Mean   :0.08108   Mean   :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.

```
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)
```

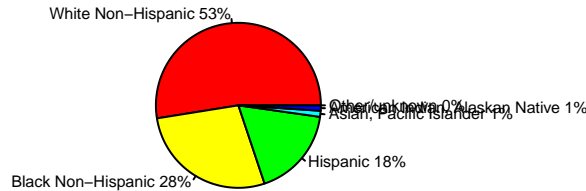
Gender Distribution



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 Indian, Alaskan Native", "Other/unknown")
pct <- round(slices/sum(slices)*100)
lbls <- paste(lbls, pct)
lbls <- paste(lbls,"%",sep="")
```

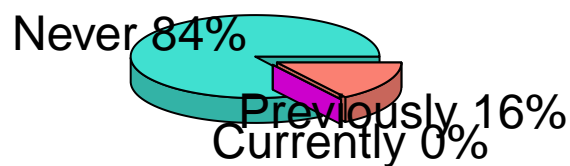
```
pie(slices,lbls,col = rainbow(length(lbls)), cex=0.5 )
```



The distribution of race/ethnicity shows that the greatest number of participants consists of white non-hispanic identifying individuals, 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 ")
```

IV Drug Use History



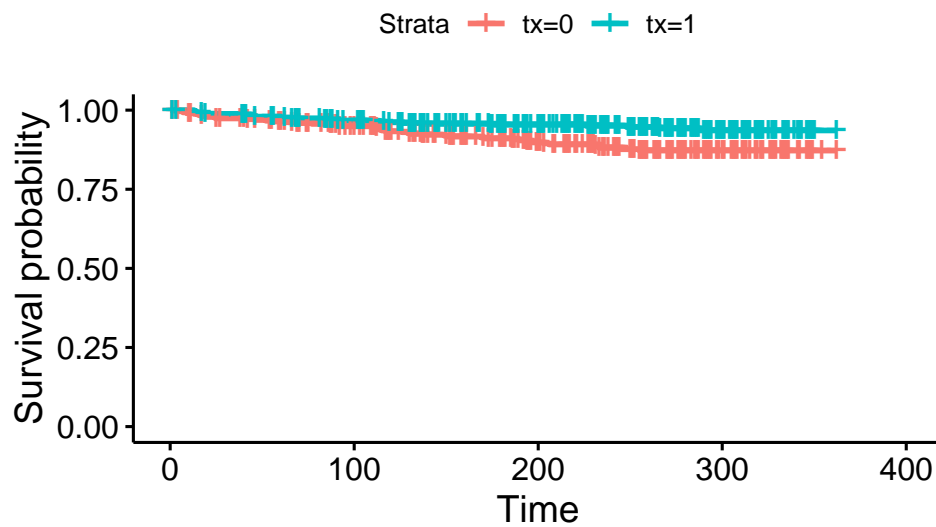
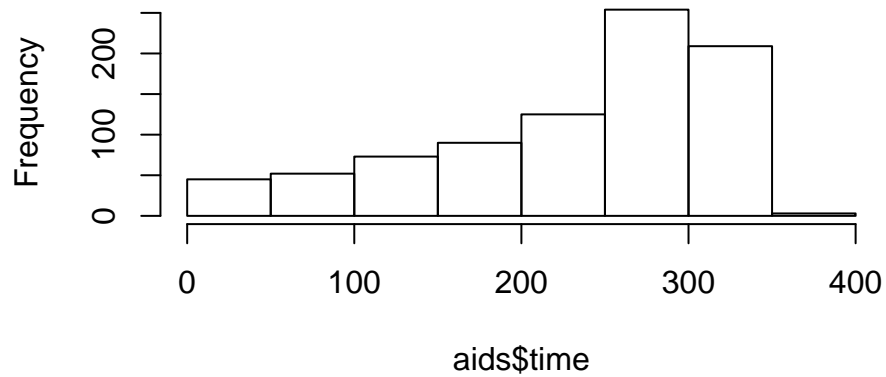
From this chart we see that most of the participants (84%) have never used IV drugs, whereas 16% of participants have some type of history of usage and none of the participants reported to be currently using the drugs.

```
hist(aids$time)

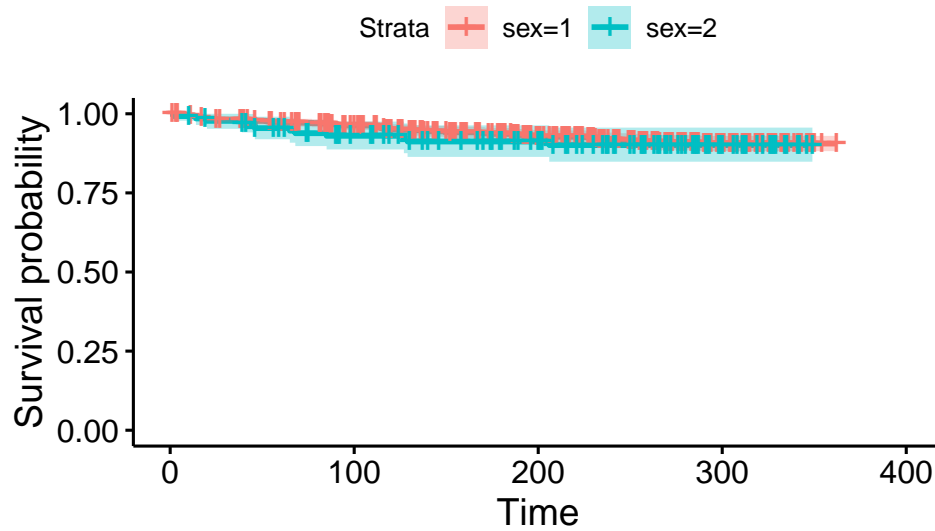
###Data Plots

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

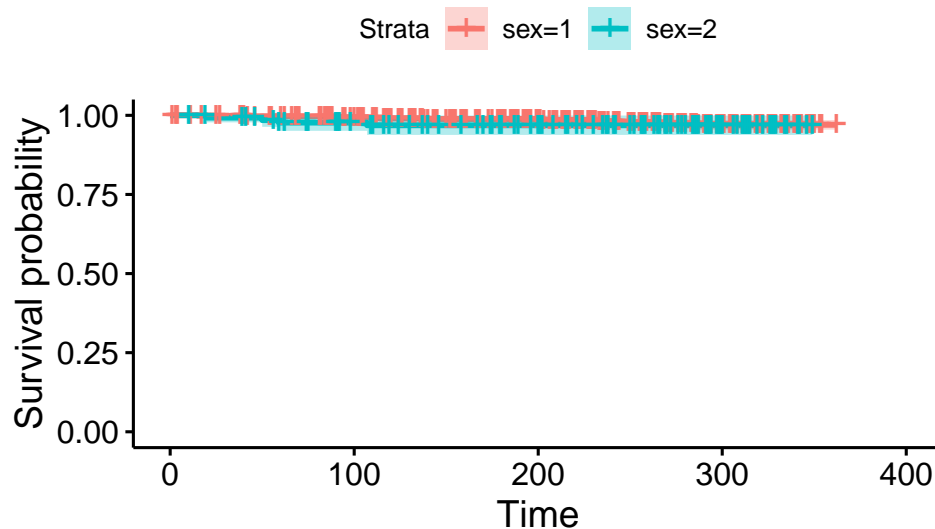
Histogram of aids\$time



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



```
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

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

```
sex = ifelse(sex == 2, "male", "female"))
```

Since there are many values of the explanatory variable “age” in the original data, we’ve decided to mutate the variable into age categories from under 20 to over 70 in increments of 10 years.

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

```
##### backwards selection #####
```

```
#full model
```

```
cph_full <- coxph(Surv(time, censor) ~ ., data = aids)
cph_full$loglik
```

```
## [1] -452.6325 -380.7368
```

```
cph_full
```

```
## Call:
```

```
## coxph(formula = Surv(time, censor) ~ ., data = aids)
```

```
##
```

	coef	exp(coef)	se(coef)	z	p
## id	2.136e-05	1.000e+00	3.956e-04	0.054	0.95695
## time_d	1.362e-03	1.001e+00	2.139e-03	0.637	0.52432
## censor_d	2.887e+00	1.795e+01	3.990e-01	7.237	4.59e-13
## tx	-3.917e-01	6.759e-01	2.757e-01	-1.421	0.15540
## txgrp	NA	NA	0.000e+00	NA	NA
## strat2	3.418e-01	1.408e+00	4.397e-01	0.777	0.43690
## sexmale	3.152e-01	1.371e+00	3.518e-01	0.896	0.37024
## raceth	-8.821e-02	9.156e-01	1.543e-01	-0.572	0.56759
## ivdrug	-3.625e-01	6.959e-01	1.942e-01	-1.867	0.06197
## hemophil	-1.247e-01	8.828e-01	7.136e-01	-0.175	0.86132
## karnof	-4.400e-02	9.569e-01	1.555e-02	-2.829	0.00467
## cd4	-1.592e-02	9.842e-01	4.988e-03	-3.191	0.00142
## priorzd	-1.722e-04	9.998e-01	5.076e-03	-0.034	0.97293
## age20-30	-8.852e-01	4.126e-01	1.249e+00	-0.709	0.47862
## age30-40	-8.065e-01	4.464e-01	1.216e+00	-0.663	0.50706
## age40-50	-7.004e-01	4.964e-01	1.207e+00	-0.580	0.56174
## age50-60	-3.926e-01	6.753e-01	1.252e+00	-0.314	0.75384
## age60-70	-1.054e+00	3.485e-01	1.617e+00	-0.652	0.51443
## ageover70	-1.362e+01	1.214e-06	2.189e+03	-0.006	0.99503

```
##
```

```
## Likelihood ratio test=143.8 on 18 df, p=< 2.2e-16
```

```
## n= 851, number of events= 69
```

```
#reduced model 1
```

```
cph_r1 <- coxph(Surv(time, censor) ~ . - priorzd, data = aids)
cph_r1$loglik
```

```
## [1] -452.6325 -380.7374
```

```
cph_r1
```

```
## Call:
```

```
## coxph(formula = Surv(time, censor) ~ . - priorzd, data = aids)
```

```
##
```

```
##          coef exp(coef) se(coef)      z      p
## id          2.138e-05 1.000e+00 3.956e-04 0.054 0.95690
## time_d       1.364e-03 1.001e+00 2.137e-03 0.638 0.52338
## censor_d     2.889e+00 1.797e+01 3.977e-01 7.263 3.78e-13
## tx          -3.918e-01 6.758e-01 2.756e-01 -1.422 0.15513
## txgrp         NA         NA 0.000e+00    NA     NA
## strat2       3.417e-01 1.407e+00 4.398e-01 0.777 0.43720
## sexmale      3.150e-01 1.370e+00 3.517e-01 0.896 0.37046
## raceth      -8.808e-02 9.157e-01 1.543e-01 -0.571 0.56802
## ivdrug      -3.630e-01 6.956e-01 1.936e-01 -1.875 0.06080
## hemophil    -1.251e-01 8.824e-01 7.137e-01 -0.175 0.86086
## karnof      -4.397e-02 9.570e-01 1.551e-02 -2.835 0.00459
## cd4         -1.592e-02 9.842e-01 4.987e-03 -3.193 0.00141
## age20-30    -8.791e-01 4.151e-01 1.237e+00 -0.711 0.47738
## age30-40    -8.014e-01 4.487e-01 1.207e+00 -0.664 0.50669
## age40-50    -6.951e-01 4.990e-01 1.198e+00 -0.580 0.56163
## age50-60    -3.881e-01 6.783e-01 1.246e+00 -0.312 0.75539
## age60-70    -1.048e+00 3.508e-01 1.606e+00 -0.652 0.51426
## ageover70   -1.362e+01 1.216e-06 2.190e+03 -0.006 0.99504
##
```

```
## Likelihood ratio test=143.8 on 17 df, p=< 2.2e-16
```

```
## n= 851, number of events= 69
```

```
#likelihood ratio test
```

```
stat1<- 2*(cph_full$loglik[2]-cph_r1$loglik[2])
1-pchisq(stat1,1)
```

```
## [1] 0.9728893
```

```
#reduced model 2
```

```
cph_r2 <- coxph(Surv(time,censor)~.-priorzdv -id, data = aids)
cph_r2$loglik
```

```
## [1] -452.6325 -380.7389
```

```
cph_r2
```

```
## Call:
```

```
## coxph(formula = Surv(time, censor) ~ . - priorzdv - id, data = aids)
```

```
##
```

```
##          coef exp(coef) se(coef)      z      p
## time_d       1.382e-03 1.001e+00 2.111e-03 0.654 0.51285
## censor_d     2.894e+00 1.807e+01 3.831e-01 7.555 4.18e-14
## tx          -3.910e-01 6.764e-01 2.752e-01 -1.421 0.15535
## txgrp         NA         NA 0.000e+00    NA     NA
## strat2       3.434e-01 1.410e+00 4.388e-01 0.783 0.43391
## sexmale      3.145e-01 1.370e+00 3.516e-01 0.895 0.37103
## raceth      -8.832e-02 9.155e-01 1.542e-01 -0.573 0.56676
## ivdrug      -3.621e-01 6.962e-01 1.928e-01 -1.878 0.06041
## hemophil    -1.282e-01 8.797e-01 7.115e-01 -0.180 0.85705
## karnof      -4.404e-02 9.569e-01 1.546e-02 -2.849 0.00439
## cd4         -1.592e-02 9.842e-01 4.987e-03 -3.193 0.00141
## age20-30    -8.819e-01 4.140e-01 1.236e+00 -0.713 0.47563
## age30-40    -8.049e-01 4.472e-01 1.205e+00 -0.668 0.50419
## age40-50    -6.981e-01 4.975e-01 1.196e+00 -0.584 0.55950
## age50-60    -3.908e-01 6.765e-01 1.245e+00 -0.314 0.75354
## age60-70    -1.053e+00 3.488e-01 1.603e+00 -0.657 0.51119
## ageover70   -1.362e+01 1.218e-06 2.188e+03 -0.006 0.99503
##
```

```
## Likelihood ratio test=143.8 on 16 df, p=< 2.2e-16
## n= 851, number of events= 69
#likelihood ratio test
stat2 <- 2*(cph_r1$loglik[2]-cph_r2$loglik[2])
1-pchisq(stat2,1)

## [1] 0.9569002
#reduced model 3
cph_r3 <- coxph(Surv(time,censor)~.-priorzdv -id -hemophil, data = aids)
cph_r3$loglik

## [1] -452.6325 -380.7555
cph_r3

## Call:
## coxph(formula = Surv(time, censor) ~ . - priorzdv - id - hemophil,
##       data = aids)
##
##               coef exp(coef) se(coef)      z      p
## time_d      1.359e-03  1.001e+00  2.108e-03  0.645  0.51912
## censor_d    2.882e+00  1.785e+01  3.765e-01  7.654  1.94e-14
## tx         -3.895e-01  6.774e-01  2.752e-01 -1.415  0.15692
## txgrp              NA              NA  0.000e+00    NA      NA
## strat2       3.381e-01  1.402e+00  4.387e-01  0.771  0.44085
## sexmale       3.186e-01  1.375e+00  3.509e-01  0.908  0.36394
## raceth      -8.537e-02  9.182e-01  1.530e-01 -0.558  0.57691
## ivdrug      -3.605e-01  6.973e-01  1.927e-01 -1.871  0.06135
## karnof      -4.402e-02  9.569e-01  1.546e-02 -2.847  0.00441
## cd4         -1.600e-02  9.841e-01  4.990e-03 -3.206  0.00134
## age20-30    -7.754e-01  4.605e-01  1.089e+00 -0.712  0.47650
## age30-40    -6.919e-01  5.006e-01  1.032e+00 -0.670  0.50275
## age40-50    -5.925e-01  5.529e-01  1.045e+00 -0.567  0.57085
## age50-60    -2.756e-01  7.591e-01  1.071e+00 -0.257  0.79702
## age60-70    -9.293e-01  3.948e-01  1.451e+00 -0.640  0.52190
## ageover70  -1.350e+01  1.374e-06  2.187e+03 -0.006  0.99508
##
## Likelihood ratio test=143.8 on 15 df, p=< 2.2e-16
## n= 851, number of events= 69
#likelihood ratio test
stat3 <- 2*(cph_r3$loglik[2]-cph_r2$loglik[2])
1-pchisq(stat3,1)

## [1] 1
#reduced model 4
cph_r4 <- coxph(Surv(time,censor)~.-priorzdv -id -hemophil -raceth, data = aids)
cph_r4$loglik

## [1] -452.6325 -380.9154
cph_r4

## Call:
## coxph(formula = Surv(time, censor) ~ . - priorzdv - id - hemophil -
##       raceth, data = aids)
##
##               coef exp(coef) se(coef)      z      p
```



```
## time_d      1.282e-03  1.001e+00  2.093e-03  0.612  0.54042
## censor_d    2.861e+00  1.748e+01  3.737e-01  7.657  1.91e-14
## tx          -3.907e-01  6.766e-01  2.752e-01 -1.419  0.15576
## txgrp       NA        NA      0.000e+00    NA        NA
## strat2      3.386e-01  1.403e+00  4.373e-01  0.774  0.43871
## sexmale     3.215e-01  1.379e+00  3.487e-01  0.922  0.35665
## ivdrug      -3.823e-01  6.823e-01  1.886e-01 -2.027  0.04265
## karnof      -4.462e-02  9.564e-01  1.549e-02 -2.880  0.00397
## cd4         -1.588e-02  9.842e-01  4.961e-03 -3.202  0.00137
## age20-30    -7.510e-01  4.719e-01  1.087e+00 -0.691  0.48974
## age30-40    -6.587e-01  5.175e-01  1.030e+00 -0.639  0.52254
## age40-50    -5.503e-01  5.768e-01  1.042e+00 -0.528  0.59749
## age50-60    -2.362e-01  7.896e-01  1.069e+00 -0.221  0.82503
## age60-70    -8.498e-01  4.275e-01  1.444e+00 -0.589  0.55611
## ageover70   -1.347e+01  1.418e-06  2.181e+03 -0.006  0.99507
##
## Likelihood ratio test=143.4 on 14 df, p=< 2.2e-16
## n= 851, number of events= 69
```

```
#likelihood ratio test
```

```
stat4 <- 2*(cph_r3$loglik[2]-cph_r4$loglik[2])
1-pchisq(stat4,1)
```

```
## [1] 0.5718012
```

```
#reduced model 5
```

```
cph_r5 <- coxph(Surv(time,censor)~.-priorzdv -id -hemophil -raceth -time_d, data = aids)
cph_r5$loglik
```

```
## [1] -452.6325 -381.1059
```

```
cph_r5
```

```
## Call:
```

```
## coxph(formula = Surv(time, censor) ~ . - priorzdv - id - hemophil -
##       raceth - time_d, data = aids)
```

```
##
```

	coef	exp(coef)	se(coef)	z	p
## censor_d	2.741e+00	1.550e+01	3.178e-01	8.625	< 2e-16
## tx	-4.008e-01	6.698e-01	2.738e-01	-1.464	0.14321
## txgrp	NA	NA	0.000e+00	NA	NA
## strat2	3.581e-01	1.431e+00	4.351e-01	0.823	0.41051
## sexmale	2.735e-01	1.315e+00	3.409e-01	0.802	0.42232
## ivdrug	-3.773e-01	6.857e-01	1.881e-01	-2.006	0.04487
## karnof	-4.545e-02	9.556e-01	1.539e-02	-2.953	0.00315
## cd4	-1.602e-02	9.841e-01	4.953e-03	-3.234	0.00122
## age20-30	-6.860e-01	5.036e-01	1.082e+00	-0.634	0.52598
## age30-40	-5.895e-01	5.546e-01	1.024e+00	-0.576	0.56483
## age40-50	-4.787e-01	6.196e-01	1.036e+00	-0.462	0.64393
## age50-60	-1.506e-01	8.602e-01	1.059e+00	-0.142	0.88700
## age60-70	-8.000e-01	4.493e-01	1.443e+00	-0.554	0.57945
## ageover70	-1.342e+01	1.481e-06	2.176e+03	-0.006	0.99508

```
##
```

```
## Likelihood ratio test=143.1 on 13 df, p=< 2.2e-16
```

```
## n= 851, number of events= 69
```

```
#likelihood ratio test
```

```
stat5 <- 2*(cph_r5$loglik[2]-cph_r4$loglik[2])
1-pchisq(stat5,1)
```

```
## [1] 1
#reduced model 6
cph_r6 <- coxph(Surv(time,censor)~.-priorzdv -id -hemophil -raceth -time_d -strat2, data = aids)
cph_r6$loglik

## [1] -452.6325 -381.4390
cph_r6

## Call:
## coxph(formula = Surv(time, censor) ~ . - priorzdv - id - hemophil -
##       raceth - time_d - strat2, data = aids)
##
##               coef exp(coef)   se(coef)      z        p
## censor_d    2.727e+00  1.529e+01  3.159e-01   8.635 < 2e-16
## tx          -4.203e-01  6.568e-01  2.726e-01  -1.542  0.12303
## txgrp        NA         NA  0.000e+00    NA      NA
## sexmale      2.625e-01  1.300e+00  3.415e-01   0.769  0.44201
## ivdrug       -3.941e-01  6.743e-01  1.873e-01  -2.104  0.03542
## karnof       -4.573e-02  9.553e-01  1.541e-02  -2.967  0.00301
## cd4          -1.295e-02  9.871e-01  3.012e-03  -4.301  1.7e-05
## age20-30     -6.334e-01  5.308e-01  1.079e+00  -0.587  0.55725
## age30-40     -5.580e-01  5.723e-01  1.023e+00  -0.546  0.58539
## age40-50     -4.327e-01  6.487e-01  1.033e+00  -0.419  0.67536
## age50-60     -7.496e-02  9.278e-01  1.054e+00  -0.071  0.94333
## age60-70     -6.578e-01  5.180e-01  1.430e+00  -0.460  0.64555
## ageover70    -1.329e+01  1.691e-06  2.197e+03  -0.006  0.99517
##
## Likelihood ratio test=142.4  on 12 df, p=< 2.2e-16
## n= 851, number of events= 69
#likelihood ratio test
stat6 <- 2*(cph_r5$loglik[2]-cph_r6$loglik[2])
1-pchisq(stat6,1)

## [1] 0.4144233
#reduced model 7
cph_r7 <- coxph(Surv(time,censor)~.-priorzdv -id -hemophil -raceth -time_d -strat2 -sex,
                data = aids)
cph_r7$loglik

## [1] -452.6325 -381.7212
cph_r7

## Call:
## coxph(formula = Surv(time, censor) ~ . - priorzdv - id - hemophil -
##       raceth - time_d - strat2 - sex, data = aids)
##
##               coef exp(coef)   se(coef)      z        p
## censor_d    2.723e+00  1.523e+01  3.140e-01   8.672 < 2e-16
## tx          -4.284e-01  6.516e-01  2.723e-01  -1.573  0.11567
## txgrp        NA         NA  0.000e+00    NA      NA
## ivdrug       -4.023e-01  6.688e-01  1.875e-01  -2.146  0.03189
## karnof       -4.622e-02  9.548e-01  1.530e-02  -3.020  0.00253
## cd4          -1.301e-02  9.871e-01  3.012e-03  -4.319  1.57e-05
## age20-30     -5.567e-01  5.731e-01  1.074e+00  -0.518  0.60438
## age30-40     -5.760e-01  5.621e-01  1.023e+00  -0.563  0.57333
## age40-50     -4.452e-01  6.407e-01  1.034e+00  -0.431  0.66667
```

```

## age50-60 -4.385e-02  9.571e-01  1.054e+00 -0.042  0.96680
## age60-70 -6.931e-01  5.000e-01  1.429e+00 -0.485  0.62774
## ageover70 -1.332e+01  1.642e-06  2.195e+03 -0.006  0.99516
##
## Likelihood ratio test=141.8 on 11 df, p=< 2.2e-16
## n= 851, number of events= 69
#likelihood ratio test
stat7 <- 2*(cph_r6$loglik[2]-cph_r7$loglik[2])
1-pchisq(stat7,1)

## [1] 0.45249
#reduced model 8
cph_r8 <- coxph(Surv(time,censor)~.-priorzdvd -id -hemophil -raceth -time_d -strat2
               -sex -txgrp -age, data = aids)
cph_r8$loglik

## [1] -452.6325 -383.0225
cph_r8

## Call:
## coxph(formula = Surv(time, censor) ~ . - priorzdvd - id - hemophil -
##       raceth - time_d - strat2 - sex - txgrp - age, data = aids)
##
##               coef exp(coef) se(coef)      z      p
## censor_d  2.801853 16.475139  0.303119  9.243 < 2e-16
## tx        -0.406626  0.665893  0.267694 -1.519  0.12876
## ivdrug    -0.401503  0.669313  0.187580 -2.140  0.03232
## karnof    -0.045366  0.955648  0.015162 -2.992  0.00277
## cd4       -0.012959  0.987125  0.003004 -4.314 1.61e-05
##
## Likelihood ratio test=139.2 on 5 df, p=< 2.2e-16
## n= 851, number of events= 69
#likelihood ratio test
stat8 <- 2*(cph_r7$loglik[2]-cph_r8$loglik[2])
1-pchisq(stat8,1)

## [1] 0.1066782
#reduced model 9
cph_r9 <- coxph(Surv(time,censor)~.-priorzdvd -id -hemophil -raceth -time_d -strat2 -sex
               -txgrp -age -tx, data = aids)
cph_r9$loglik

## [1] -452.6325 -384.2077
cph_r9

## Call:
## coxph(formula = Surv(time, censor) ~ . - priorzdvd - id - hemophil -
##       raceth - time_d - strat2 - sex - txgrp - age - tx, data = aids)
##
##               coef exp(coef) se(coef)      z      p
## censor_d  2.919993 18.541150  0.293976  9.933 < 2e-16
## ivdrug    -0.379834  0.683975  0.186804 -2.033  0.04202
## karnof    -0.045797  0.955235  0.015201 -3.013  0.00259
## cd4       -0.013233  0.986854  0.002997 -4.415 1.01e-05
##

```

```
## Likelihood ratio test=136.8 on 4 df, p=< 2.2e-16
## n= 851, number of events= 69
###best model using backwards selection?
#likelihood ratio test
stat9 <- 2*(cph_r8$loglik[2]-cph_r9$loglik[2])
1-pchisq(stat9,1)

## [1] 0.1236681
#reduced model 10
cph_r10 <- coxph(Surv(time,censor)~.-priorzdv -id -hemophil -raceth -time_d -strat2 -sex
                 -txgrp -age -tx -censor_d, data = aids)
cph_r10$loglik

## [1] -452.6325 -417.9688
cph_r10

## Call:
## coxph(formula = Surv(time, censor) ~ . - priorzdv - id - hemophil -
##       raceth - time_d - strat2 - sex - txgrp - age - tx - censor_d,
##       data = aids)
##
##              coef exp(coef) se(coef)      z      p
## ivdrug -0.216832  0.805065  0.180491 -1.201    0.23
## karnof -0.061043  0.940783  0.014157 -4.312 1.62e-05
## cd4     -0.015127  0.984987  0.003076 -4.917 8.77e-07
##
## Likelihood ratio test=69.33 on 3 df, p=5.947e-15
## n= 851, number of events= 69
#NOTE: should we take out censor_d anyways since its related to censor or keep it?
#likelihood ratio test
stat10 <- 2*(cph_r9$loglik[2]-cph_r10$loglik[2])
1-pchisq(stat10,1)

## [1] 2.220446e-16
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
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
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
```

```
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
```

```
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
```

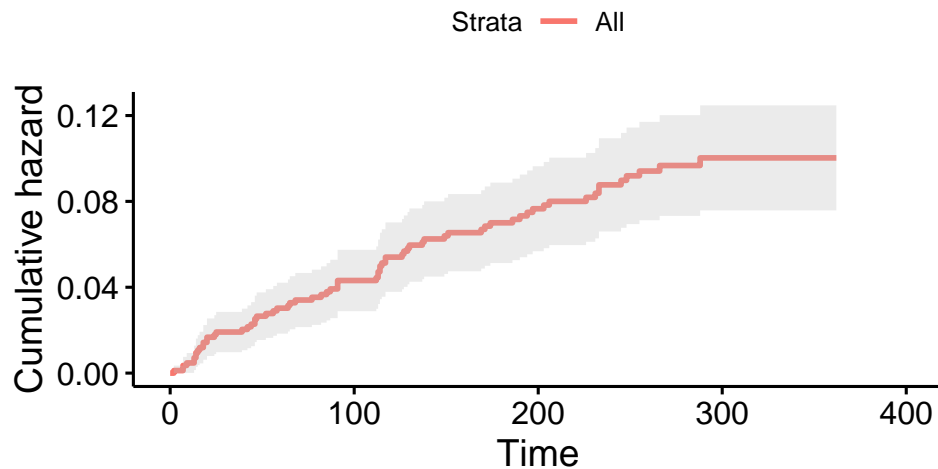
```
cox.zph(coxph(Surv(time,censor) ~ age *txgrp*karnof, data=aids))
```

```
##          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
```

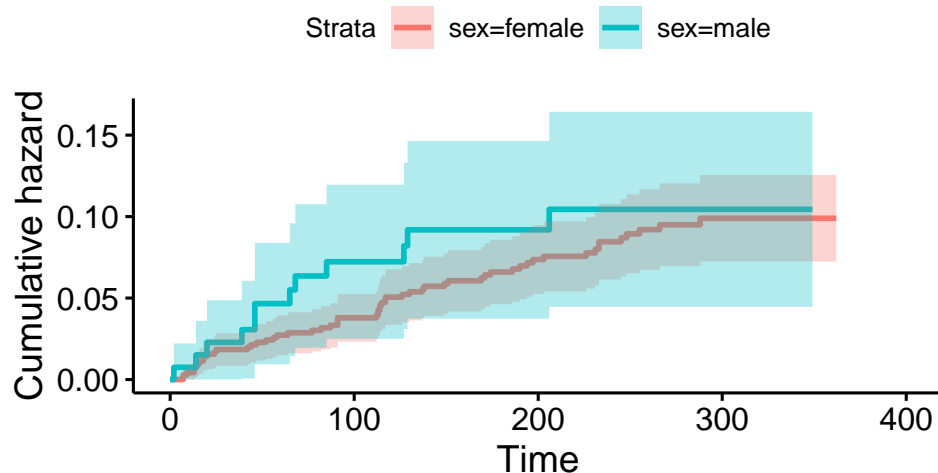
```
ggsurvplot(survfit(Surv(time,censor) ~ 1, data=aids),
  censor=F, conf.int=T, fun="cumhaz") + ggtitle("Estimated Hazard rates")
```

Estimated Hazard rates



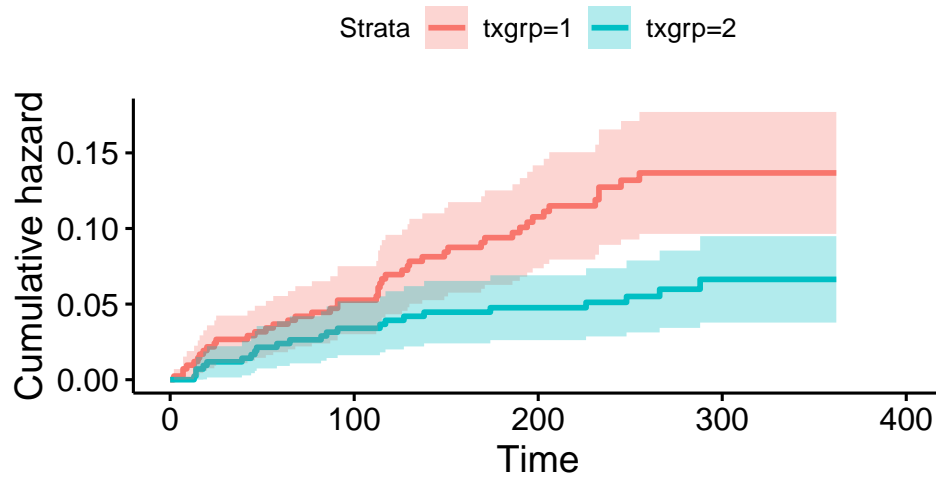
```
ggsurvplot(survfit(Surv(time,censor) ~ sex, data=aids),
  censor=F, conf.int=T, fun="cumhaz") +
  ggtitle("Estimated Hazard rates based on sex")
```

Estimated Hazard rates based on sex



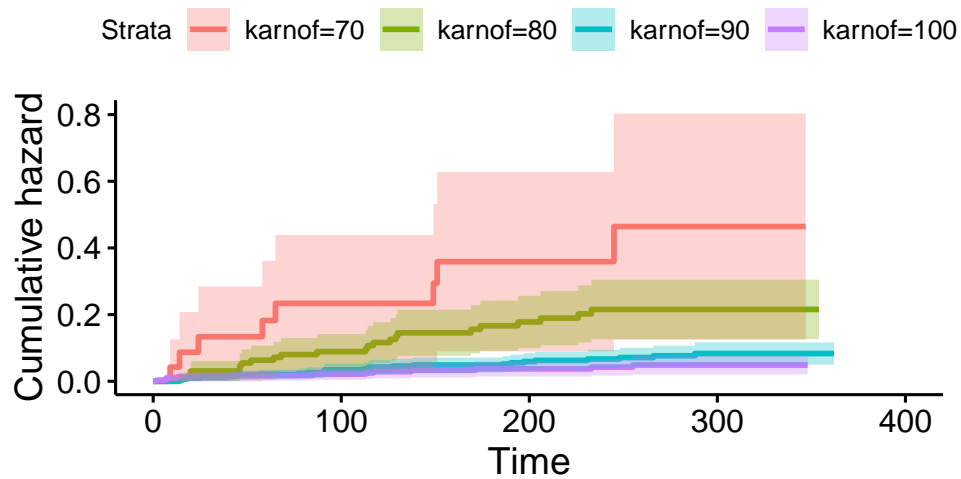
```
ggsurvplot(survfit(Surv(time,censor) ~ txgrp, data=aids),
  censor=F, conf.int=T, fun="cumhaz") +
  ggtitle("Estimated Hazard rates based on treatment group")
```

Estimated Hazard rates based on treatment



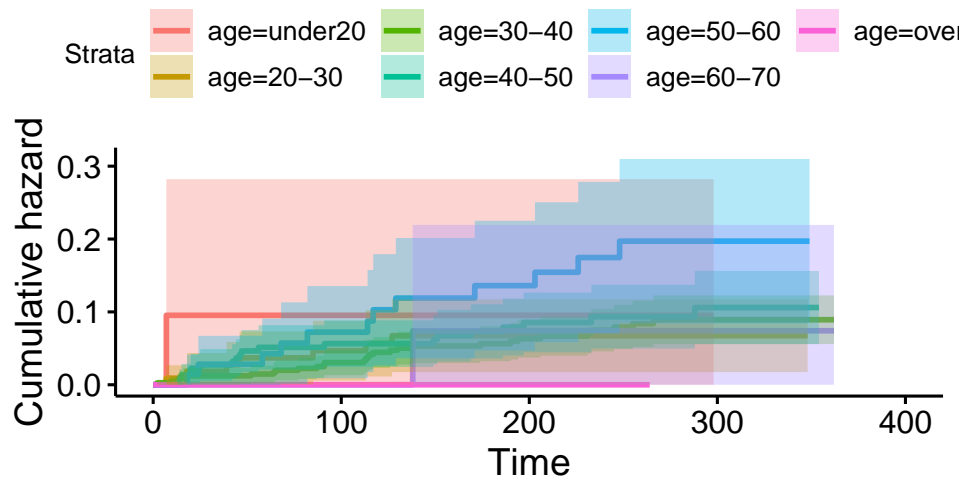
```
ggsurvplot(survfit(Surv(time,censor) ~ karnof, data=aids),
  censor=F, conf.int=T, fun="cumhaz") +
  ggtitle("Estimated Hazard rates based on karnofsky")
```

Estimated Hazard rates based on karnofsky

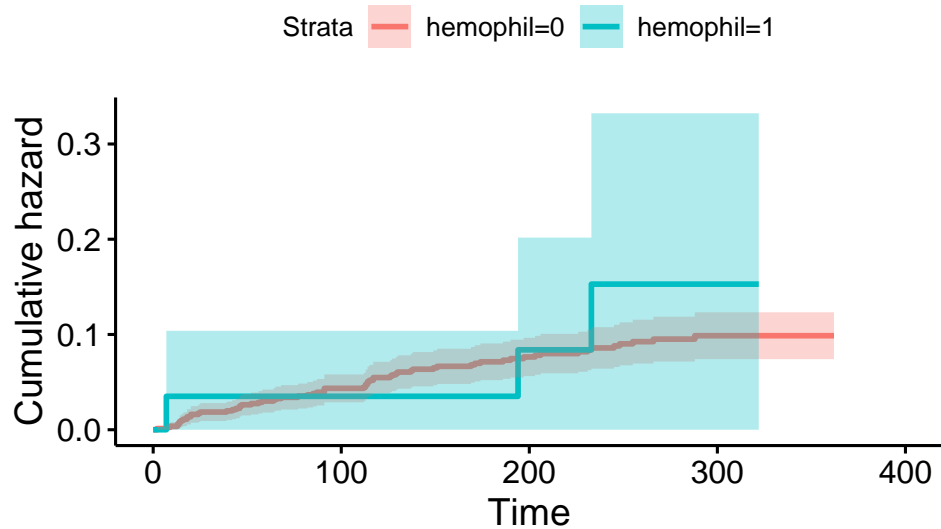


```
ggsurvplot(survfit(Surv(time,censor) ~ age, data=aids),
  censor=F, conf.int=T, fun="cumhaz") +
  ggtitle("Estimated Hazard rates based on age")
```

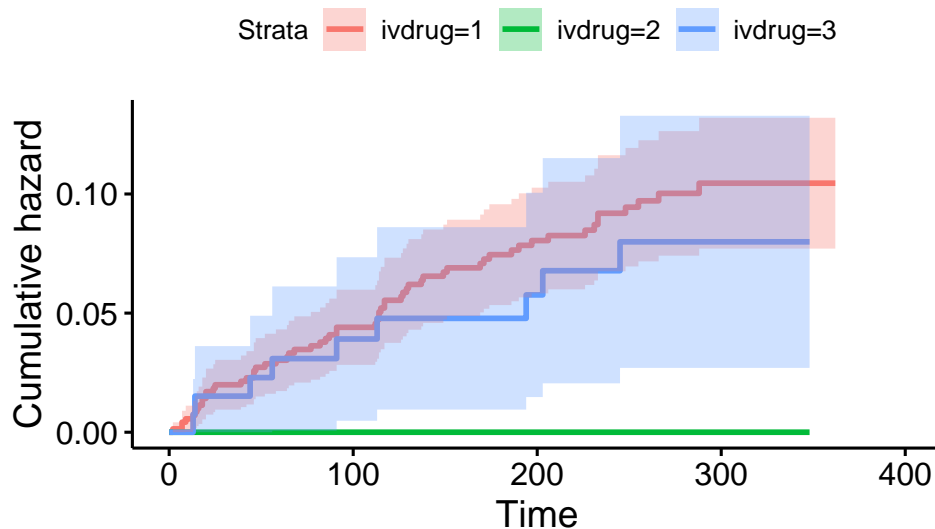
Estimated Hazard rates based on age



```
ggsurvplot(survfit(Surv(time, censor)~hemophil, data = aids),
  censor=F, conf.int = T, fun = "cumhaz")
```



```
ggsurvplot(survfit(Surv(time, censor)~ivdrug, data = aids),
  censor=F, conf.int = T, fun = "cumhaz")
```

```
coxph(Surv(time,censor) ~ ivdrug, 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 ivdrug    -0.130     0.179    -0.723   0.470   -0.481   0.222
```

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

```
## # A tibble: 3 x 7
##   term      estimate std.error statistic p.value conf.low conf.high
##   <chr>      <dbl>    <dbl>    <dbl>   <dbl>   <dbl>   <dbl>
## 1 ivdrug    -0.711     1.71    -0.416  0.678   -4.07    2.64
## 2 karnof     -0.0903    0.0294   -3.07  0.00214 -0.148   -0.0326
## 3 ivdrug:karnof 0.00573    0.0201    0.285  0.775   -0.0336  0.0451
```

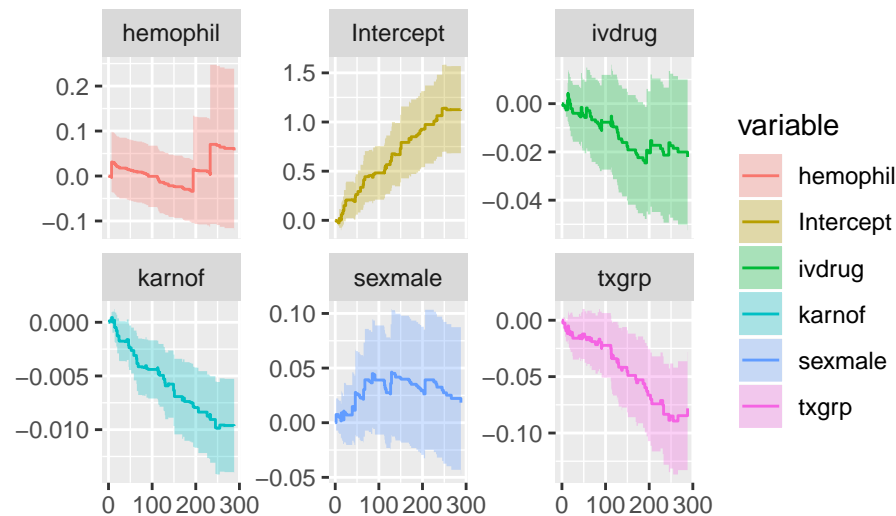
```
coxph(Surv(time,censor)~sex+tx+age+txgrp, data = aids) %>% tidy()
```

```
## # A tibble: 9 x 7
##   term      estimate std.error statistic p.value conf.low conf.high
##   <chr>      <dbl>    <dbl>    <dbl>   <dbl>   <dbl>   <dbl>
## 1 sexmale    0.302     0.324    0.931   0.352   -0.333    0.937
## 2 tx         -0.790     0.256   -3.08   0.00205 -1.29    -0.288
## 3 age20-30   -0.424     1.07    -0.396  0.692   -2.52     1.67
## 4 age30-40   -0.214     1.02    -0.209  0.834   -2.21     1.79
## 5 age40-50   -0.0490     1.03    -0.0475  0.962   -2.07     1.97
## 6 age50-60    0.639     1.05     0.611  0.541   -1.41     2.69
## 7 age60-70   -0.328     1.42    -0.231  0.817   -3.11     2.46
## 8 ageover70 -14.1     2672.    -0.00528  0.996   -Inf      Inf
## 9 txgrp      NA         0      NA      NA      NA      NA
```

```
library(ggfortify)
```

```
aa_fit <-aareg(Surv(time, censor) ~ txgrp + sex + ivdrug + hemophil + karnof,
  data = aids)
```

```
autoplot(aa_fit)
```



The Aalen model assumes that the cumulative hazard $H(t)$ for a subject can be expressed as $a(t) + X B(t)$, where $a(t)$ is a time-dependent intercept term, X is the vector of covariates for the subject possibly time-dependent, and $B(t)$ is a time-dependent matrix of coefficients.

The plots show how the effects of the covariates change over time.

Patricia's "Something New"

I will be doing a power analysis by simulating survival analysis curves

1. What is the topic?

The topic is using `sim.survdata` in R to simulate survival data. Using that simulated data, we will make that the alternative and control for the coefficient beta by setting it equal to some value. Then using power analysis, we will see how many times we reject H_0 .

2. How it is relevant? How it relates to survival analysis/analysis at hand?

Power analysis relates to survival analysis because if power is large after comparing our data to the simulated survival data, this tells us that there is a high chance that we would reject the null in favor of the alternative (control versus treatment?)

3. Resources to learn about the topic.

Below are some of the resources I have begun to use to learn about creating simulations of survival curves and performing power analysis:

a). https://cran.r-project.org/web/packages/coxed/vignettes/simulating_survival_data.html b). http://www.icssc.org/documents/advbiosgoa/tab%2026.00_survss.pdf

4. What will be challenging about learning something new?

Learning something new will be challenging because in this case, the concept of power analysis is something I just recently learned in Intro to Statistics. So learning to apply this concept in the context of survival analysis curves

will be a challenge for me to learn. Learning how to simulate survival curves will also be challenging because I will have to learn how to use and interpret new functions in R.

Power Analysis code and simulation

```
simdata <- sim.survdata(N=1000, T=100, num.data.frames=1, beta = c(0.01,0.07,0.3))
head(simdata$data,10)
```

```
##           X1           X2           X3    y failed
## 1  0.1390272  2.2018658 -0.61603972  64    TRUE
## 2  0.2989827 -2.0487913  0.72235599  57    TRUE
## 3  0.9431141  0.0143370 -0.34850719  23    TRUE
## 4  0.1173749  0.1154529  1.23296541  93 FALSE
## 5 -1.3184045 -0.3076940  1.24192379 100    TRUE
## 6  0.3886520 -0.3847928  0.16304862   1    TRUE
## 7 -1.2892947  1.4026664 -0.23776499   1    TRUE
## 8  1.0974116  0.9735271 -0.79900969  59    TRUE
## 9  1.1071629 -0.5285643 -1.02885821  99    TRUE
## 10 -0.8741064  0.2450979 -0.06074939 100 FALSE
```

```
simdata$betas
```

```
##      [,1]
## [1,] 0.01
## [2,] 0.07
## [3,] 0.30
```

```
head(simdata$baseline,10)
```

```
##      time  failure.PDF failure.CDF survivor      hazard
## 1      1  0.2243766478   0.2243766  0.7756234  0.2243766478
## 2      2  0.1198731707   0.3442498  0.6557502  0.1545507498
## 3      3  0.0033308083   0.3475806  0.6524194  0.0050793860
## 4      4  0.0027770719   0.3503577  0.6496423  0.0042565749
## 5      5  0.0022736752   0.3526314  0.6473686  0.0034998879
## 6      6  0.0018206182   0.3544520  0.6455480  0.0028123361
## 7      7  0.0014179008   0.3558699  0.6441301  0.0021964296
## 8      8  0.0010655231   0.3569354  0.6430646  0.0016542047
## 9      9  0.0007634850   0.3576989  0.6423011  0.0011872603
## 10    10  0.0005117867   0.3582107  0.6417893  0.0007968018
```

```
#ggsurvplot(survfit(Surv(y,failed) ~ X1 + X2 + X3, data = simdata$data))
```

```
model <- coxph(Surv(y, failed) ~ X1 + X2 + X3, data = simdata$data)
```

```
library(dplyr)
```

```
library(broom)
```

```
model %>% tidy()
```

```
## # A tibble: 3 x 7
```

```
##   term estimate std.error statistic p.value conf.low conf.high
##   <chr>    <dbl>    <dbl>    <dbl>   <dbl>   <dbl>    <dbl>
## 1 X1      0.0187    0.0344     0.543   0.587   -0.0488  0.0861
## 2 X2     -0.00992    0.0333    -0.298   0.766   -0.0753  0.0554
## 3 X3     -0.0595    0.0328    -1.81    0.0699  -0.124   0.00484
```

```
n.reps <- 100
```

```
simoutput <- c()
```

```
for(i in 1:n.reps){
```

```

simdata <- sim.survdata(N=1000, T=100, num.data.frames=1, xvars=4, beta = c(0,0.01,0.07,0.3))
model <- coxph(Surv(y, failed) ~ X1 + X2 + X3 + X4, data = simdata$data)
simoutput <- rbind(simoutput, cbind(rep = rep(i, 4), model %>% tidy()))
}

```

simoutput

##	rep	term	estimate	std.error	statistic	p.value
## 1	1	X1	-2.942375e-03	0.03280299	-0.089698384	9.285269e-01
## 2	1	X2	-4.341808e-03	0.03307349	-0.131277577	8.955557e-01
## 3	1	X3	5.204506e-02	0.03444830	1.510816718	1.308352e-01
## 4	1	X4	2.894434e-01	0.03562147	8.125531261	4.454072e-16
## 5	2	X1	-5.158064e-02	0.03340164	-1.544254896	1.225266e-01
## 6	2	X2	3.197743e-02	0.03289656	0.972059791	3.310208e-01
## 7	2	X3	5.009229e-02	0.03210825	1.560106304	1.187348e-01
## 8	2	X4	1.160173e-02	0.03316143	0.349856095	7.264467e-01
## 9	3	X1	-5.201846e-03	0.03353868	-0.155099912	8.767426e-01
## 10	3	X2	-1.501617e-02	0.03298510	-0.455241117	6.489358e-01
## 11	3	X3	2.190895e-02	0.03229475	0.678406079	4.975143e-01
## 12	3	X4	1.522862e-01	0.03268185	4.659655302	3.167393e-06
## 13	4	X1	4.953353e-02	0.03360603	1.473947498	1.404957e-01
## 14	4	X2	-2.984262e-02	0.03442505	-0.866886575	3.860042e-01
## 15	4	X3	7.383681e-02	0.03275996	2.253873755	2.420411e-02
## 16	4	X4	3.384017e-01	0.03524821	9.600536936	7.952904e-22
## 17	5	X1	-1.278007e-02	0.03555141	-0.359481407	7.192350e-01
## 18	5	X2	1.001004e-02	0.03345003	0.299253461	7.647467e-01
## 19	5	X3	8.177433e-02	0.03327416	2.457592669	1.398717e-02
## 20	5	X4	2.960095e-01	0.03612804	8.193346307	2.540618e-16
## 21	6	X1	-1.272116e-02	0.03442776	-0.369503095	7.117528e-01
## 22	6	X2	-1.112505e-02	0.03377103	-0.329425949	7.418338e-01
## 23	6	X3	8.122775e-02	0.03342231	2.430345423	1.508444e-02
## 24	6	X4	2.729298e-01	0.03614649	7.550658214	4.330640e-14
## 25	7	X1	5.857933e-02	0.03391508	1.727235605	8.412536e-02
## 26	7	X2	-5.873707e-03	0.03403403	-0.172583332	8.629790e-01
## 27	7	X3	-1.472681e-02	0.03633756	-0.405278072	6.852731e-01
## 28	7	X4	1.059988e-01	0.03318951	3.193743932	1.404406e-03
## 29	8	X1	-9.640695e-03	0.03296757	-0.292429684	7.699581e-01
## 30	8	X2	-4.379905e-02	0.03236760	-1.353175649	1.759995e-01
## 31	8	X3	5.121126e-02	0.03451233	1.483853828	1.378477e-01
## 32	8	X4	2.621929e-01	0.03510162	7.469536412	8.047784e-14
## 33	9	X1	7.042053e-02	0.03427516	2.054564430	3.992109e-02
## 34	9	X2	1.430208e-02	0.03269872	0.437389575	6.618288e-01
## 35	9	X3	4.900188e-02	0.03510057	1.396042160	1.627018e-01
## 36	9	X4	1.682008e-01	0.03394202	4.955533511	7.213209e-07
## 37	10	X1	-2.359897e-03	0.03255529	-0.072488893	9.422128e-01
## 38	10	X2	8.726394e-03	0.03337186	0.261489589	7.937150e-01
## 39	10	X3	5.626856e-02	0.03366107	1.671621268	9.459903e-02
## 40	10	X4	3.046236e-01	0.03535263	8.616716460	6.890148e-18
## 41	11	X1	-4.009897e-02	0.03208430	-1.249800525	2.113724e-01
## 42	11	X2	-2.023304e-03	0.03308808	-0.061149030	9.512405e-01
## 43	11	X3	-1.097379e-04	0.03396241	-0.003231158	9.974219e-01
## 44	11	X4	1.369901e-01	0.03292644	4.160487504	3.175690e-05
## 45	12	X1	1.897598e-02	0.03268213	0.580622497	5.614949e-01
## 46	12	X2	9.361520e-02	0.03388709	2.762562217	5.734963e-03
## 47	12	X3	4.961232e-02	0.03324738	1.492217468	1.356421e-01

## 48	12	X4	3.085376e-01	0.03382345	9.122003333	7.374826e-20
## 49	13	X1	5.553288e-02	0.03153764	1.760844698	7.826469e-02
## 50	13	X2	-1.555896e-02	0.03267357	-0.476194063	6.339361e-01
## 51	13	X3	1.134710e-01	0.03234010	3.508678503	4.503389e-04
## 52	13	X4	2.913628e-01	0.03485391	8.359543814	6.296124e-17
## 53	14	X1	-2.874956e-02	0.03512822	-0.818417682	4.131187e-01
## 54	14	X2	4.512509e-02	0.03428363	1.316228430	1.880974e-01
## 55	14	X3	8.548869e-02	0.03176486	2.691297462	7.117470e-03
## 56	14	X4	1.368406e-01	0.03338518	4.098841775	4.152228e-05
## 57	15	X1	-1.441500e-02	0.03336081	-0.432093795	6.656732e-01
## 58	15	X2	8.567007e-03	0.03436935	0.249262995	8.031574e-01
## 59	15	X3	7.537933e-02	0.03331200	2.262828109	2.364629e-02
## 60	15	X4	2.622307e-01	0.03637812	7.208472711	5.658291e-13
## 61	16	X1	2.239479e-03	0.03413475	0.065607013	9.476907e-01
## 62	16	X2	4.587118e-02	0.03215380	1.426617771	1.536901e-01
## 63	16	X3	2.741006e-02	0.03252814	0.842656779	3.994204e-01
## 64	16	X4	3.466934e-01	0.03475005	9.976773145	1.926296e-23
## 65	17	X1	-1.005876e-01	0.03501322	-2.872845186	4.067934e-03
## 66	17	X2	1.752665e-02	0.03468651	0.505287274	6.133571e-01
## 67	17	X3	4.241196e-02	0.03353194	1.264822794	2.059349e-01
## 68	17	X4	2.434752e-01	0.03593854	6.774766858	1.246070e-11
## 69	18	X1	-2.153129e-02	0.03212092	-0.670320001	5.026538e-01
## 70	18	X2	3.024077e-02	0.03349452	0.902857439	3.666016e-01
## 71	18	X3	1.598158e-02	0.03238006	0.493562318	6.216153e-01
## 72	18	X4	1.986424e-01	0.03423023	5.803129020	6.508867e-09
## 73	19	X1	4.260758e-02	0.03293410	1.293722226	1.957614e-01
## 74	19	X2	1.004401e-02	0.03417492	0.293899910	7.688344e-01
## 75	19	X3	2.824325e-02	0.03423134	0.825069922	4.093319e-01
## 76	19	X4	2.084557e-01	0.03212868	6.488147954	8.689793e-11
## 77	20	X1	-1.012963e-03	0.03445606	-0.029398706	9.765466e-01
## 78	20	X2	-2.624491e-03	0.03428500	-0.076549248	9.389821e-01
## 79	20	X3	9.412167e-02	0.03383980	2.781390053	5.412666e-03
## 80	20	X4	2.391264e-01	0.03234851	7.392191067	1.444288e-13
## 81	21	X1	-2.703129e-02	0.03501859	-0.771912578	4.401662e-01
## 82	21	X2	-1.695473e-02	0.03168590	-0.535087571	5.925893e-01
## 83	21	X3	5.986037e-03	0.03152753	0.189866996	8.494134e-01
## 84	21	X4	2.188586e-01	0.03454073	6.336246007	2.354308e-10
## 85	22	X1	5.328262e-02	0.03260545	1.634163051	1.022246e-01
## 86	22	X2	-2.008125e-02	0.03398095	-0.590956078	5.545499e-01
## 87	22	X3	6.167153e-02	0.03540773	1.741753430	8.155160e-02
## 88	22	X4	1.769714e-01	0.03522848	5.023532697	5.072958e-07
## 89	23	X1	-4.354270e-02	0.03506424	-1.241797960	2.143111e-01
## 90	23	X2	-4.610575e-02	0.03428726	-1.344690608	1.787252e-01
## 91	23	X3	5.751532e-02	0.03480952	1.652286858	9.847609e-02
## 92	23	X4	2.217008e-02	0.03502852	0.632915098	5.267891e-01
## 93	24	X1	-3.777205e-02	0.03531320	-1.069629865	2.847859e-01
## 94	24	X2	3.435317e-02	0.03565401	0.963514745	3.352893e-01
## 95	24	X3	-1.305561e-02	0.03419319	-0.381818944	7.025957e-01
## 96	24	X4	2.863849e-01	0.03767535	7.601386277	2.929752e-14
## 97	25	X1	-8.466420e-03	0.03219986	-0.262933444	7.926019e-01
## 98	25	X2	5.639743e-03	0.03384184	0.166650013	8.676454e-01
## 99	25	X3	4.863435e-02	0.03545621	1.371673877	1.701650e-01
## 100	25	X4	3.048354e-01	0.03535462	8.622222600	6.566690e-18
## 101	26	X1	8.095773e-03	0.03196031	0.253307076	8.000309e-01
## 102	26	X2	-1.592221e-02	0.03200477	-0.497494958	6.188401e-01
## 103	26	X3	4.235576e-02	0.03341435	1.267592135	2.049436e-01

## 104	26	X4	1.894526e-01	0.03382589	5.600817689	2.133430e-08
## 105	27	X1	-1.824187e-02	0.03384945	-0.538911958	5.899476e-01
## 106	27	X2	1.333063e-02	0.03358236	0.396953287	6.914019e-01
## 107	27	X3	1.027667e-01	0.03279192	3.133902290	1.724983e-03
## 108	27	X4	3.747933e-01	0.03569026	10.501275824	8.522044e-26
## 109	28	X1	-2.737909e-02	0.03370558	-0.812301196	4.166188e-01
## 110	28	X2	-1.415477e-02	0.03327001	-0.425451430	6.705076e-01
## 111	28	X3	9.904894e-02	0.03450658	2.870436769	4.099052e-03
## 112	28	X4	1.470291e-01	0.03629352	4.051110373	5.097515e-05
## 113	29	X1	8.569083e-03	0.03357629	0.255212299	7.985591e-01
## 114	29	X2	5.436153e-02	0.03243721	1.675900212	9.375774e-02
## 115	29	X3	7.137181e-02	0.03355515	2.127000169	3.342007e-02
## 116	29	X4	2.809085e-01	0.03453441	8.134162396	4.147962e-16
## 117	30	X1	-1.990298e-02	0.03240225	-0.614246706	5.390523e-01
## 118	30	X2	-1.128787e-02	0.03254888	-0.346797658	7.287433e-01
## 119	30	X3	1.095390e-01	0.03342791	3.276872832	1.049636e-03
## 120	30	X4	2.269321e-01	0.03366000	6.741891455	1.563379e-11
## 121	31	X1	5.785619e-02	0.03375991	1.713754499	8.657382e-02
## 122	31	X2	-1.872523e-02	0.03160131	-0.592546049	5.534850e-01
## 123	31	X3	1.018464e-01	0.03286570	3.098867307	1.942620e-03
## 124	31	X4	2.992125e-01	0.03446567	8.681463272	3.907092e-18
## 125	32	X1	-4.235542e-02	0.03412684	-1.241117494	2.145623e-01
## 126	32	X2	3.712511e-02	0.03334019	1.113524219	2.654834e-01
## 127	32	X3	4.381289e-03	0.03320797	0.131934856	8.950358e-01
## 128	32	X4	2.093635e-02	0.03307812	0.632936509	5.267751e-01
## 129	33	X1	-5.246364e-02	0.03422890	-1.532729287	1.253426e-01
## 130	33	X2	-3.308923e-02	0.03378120	-0.979515979	3.273251e-01
## 131	33	X3	1.035507e-01	0.03293227	3.144352461	1.664548e-03
## 132	33	X4	2.390171e-01	0.03366821	7.099192264	1.254881e-12
## 133	34	X1	3.010674e-02	0.03513828	0.856807383	3.915513e-01
## 134	34	X2	-8.204749e-04	0.03445902	-0.023810165	9.810040e-01
## 135	34	X3	4.208679e-02	0.03411478	1.233682139	2.173214e-01
## 136	34	X4	2.370527e-01	0.03439411	6.892246011	5.491829e-12
## 137	35	X1	2.147200e-02	0.03365577	0.637988564	5.234811e-01
## 138	35	X2	-2.876981e-02	0.03335861	-0.862440377	3.884452e-01
## 139	35	X3	7.070044e-02	0.03432486	2.059744485	3.942297e-02
## 140	35	X4	3.277280e-01	0.03464607	9.459313027	3.099729e-21
## 141	36	X1	-9.313057e-04	0.03230382	-0.028829586	9.770005e-01
## 142	36	X2	-2.343826e-04	0.03426159	-0.006840973	9.945417e-01
## 143	36	X3	2.947623e-02	0.03222456	0.914713417	3.603421e-01
## 144	36	X4	2.813087e-01	0.03355813	8.382728837	5.171452e-17
## 145	37	X1	-3.875559e-02	0.03413389	-1.135399083	2.562081e-01
## 146	37	X2	-2.845373e-02	0.03386850	-0.840123643	4.008391e-01
## 147	37	X3	2.294456e-03	0.03496339	0.065624521	9.476768e-01
## 148	37	X4	5.317012e-02	0.03496632	1.520609435	1.283579e-01
## 149	38	X1	-3.087677e-02	0.03368009	-0.916766082	3.592652e-01
## 150	38	X2	-3.176692e-02	0.03320218	-0.956772225	3.386822e-01
## 151	38	X3	5.500942e-02	0.03385518	1.624844760	1.041956e-01
## 152	38	X4	2.042186e-01	0.03401024	6.004623120	1.917768e-09
## 153	39	X1	-2.687831e-02	0.03433742	-0.782770084	4.337621e-01
## 154	39	X2	-4.364375e-02	0.03195816	-1.365652808	1.720480e-01
## 155	39	X3	7.381026e-02	0.03281953	2.248974038	2.451415e-02
## 156	39	X4	3.276968e-01	0.03547414	9.237626357	2.520258e-20
## 157	40	X1	1.463456e-02	0.03322974	0.440405513	6.596434e-01
## 158	40	X2	5.603734e-02	0.03466247	1.616657682	1.059522e-01
## 159	40	X3	4.147747e-02	0.03248167	1.276950001	2.016199e-01

## 160	40	X4	2.735820e-01	0.03461835	7.902802427	2.727017e-15
## 161	41	X1	-2.841173e-02	0.03325607	-0.854332300	3.929209e-01
## 162	41	X2	2.348130e-02	0.03407624	0.689081247	4.907721e-01
## 163	41	X3	2.666475e-02	0.03115491	0.855876354	3.920662e-01
## 164	41	X4	3.546157e-02	0.03160266	1.122107041	2.618169e-01
## 165	42	X1	-3.841942e-02	0.03312155	-1.159952483	2.460682e-01
## 166	42	X2	-3.431501e-02	0.03312559	-1.035906350	3.002458e-01
## 167	42	X3	5.575775e-02	0.03253254	1.713907106	8.654579e-02
## 168	42	X4	2.218091e-01	0.03362044	6.597448262	4.182946e-11
## 169	43	X1	4.150710e-02	0.03355802	1.236875641	2.161333e-01
## 170	43	X2	-3.363367e-03	0.03129476	-0.107473785	9.144131e-01
## 171	43	X3	1.620468e-02	0.03322353	0.487747088	6.257290e-01
## 172	43	X4	1.174852e-01	0.03233086	3.633839096	2.792350e-04
## 173	44	X1	3.006563e-02	0.03485896	0.862493763	3.884159e-01
## 174	44	X2	5.612645e-02	0.03440675	1.631262447	1.028350e-01
## 175	44	X3	2.358197e-02	0.03331310	0.707888711	4.790144e-01
## 176	44	X4	1.860959e-01	0.03532090	5.268719516	1.373787e-07
## 177	45	X1	4.990570e-02	0.03289865	1.516952792	1.292786e-01
## 178	45	X2	-2.835655e-02	0.03383895	-0.837985419	4.020389e-01
## 179	45	X3	8.354431e-02	0.03274927	2.551028447	1.074056e-02
## 180	45	X4	2.222337e-01	0.03534012	6.288425680	3.207015e-10
## 181	46	X1	1.188751e-02	0.03369692	0.352777249	7.242554e-01
## 182	46	X2	2.197037e-02	0.03240266	0.678042045	4.977450e-01
## 183	46	X3	1.001409e-01	0.03462518	2.892141468	3.826256e-03
## 184	46	X4	2.769402e-01	0.03501762	7.908598221	2.603032e-15
## 185	47	X1	-3.346525e-02	0.03314681	-1.009606791	3.126837e-01
## 186	47	X2	-1.434724e-03	0.03375581	-0.042503029	9.660977e-01
## 187	47	X3	1.531653e-02	0.03360060	0.455841023	6.485043e-01
## 188	47	X4	-4.587290e-02	0.03371623	-1.360558493	1.736533e-01
## 189	48	X1	1.442626e-02	0.03530500	0.408618026	6.828200e-01
## 190	48	X2	2.427122e-02	0.03430502	0.707512010	4.792484e-01
## 191	48	X3	6.424467e-02	0.03356776	1.913879939	5.563550e-02
## 192	48	X4	1.484379e-01	0.03522167	4.214391571	2.504524e-05
## 193	49	X1	6.270038e-02	0.03376774	1.856812936	6.333777e-02
## 194	49	X2	-5.592047e-05	0.03248438	-0.001721457	9.986265e-01
## 195	49	X3	5.469215e-02	0.03414793	1.601624103	1.092388e-01
## 196	49	X4	2.128810e-01	0.03244451	6.561385918	5.330995e-11
## 197	50	X1	5.946816e-02	0.03312070	1.795498086	7.257438e-02
## 198	50	X2	-6.265913e-03	0.03346156	-0.187257076	8.514591e-01
## 199	50	X3	-2.537159e-02	0.03262835	-0.777593519	4.368087e-01
## 200	50	X4	1.349431e-01	0.03374901	3.998430673	6.376385e-05
## 201	51	X1	-5.845197e-02	0.03134290	-1.864919041	6.219275e-02
## 202	51	X2	3.414400e-02	0.03482853	0.980345895	3.269154e-01
## 203	51	X3	7.244738e-02	0.03126421	2.317262320	2.048945e-02
## 204	51	X4	3.375380e-01	0.03362419	10.038548785	1.031809e-23
## 205	52	X1	4.959085e-03	0.03252983	0.152447309	8.788341e-01
## 206	52	X2	-3.790573e-02	0.03483306	-1.088211160	2.765019e-01
## 207	52	X3	6.582901e-02	0.03504119	1.878617940	6.029668e-02
## 208	52	X4	2.631186e-01	0.03441203	7.646123993	2.071279e-14
## 209	53	X1	-1.566442e-02	0.03424806	-0.457381249	6.473970e-01
## 210	53	X2	2.525773e-02	0.03483076	0.725155750	4.683565e-01
## 211	53	X3	2.025461e-02	0.03262112	0.620904702	5.346623e-01
## 212	53	X4	1.963734e-01	0.03445830	5.698869346	1.206046e-08
## 213	54	X1	-1.084067e-03	0.03325080	-0.032602723	9.739914e-01
## 214	54	X2	3.914441e-02	0.03280295	1.193319635	2.327442e-01
## 215	54	X3	3.297167e-02	0.03132769	1.052476928	2.925808e-01

##	216	54	X4	2.115446e-01	0.03505951	6.033872635	1.600762e-09
##	217	55	X1	1.347382e-02	0.03319005	0.405959650	6.847722e-01
##	218	55	X2	3.665326e-02	0.03343581	1.096227679	2.729791e-01
##	219	55	X3	4.448275e-02	0.03300034	1.347948346	1.776750e-01
##	220	55	X4	2.818621e-01	0.03438972	8.196115414	2.482800e-16
##	221	56	X1	-2.325012e-02	0.03422742	-0.679283614	4.969582e-01
##	222	56	X2	5.549962e-02	0.03311773	1.675828113	9.377187e-02
##	223	56	X3	-8.334309e-03	0.03387934	-0.245999764	8.056824e-01
##	224	56	X4	1.461933e-01	0.03478643	4.202596638	2.638705e-05
##	225	57	X1	7.328166e-02	0.03252554	2.253049976	2.425600e-02
##	226	57	X2	-6.266939e-03	0.03467941	-0.180710671	8.565947e-01
##	227	57	X3	-1.694368e-02	0.03364262	-0.503637443	6.145162e-01
##	228	57	X4	5.369228e-02	0.03231404	1.661577555	9.659751e-02
##	229	58	X1	1.231562e-02	0.03345264	0.368150901	7.127607e-01
##	230	58	X2	5.976734e-02	0.03361382	1.778058542	7.539424e-02
##	231	58	X3	8.588573e-02	0.03369833	2.548664444	1.081363e-02
##	232	58	X4	2.305254e-01	0.03529833	6.530773912	6.543071e-11
##	233	59	X1	-7.036701e-02	0.03299517	-2.132645582	3.295381e-02
##	234	59	X2	-1.012107e-02	0.03461281	-0.292408118	7.699746e-01
##	235	59	X3	-7.138345e-03	0.03414069	-0.209086147	8.343810e-01
##	236	59	X4	6.860452e-02	0.03242828	2.115576853	3.438081e-02
##	237	60	X1	2.134177e-02	0.03339636	0.639044859	5.227937e-01
##	238	60	X2	1.426739e-02	0.03366007	0.423867035	6.716628e-01
##	239	60	X3	7.471042e-02	0.03321525	2.249280641	2.449465e-02
##	240	60	X4	3.151222e-01	0.03488643	9.032801099	1.673326e-19
##	241	61	X1	-5.223472e-02	0.03236230	-1.614060856	1.065142e-01
##	242	61	X2	4.644161e-02	0.03332803	1.393470050	1.634777e-01
##	243	61	X3	7.911858e-02	0.03200410	2.472139124	1.343072e-02
##	244	61	X4	2.358183e-01	0.03454769	6.825877926	8.738922e-12
##	245	62	X1	-1.428354e-02	0.03318983	-0.430359113	6.669344e-01
##	246	62	X2	1.094555e-02	0.03324815	0.329207841	7.419986e-01
##	247	62	X3	1.047741e-03	0.03295263	0.031795375	9.746352e-01
##	248	62	X4	2.888000e-01	0.03297703	8.757609395	1.994349e-18
##	249	63	X1	2.886358e-02	0.03512250	0.821797444	4.111922e-01
##	250	63	X2	-7.222087e-03	0.03453069	-0.209149797	8.343313e-01
##	251	63	X3	1.131008e-01	0.03390260	3.336051430	8.497744e-04
##	252	63	X4	1.809742e-01	0.03284611	5.509762722	3.593177e-08
##	253	64	X1	1.342023e-02	0.03476062	0.386075727	6.994406e-01
##	254	64	X2	4.587802e-02	0.03345047	1.371520749	1.702127e-01
##	255	64	X3	-1.074865e-02	0.03352602	-0.320606097	7.485089e-01
##	256	64	X4	1.287664e-01	0.03302818	3.898682710	9.671741e-05
##	257	65	X1	5.764653e-03	0.03126417	0.184385264	8.537112e-01
##	258	65	X2	-4.960458e-02	0.03434254	-1.444406271	1.486247e-01
##	259	65	X3	6.380880e-02	0.03487061	1.829873380	6.726887e-02
##	260	65	X4	1.970329e-01	0.03509725	5.613913014	1.978017e-08
##	261	66	X1	7.469593e-03	0.03246265	0.230098066	8.180156e-01
##	262	66	X2	8.518968e-02	0.03304016	2.578367653	9.926832e-03
##	263	66	X3	6.696575e-03	0.03430222	0.195222819	8.452185e-01
##	264	66	X4	3.370085e-01	0.03593182	9.379111534	6.653097e-21
##	265	67	X1	-3.738888e-02	0.03397472	-1.100490930	2.711183e-01
##	266	67	X2	-9.118275e-03	0.03109720	-0.293218493	7.693551e-01
##	267	67	X3	5.760707e-02	0.03057242	1.884282269	5.952680e-02
##	268	67	X4	2.492939e-01	0.03330243	7.485759001	7.113482e-14
##	269	68	X1	2.947461e-02	0.03504365	0.841082856	4.003015e-01
##	270	68	X2	-4.703696e-02	0.03314086	-1.419304313	1.558103e-01
##	271	68	X3	5.311918e-02	0.03158679	1.681689579	9.262905e-02

## 272	68	X4	3.530541e-01	0.03428584	10.297372851	7.241188e-25
## 273	69	X1	2.613546e-02	0.03392894	0.770299939	4.411220e-01
## 274	69	X2	-1.486994e-02	0.03322174	-0.447596776	6.544442e-01
## 275	69	X3	2.960194e-02	0.03261746	0.907549050	3.641165e-01
## 276	69	X4	2.059053e-01	0.03467442	5.938248050	2.880839e-09
## 277	70	X1	8.513941e-03	0.03211156	0.265136317	7.909045e-01
## 278	70	X2	-4.019987e-02	0.03336245	-1.204943669	2.282250e-01
## 279	70	X3	2.543675e-02	0.03266492	0.778717567	4.361461e-01
## 280	70	X4	3.900577e-02	0.03367483	1.158306430	2.467390e-01
## 281	71	X1	-7.693492e-03	0.03360344	-0.228949546	8.189081e-01
## 282	71	X2	-3.054785e-02	0.03393724	-0.900127714	3.680523e-01
## 283	71	X3	-4.758840e-02	0.03530891	-1.347772877	1.777314e-01
## 284	71	X4	1.394694e-01	0.03372073	4.136012906	3.533923e-05
## 285	72	X1	-1.497760e-02	0.03325581	-0.450375510	6.524397e-01
## 286	72	X2	1.736625e-02	0.03487213	0.497998048	6.184854e-01
## 287	72	X3	8.937743e-02	0.03302629	2.706250990	6.804759e-03
## 288	72	X4	3.152468e-01	0.03559909	8.855473562	8.332927e-19
## 289	73	X1	-1.967423e-03	0.03482241	-0.056498758	9.549445e-01
## 290	73	X2	-2.510619e-02	0.03243024	-0.774159908	4.388362e-01
## 291	73	X3	7.572253e-02	0.03404029	2.224497209	2.611501e-02
## 292	73	X4	2.200275e-01	0.03437055	6.401629580	1.537273e-10
## 293	74	X1	-5.079143e-02	0.03375666	-1.504634147	1.324182e-01
## 294	74	X2	1.840316e-02	0.03376144	0.545093992	5.856889e-01
## 295	74	X3	5.274042e-02	0.03426291	1.539286032	1.237345e-01
## 296	74	X4	2.257929e-01	0.03295712	6.851110184	7.327904e-12
## 297	75	X1	-3.612296e-02	0.03414769	-1.057845131	2.901261e-01
## 298	75	X2	-2.497991e-02	0.03218855	-0.776049453	4.377198e-01
## 299	75	X3	4.785515e-02	0.03390166	1.411587058	1.580716e-01
## 300	75	X4	2.463614e-01	0.03659906	6.731360236	1.680842e-11
## 301	76	X1	7.458724e-03	0.03236313	0.230469792	8.177267e-01
## 302	76	X2	-3.091735e-02	0.03382613	-0.914008052	3.607126e-01
## 303	76	X3	-3.113884e-03	0.03436095	-0.090622772	9.277923e-01
## 304	76	X4	1.226418e-01	0.03248922	3.774845279	1.601070e-04
## 305	77	X1	5.032948e-02	0.03351003	1.501922830	1.331170e-01
## 306	77	X2	-2.952622e-02	0.03471632	-0.850499746	3.950473e-01
## 307	77	X3	2.189109e-02	0.03403187	0.643252620	5.200602e-01
## 308	77	X4	2.924730e-01	0.03518932	8.311414082	9.456831e-17
## 309	78	X1	4.225085e-03	0.03296308	0.128176255	8.980095e-01
## 310	78	X2	2.782812e-02	0.03434881	0.810162437	4.178468e-01
## 311	78	X3	9.270956e-02	0.03393084	2.732309873	6.289196e-03
## 312	78	X4	2.706544e-01	0.03630596	7.454821139	8.998983e-14
## 313	79	X1	-5.013012e-02	0.03327547	-1.506518849	1.319340e-01
## 314	79	X2	5.151859e-02	0.03414829	1.508672751	1.313824e-01
## 315	79	X3	2.692936e-02	0.03298267	0.816470057	4.142313e-01
## 316	79	X4	3.222589e-01	0.03612092	8.921669125	4.593127e-19
## 317	80	X1	4.036318e-02	0.03244356	1.244104445	2.134611e-01
## 318	80	X2	2.516829e-02	0.03364530	0.748047671	4.544314e-01
## 319	80	X3	1.207759e-01	0.03598843	3.355965288	7.908849e-04
## 320	80	X4	3.706696e-01	0.03539592	10.472099469	1.160404e-25
## 321	81	X1	5.239391e-02	0.03630534	1.443146157	1.489793e-01
## 322	81	X2	4.074054e-02	0.03150099	1.293309508	1.959040e-01
## 323	81	X3	7.848190e-02	0.03341295	2.348846430	1.883167e-02
## 324	81	X4	2.884923e-01	0.03456740	8.345792711	7.073779e-17
## 325	82	X1	5.546863e-02	0.03459523	1.603360897	1.088550e-01
## 326	82	X2	5.653877e-02	0.03285762	1.720719989	8.530165e-02
## 327	82	X3	7.304612e-02	0.03235399	2.257715713	2.396339e-02

## 328	82	X4	2.826928e-01	0.03378573	8.367226698	5.899014e-17
## 329	83	X1	-1.536186e-02	0.03235266	-0.474825217	6.349116e-01
## 330	83	X2	-1.691366e-02	0.03301460	-0.512308406	6.084352e-01
## 331	83	X3	4.602831e-02	0.03434378	1.340222421	1.801730e-01
## 332	83	X4	2.796547e-01	0.03448816	8.108716835	5.115711e-16
## 333	84	X1	-9.204563e-02	0.03267344	-2.817139332	4.845350e-03
## 334	84	X2	-4.642166e-02	0.03221107	-1.441171039	1.495364e-01
## 335	84	X3	4.283950e-02	0.03305308	1.296081964	1.949472e-01
## 336	84	X4	2.450675e-01	0.03392648	7.223488475	5.067060e-13
## 337	85	X1	-2.173282e-02	0.03307573	-0.657062509	5.111407e-01
## 338	85	X2	1.554076e-02	0.03048861	0.509723516	6.102452e-01
## 339	85	X3	4.617025e-03	0.03343550	0.138087514	8.901713e-01
## 340	85	X4	-5.751054e-02	0.03256348	-1.766105458	7.737816e-02
## 341	86	X1	5.465058e-02	0.03336003	1.638205397	1.013789e-01
## 342	86	X2	3.315058e-02	0.03320858	0.998253368	3.181565e-01
## 343	86	X3	9.692767e-02	0.03506369	2.764331878	5.703949e-03
## 344	86	X4	2.835047e-01	0.03871077	7.323666718	2.412855e-13
## 345	87	X1	-4.384124e-02	0.03527251	-1.242929404	2.138938e-01
## 346	87	X2	2.151020e-02	0.03399985	0.632655671	5.269585e-01
## 347	87	X3	6.882446e-02	0.03208230	2.145246972	3.193311e-02
## 348	87	X4	3.870674e-01	0.03475519	11.136965263	8.289610e-29
## 349	88	X1	7.600160e-03	0.03448919	0.220363546	8.255880e-01
## 350	88	X2	1.740389e-02	0.03434359	0.506757934	6.123247e-01
## 351	88	X3	3.140490e-02	0.03515821	0.893245204	3.717259e-01
## 352	88	X4	6.467945e-02	0.03291546	1.965017110	4.941226e-02
## 353	89	X1	1.036688e-02	0.03315136	0.312713635	7.544982e-01
## 354	89	X2	-3.454672e-02	0.03281962	-1.052623952	2.925134e-01
## 355	89	X3	3.400926e-02	0.03312680	1.026638788	3.045906e-01
## 356	89	X4	4.186194e-02	0.03380710	1.238258756	2.156201e-01
## 357	90	X1	3.575505e-02	0.03391328	1.054308151	2.917419e-01
## 358	90	X2	-3.583262e-02	0.03336660	-1.073907069	2.828643e-01
## 359	90	X3	7.135431e-02	0.03374711	2.114383055	3.448256e-02
## 360	90	X4	3.125650e-01	0.03484351	8.970538744	2.950676e-19
## 361	91	X1	-1.065532e-02	0.03228530	-0.330036154	7.413726e-01
## 362	91	X2	3.145756e-02	0.03394373	0.926756009	3.540532e-01
## 363	91	X3	1.512188e-02	0.03373024	0.448318191	6.539236e-01
## 364	91	X4	3.301935e-01	0.03435358	9.611617846	7.141788e-22
## 365	92	X1	-6.948612e-02	0.03294147	-2.109381550	3.491166e-02
## 366	92	X2	-1.293863e-02	0.03123425	-0.414244990	6.786947e-01
## 367	92	X3	-4.191962e-02	0.03344638	-1.253337808	2.100828e-01
## 368	92	X4	9.057743e-02	0.03388997	2.672691735	7.524536e-03
## 369	93	X1	4.079022e-02	0.03415279	1.194345249	2.323429e-01
## 370	93	X2	-1.652138e-02	0.03472235	-0.475813955	6.342069e-01
## 371	93	X3	4.627906e-02	0.03198707	1.446805074	1.479515e-01
## 372	93	X4	2.027673e-01	0.03479796	5.826987243	5.643692e-09
## 373	94	X1	3.698127e-02	0.03281526	1.126953392	2.597622e-01
## 374	94	X2	-1.318634e-02	0.03433079	-0.384096694	7.009068e-01
## 375	94	X3	6.396709e-02	0.03479522	1.838387011	6.600540e-02
## 376	94	X4	2.142899e-01	0.03520441	6.087016997	1.150338e-09
## 377	95	X1	-1.050808e-02	0.03426119	-0.306705102	7.590678e-01
## 378	95	X2	1.957859e-02	0.03335512	0.586974079	5.572211e-01
## 379	95	X3	1.070691e-01	0.03381558	3.166265962	1.544095e-03
## 380	95	X4	3.379633e-01	0.03469319	9.741487203	2.005968e-22
## 381	96	X1	2.997712e-02	0.03485143	0.860140201	3.897118e-01
## 382	96	X2	1.789653e-02	0.03348160	0.534518526	5.929828e-01
## 383	96	X3	4.542387e-02	0.03389207	1.340250642	1.801639e-01

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## 384 96 X4 2.936252e-01 0.03701853 7.931844492 2.159147e-15
## 385 97 X1 1.287701e-02 0.03388646 0.380004658 7.039420e-01
## 386 97 X2 -3.014094e-03 0.03484587 -0.086497886 9.310706e-01
## 387 97 X3 4.354489e-02 0.03429667 1.269653565 2.042081e-01
## 388 97 X4 1.131764e-01 0.03512295 3.222291154 1.271698e-03
## 389 98 X1 1.687233e-02 0.03293156 0.512345311 6.084094e-01
## 390 98 X2 -2.865331e-02 0.03445685 -0.831570744 4.056513e-01
## 391 98 X3 2.664582e-02 0.03427548 0.777401920 4.369217e-01
## 392 98 X4 7.650937e-02 0.03171793 2.412180507 1.585743e-02
## 393 99 X1 2.381387e-02 0.03359568 0.708837421 4.784254e-01
## 394 99 X2 -9.311286e-03 0.03334445 -0.279245482 7.800564e-01
## 395 99 X3 1.145219e-01 0.03309145 3.460770857 5.386311e-04
## 396 99 X4 1.151180e-01 0.03482557 3.305560486 9.478664e-04
## 397 100 X1 7.211333e-03 0.03372500 0.213827495 8.306816e-01
## 398 100 X2 -2.436007e-02 0.03374014 -0.721990880 4.703001e-01
## 399 100 X3 7.079161e-02 0.03384917 2.091384118 3.649364e-02
## 400 100 X4 1.809244e-01 0.03256998 5.554944848 2.776994e-08
## conf.low conf.high
## 1 -0.067235052 0.061350301
## 2 -0.069164665 0.060481048
## 3 -0.015472359 0.119562487
## 4 0.219626585 0.359260190
## 5 -0.117046651 0.013885365
## 6 -0.032498652 0.096453505
## 7 -0.012838732 0.113023314
## 8 -0.053393482 0.076596940
## 9 -0.070936442 0.060532750
## 10 -0.079665773 0.049633429
## 11 -0.041387590 0.085205498
## 12 0.088230919 0.216341434
## 13 -0.016333085 0.115400138
## 14 -0.097314479 0.037629247
## 15 0.009628472 0.138045150
## 16 0.269316525 0.407486972
## 17 -0.082459549 0.056899409
## 18 -0.055550823 0.075570900
## 19 0.016558175 0.146990477
## 20 0.225199872 0.366819177
## 21 -0.080198325 0.054756000
## 22 -0.077315049 0.055064943
## 23 0.015721233 0.146734268
## 24 0.202083999 0.343775654
## 25 -0.007893001 0.125051666
## 26 -0.072579186 0.060831772
## 27 -0.085947114 0.056493485
## 28 0.040948556 0.171049057
## 29 -0.074255935 0.054974546
## 30 -0.107238381 0.019640283
## 31 -0.016431673 0.118854193
## 32 0.193394943 0.330990783
## 33 0.003242446 0.137598618
## 34 -0.049786240 0.078390402
## 35 -0.019793980 0.117797743
## 36 0.101675682 0.234725958
## 37 -0.066167095 0.061447301
## 38 -0.056681251 0.074134039

```

## 39	-0.009705924	0.122243044
## 40	0.235333690	0.373913443
## 41	-0.102983047	0.022785097
## 42	-0.066874748	0.062828140
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## 47	-0.015551347	0.114775993
## 48	0.242244898	0.374830395
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## 50	-0.079597979	0.048480060
## 51	0.050085577	0.176856426
## 52	0.223050355	0.359675157
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## 54	-0.022069592	0.112319769
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## 57	-0.079800984	0.050970986
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## 59	0.010089010	0.140669653
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## 61	-0.064663402	0.069142360
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## 63	-0.036343929	0.091164049
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## 66	-0.050457656	0.085510959
## 67	-0.023309430	0.108133346
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## 69	-0.084487136	0.041424549
## 70	-0.035407272	0.095888819
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## 75	-0.038848940	0.095335430
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## 81	-0.095666463	0.041603884
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## 88	0.107924866	0.246017967
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## 92	-0.046484562	0.090824723
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## 155	0.009485173	0.138135348
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## 166	-0.099239969	0.030609953
## 167	-0.008004855	0.119520353
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## 170	-0.064699978	0.057973245
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## 183	0.032276813	0.168005025
## 184	0.208306984	0.345573513
## 185	-0.098431809	0.031501313
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## 187	-0.050539440	0.081172507
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## 197	-0.005447226	0.124383546
## 198	-0.071849357	0.059317531
## 199	-0.089321981	0.038578796
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## 202	-0.034118654	0.102406658
## 203	0.011170651	0.133724117
## 204	0.271635848	0.403440240
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## 217	-0.051577474	0.078525112
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## 245	-0.079334411	0.050767322
## 246	-0.054219629	0.076110734
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## 260	0.128243553	0.265822236
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## 363	-0.050988175	0.081231934
## 364	0.262861712	0.397525276
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## 373	-0.027335458	0.101297992
## 374	-0.080473448	0.054100764

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## 375 -0.004230298 0.132164477
## 376 0.145290480 0.283289245
## 377 -0.077658784 0.056642619
## 378 -0.045796237 0.084953413
## 379 0.040791803 0.173346449
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## 390 -0.096187488 0.038880874
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## 395 0.049663876 0.179379977
## 396 0.046861162 0.183374880
## 397 -0.058888459 0.073311124
## 398 -0.090489527 0.041769383
## 399 0.004448462 0.137134763
## 400 0.117088442 0.244760404
```

```
#sum(which(simoutput$p.value < 0.05))
```

```
sum(simoutput$p.value < 0.05)
```

```
## [1] 132
```

```
#simoutput%>%filter(term=="X1")%>%summarize(sum(p.value<0.05))
```

```
simoutput%>%dplyr::filter(term=="X1")%>%dplyr::summarize(sum(p.value<0.05))
```

```
## sum(p.value < 0.05)
```

```
## 1 6
```

```
simoutput%>%dplyr::filter(term=="X2")%>%dplyr::summarize(sum(p.value<0.05))
```

```
## sum(p.value < 0.05)
```

```
## 1 2
```

```
simoutput%>%dplyr::filter(term=="X3")%>%dplyr::summarize(sum(p.value<0.05))
```

```
## sum(p.value < 0.05)
```

```
## 1 34
```

```
simoutput%>%dplyr::filter(term=="X4")%>%dplyr::summarize(sum(p.value<0.05))
```

```
## sum(p.value < 0.05)
```

```
## 1 90
```

Juste's "Something New"

I will be analyzing the Shoenfeld residuals for the Cox PH model.

1. What is going on? What is the topic? 2. How it is relevant? How it relates to survival analysis/analysis at hand?

Cox proportional hazards (PH) model is considered a great way to identify combined effects of several covariates on the relative risk (hazard). This model assumes that the hazards of the different strata formed by the levels of the covariates are proportional. This proportional hazards assumption is particularly important and can be tested via three different classes of tests. The first class is focused on the piecewise estimation of models for subsets of data defined by stratification of time. The second one considers the interactions between covariates and some function of time. Finally, the third one is based on examinations of regression residuals. The Schoenfeld Residuals are a part of the third class of proportional hazard assumption testing and I will be exploring it in order to be able to eradicate a method for testing for the PH assumption in the current and future data set analyses. This topic is particularly important in relation to survival analysis since it provides an idea of whether the model is appropriate for the data set at hand and whether some covariates should be considered as variants of time in order to supply the best model for prediction of proportional hazards.

3. Resources to learn about the topic.

I have been researching articles and scientific journals that provide insights into the Schoenfeld residuals and their use in the Cox PH model. Sources include:

1. <https://onlinelibrary.wiley.com/doi/full/10.1111/ajps.12176>
2. https://rstudio-pubs-static.s3.amazonaws.com/39354_34153ff19e624116bd2fbdec7d2534aa.html

4. What will be challenging about learning something new?

Taking a completely new model of analyzing survival data is particularly 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.

Explanation of the Theory Behind Schoenfeld Residuals

Let $z_{ij}(t)$ be the j^{th} covariate of the i^{th} unit, where $i = 1, 2, \dots, n$ and $j = 1, 2, \dots, p$

This notation indicates that z_{ij} is allowed to vary as a function of the time scale.

- 1) As we know from lecture, the Cox PH model assumes that $h(t)$ of the i^{th} individual satisfies:
 - $h_i(t) = h_0(t)e^{z_i(t)\beta}$ where:
 - $h_0 \rightarrow$ baseline hazard
 - $z_i(t) \rightarrow 1 \times p$ vector of covariates for unit i each of which can be time fixed or time-varying.
- 2) However, another possibility has been presented by Therneau and Grambsch in 2000, where they proposed an idea that there could be an alternative to the current Cox model, where the coefficient of the estimate could also be varying as a function of time.

The new hazard function would look like this: $h_i(t) = h_0(t)e^{z_i(t)\beta(t)}$

Therefore, in order to examine these two models in a case when $\beta = \beta(t)$ requires a residual analysis that could indicate whether a model should consider a covariate as a variable with time.

Due to the fact that some observations might be censored and in particular, regarding the Cox PH model, the baseline hazard is not estimated, in order to analyse the residuals a particular score process. The risk score for unit i at time t is thought to be $r_i(t) = e^{z_i(t)\beta}$, where $Y_i(t)$ is the indicator function and $Y_i(t) = 1$ indicates a point in which i is under risk and thus observation and it is equal to 0 in other occasions.

The Schoenfeld residuals are given by the equations:

1. $s_k = Z_{(k)} - \frac{\sum_i Y_i(t_k)r_i(t_k)Z_i(t_k)}{\sum_i Y_i(t_k)r_i(t_k)}$
2. $s_k = Z_{(k)} - \bar{z}(\hat{\beta}, t_k)$

In this case, the $Z(k)$ is the covariate vector of the particular unit that is experiencing the event at time k ; $\hat{\beta}$ is the estimate of β and $\bar{z}(\hat{\beta}, t_k)$ is the weighted mean of covariate values.

Furthermore, the weighted variance can be represented by the derived equation at the k^{th} time as

$$V(\beta, t_k) = \sum_i Y_i(t_k)r_i(t_k)Z_i(t_k) - \bar{z}(\hat{\beta}, t_k)'Z_i(t_k) - \frac{\bar{z}(\hat{\beta}, t_k)}{\sum_i Y_i(t_k)r_i(t_k)}$$

From this, we can scale the Schoenfeld residuals by $V(\beta, t_k)$ of X at t_k via the equation:

$$s_k^* = V^{-1}(\hat{\beta}, t_k)s_k$$

The scaled Schoenfeld residuals can also be defined as follows:

$$s_k^* = m \sum_{k=1}^d V(\hat{\beta}, t_k)s_k$$

here, m is the total number of deaths in the data set.

Following the calculations, the residuals are plotted against time in order to test the proportional hazards assumption. If the assumption is correct, the residuals should be fitting around the line centered at zero ($y=0$). The further away this predicted line is from the horizontal of ($y=0$) the more likely one is to call the PH assumption to question and determine whether it is met through the model.

To go a little deeper into the analysis of the residual calculation, one can look at the calculations of the test statistic for this residual model.

By producing a least squares slope of regression and assuming a relationship between s_{kj}^* and t_{kj} or some function $g(t_k)$ allows to derive a test statistic for the proportional hazards assumption in regards to the j^{th} covariate, which is given by:

$$T_j = \frac{[\sum_{k=1}^d (g(t_k) - \hat{g})s_{kj}^*]^2}{dI^{jj} \sum_{k=1}^d (g(t_k) - \hat{g})^2}$$

Here, the distribution is asymptotical as $X^2(1)$ stating the null hypothesis that the relationship between the covariate, in this case j and the event time follows the assumption of PH.

Interpretation of Schoenfeld Residuals from plots in R and the p-values presented.

The y-axis of the Schoenfeld residuals graph can be interpreted as the log of the hazard ratio for the explanatory variable— the coefficient in Cox's model if it were allowed to vary over time. If the graph is flat, then the PH assumption is adequate. Furthermore, the Schoenfeld residuals are independent of time. A plot that shows a non-random pattern against time is evidence of violation of the PH assumption. The PH assumption is supported when there's a non-significant relationship between residuals and time. ### HIV Data Cox PH model analysis using Schoenfeld Residuals

Schoenfeld Residuals applied to our best Cox PH model for AIDS data where, we have an additive model of explanatory variables: baseline cd4 count, iv drug use history, and karnofsky performance scale score:

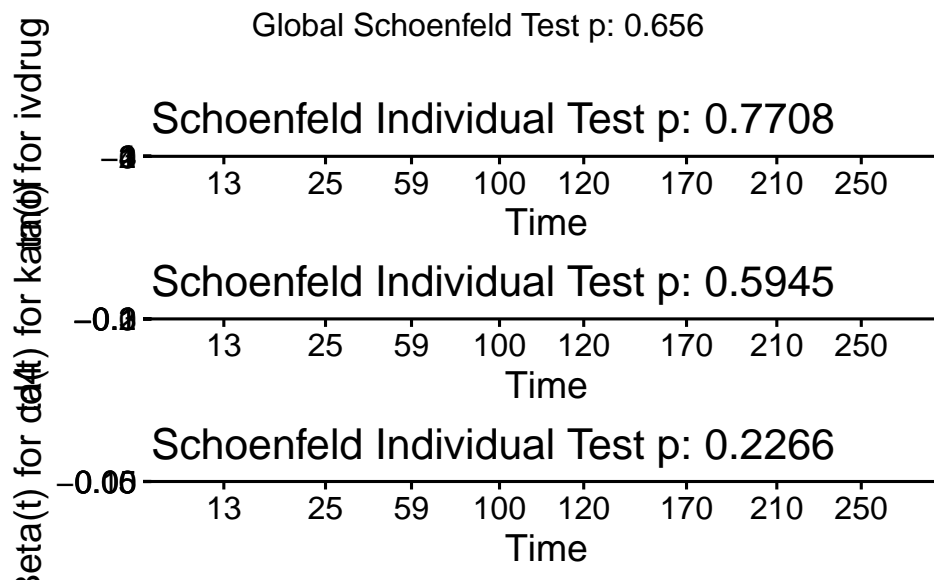
```
cph_r10 <- coxph(Surv(time,censor)~.-priorzdv -id -hemophil -raceth -time_d -strat2
               -sex -txgrp -age -tx -censor_d, data = aids)
cph_r10
```

```
## Call:
## coxph(formula = Surv(time, censor) ~ . - priorzdv - id - hemophil -
##       raceth - time_d - strat2 - sex - txgrp - age - tx - censor_d,
```

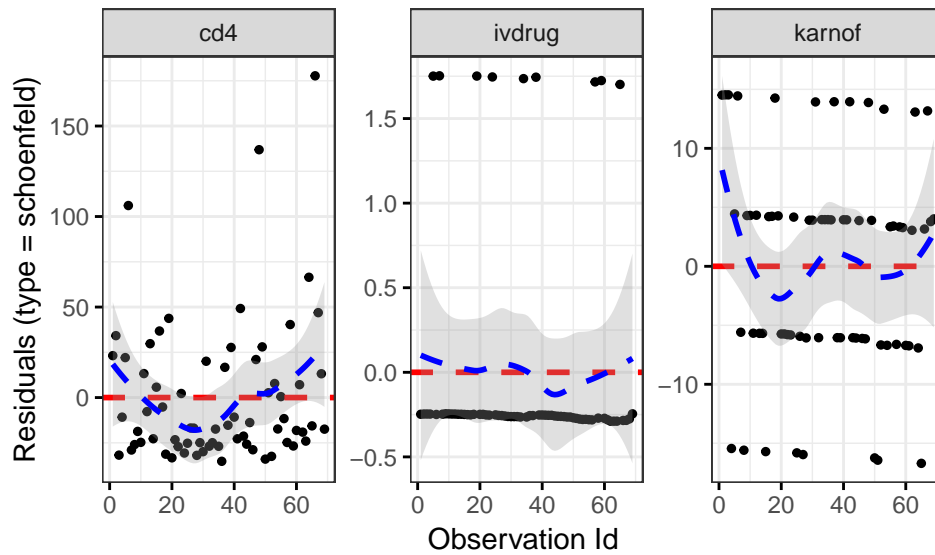
```
##      data = aids)
##
##              coef exp(coef) se(coef)      z      p
## ivdrug -0.216832  0.805065  0.180491 -1.201    0.23
## karnof -0.061043  0.940783  0.014157 -4.312 1.62e-05
## cd4      -0.015127  0.984987  0.003076 -4.917 8.77e-07
##
## Likelihood ratio test=69.33  on 3 df, p=5.947e-15
## n= 851, number of events= 69
zph_r10 <- cox.zph(cph_r10)
zph_r10
```

```
##              rho  chisq      p
## ivdrug -0.0348  0.0849  0.771
## karnof -0.0630  0.2834  0.595
## cd4      0.1524  1.4618  0.227
## GLOBAL      NA  1.6150  0.656
```

```
ggcoxzph(zph_r10)
```



```
ggcoxdiagnostics(cph_r10, type="schoenfeld")
```



Using the best determined Cox PH model for our data, we can look at the Schoenfeld residuals to determine if the PH assumption is met. Via the function “`ggcoxzph()`”, which produces, for each covariate, graphs of the scaled Schoenfeld residuals against the transformed time. Here, the solid line is a smoothing spline fit to the plot, with the dashed lines representing a ± 2 -standard-error. From these graphs, we don’t see any patterns or significance of the residual fit regarding the graphs of the covariates with time. Therefore, the assumption of proportional hazards seems to be supported for the covariates: baseline cd4 count, iv drug use history, and karnofsky performance scale score.

Using the `ggcoxdiagnostics()` function we can provide another graphic representation of the residual distribution in regards to the covariates with time. Here, we also see that there’s no particular pattern of the residuals around the line of fit, therefore again, we can state that the PH assumption has been met.