

```

opts_chunk$set (warning = FALSE, message = FALSE, tidy=TRUE, echo=TRUE)
options(warn = -1)

rm(list=ls())

library(survival)
library(knitr)
library(kableExtra)

library(glmnet)

## Loading required package: Matrix
## Loaded glmnet 4.1-7

library(ggplot2)

# Following loaded in "forest_search_v0.R"
suppressMessages(library(randomForest))
#library(SPLit)

library(grf)
library(policytree)
library(DiagrammeR)

#library(cowplot)

library(data.table)
library(plyr)
library(aVirtualTwins)
# Not sure formatR is needed?
#library(formatR)
suppressMessages(library(gridExtra))

library(speff2trial)

## Loading required package: leaps

# Location where code is stored
# Modified for MAC
codepath<-c("/Users/larryleon/Documents/GitHub/forestSearch/R/")
source(paste0(codepath,"source_forestsearch_v0.R"))
source_fs_functions(file_loc=codepath)

# Output grf, fs, and fs bootstrap
#outgrf<-c("output/actg_2v3_grf.Rdata")
outfs<-c("output/actg_2v3_fs-Nsg.Rdata")
# Boots=2000
outfsboot<-c("output/actg_2v3_fsboot-Nsg_B=2000.Rdata")
# Set to null if not outputting
outgrf<-NULL
#outfs<-NULL
#outfsboot<-NULL

t.start.all <- proc.time()[3]
# GRF analysis To guide selection of binary cutpoints

```

```

df.analysis <- subset(ACTG175, arms %in% c(2, 3))

df.analysis <- within(df.analysis, {
  id <- as.numeric(c(1:nrow(df.analysis)))
  time_days <- days
  treat <- ifelse(arms == 2, 1, 0)
})

# plot(survfit(Surv(time_days, cens)~treat, data=df.analysis))
coxph(Surv(time_days, cens) ~ treat, data = df.analysis)

## Call:
## coxph(formula = Surv(time_days, cens) ~ treat, data = df.analysis)
##
##          coef exp(coef) se(coef)      z      p
## treat -0.1102    0.8957   0.1303 -0.845 0.398
##
## Likelihood ratio test=0.72 on 1 df, p=0.3974
## n= 1085, number of events= 237

confounders.name <- c("age", "wtkg", "karnof", "cd40", "cd80", "hemo", "homo", "drugs",
  "race", "gender", "oprior", "symptom")
outcome.name <- c("time_days")
event.name <- c("cens")
id.name <- c("id")
treat.name <- c("treat")

n.min <- 60
dmin.grf <- 12
frac.tau <- 0.8

grf.est <- grf.subg.harm.survival(data = df.analysis, confounders.name = confounders.name,
  outcome.name = outcome.name, event.name = event.name, id.name = id.name, treat.name = treat.name,
  n.min = n.min, dmin.grf = dmin.grf, frac.tau = frac.tau, details = TRUE)

## tau= 816.8
##      leaf.node control.mean control.size control.se treated.mean treated.size
## 1           2  -22.353084   827.000000   9.311604   22.353084   827.000000
## 2           3   21.769331   258.000000  20.591291  -21.769331   258.000000
## 3           4   17.948528   172.000000  18.480317  -17.948528   172.000000
## 4           5  -82.086594   126.000000  28.103025   82.086594   126.000000
## 5           6  -30.303781   518.000000  11.142066   30.303781   518.000000
## 6           7   37.485537   269.000000  20.531354  -37.485537   269.000000
## 31          10  -40.053468   456.000000  12.977106   40.053468   456.000000
## 41          11    8.743941   181.000000  10.382423   -8.743941   181.000000
## 51          12  -83.121806   112.000000  29.204486   83.121806   112.000000
## 61          13   75.076454   124.000000  25.830279  -75.076454   124.000000
## 7           14  103.750525    64.000000  56.255470 -103.750525    64.000000
## 8           15  -72.418573    81.000000  30.476164   72.418573    81.000000
##      treated.se      diff depth
## 1    9.311604  -44.70617     1
## 2   20.591291   43.53866     1
## 3   18.480317   35.89706     2
## 4   28.103025 -164.17319     2
## 5   11.142066  -60.60756     2
## 6   20.531354   74.97107     2

```

```
## 31 12.977106 -80.10694 3
## 41 10.382423 17.48788 3
## 51 29.204486 -166.24361 3
## 61 25.830279 150.15291 3
## 7 56.255470 207.50105 3
## 8 30.476164 -144.83715 3
## leaf.node control.mean control.size control.se treated.mean treated.size
## 7 14 103.75052 64.00000 56.25547 -103.75052 64.00000
## treated.se diff depth
## 7 56.25547 207.501 3
```

```
cat("Truncation point for RMST:", c(grf.est$tau.rmst), "\n")
```

```
## Truncation point for RMST: 816.8
```

```
# Plot manually
```

```
# plot(grf.est$tree) plot(grf.est$tree1) plot(grf.est$tree2)
# plot(grf.est$tree3)
```

```
df0.grf <- subset(grf.est$data, treat.recommend == 0)
df1.grf <- subset(grf.est$data, treat.recommend == 1)
```

```
# Terminal leaf corresponding to selected SG
cat("Terminal leaf:", c(grf.est$sg.harm.id), "\n")
```

```
## Terminal leaf: karnof <= 90
```

```
# action=1 --> recommend control
```

```
# Manually identify the subgroup looking at tree and terminal leaf
print(dim(df0.grf))
```

```
## [1] 64 34
```

```
check <- subset(df.analysis, karnof <= 90 & cd80 > 1034 & age > 37)
print(dim(check))
```

```
## [1] 64 29
```

```
# plot(survfit(Surv(time_days,cens)~treat,data=df.analysis))
# coxph(Surv(time_days,cens)~treat,data=df.analysis)
```

```
if (!is.null(outgrf)) save(grf.est, file = outgrf)
```

```
t.done <- proc.time()[3]
t.min <- (t.done - t.start.all)/60
cat("Minutes and hours for GRF estimation", c(t.min, t.min/60), "\n")
```

```
## Minutes and hours for GRF estimation 2.914333 0.04857222
```

```
t.start <- proc.time()[3]
```

```
cat("GRF variables in selected tree", "\n")
```

```
## GRF variables in selected tree
```

```

print(grf.est$tree.names)

## [1] "age"      "cd80"      "wtkg"      "cd40"      "karnof"

cat("GRF cuts wrt selected tree:", "\n")

## GRF cuts wrt selected tree:

print(grf.est$tree.cuts)

## [1] "age <= 37"      "cd80 <= 499"      "cd80 <= 1034"      "wtkg <= 64.64"
## [5] "cd40 <= 417"      "cd80 <= 680"      "karnof <= 90"

# Reduce dimension via Cox lasso

xx <- as.matrix(df.analysis[, confounders.name])
yy <- as.matrix(df.analysis[, c("time_days", "cens")])
colnames(yy) <- c("time", "status")

cvfit <- cv.glmnet(xx, yy, family = "cox") #first do 10-fold cross-validation to select lambda
m <- glmnet(xx, yy, family = "cox", lambda = cvfit$lambda.min) #plugin the optimal lambda

conflasso.name <- confounders.name[which(m$beta != 0)]

cat("Cox-LASSO selected:", c(conflasso.name), "\n")

## Cox-LASSO selected: age wtkg karnof cd40 cd80 drugs oprior symptom

cat("GRF cuts wrt selected tree:", "\n")

## GRF cuts wrt selected tree:

print(grf.est$tree.cuts)

## [1] "age <= 37"      "cd80 <= 499"      "cd80 <= 1034"      "wtkg <= 64.64"
## [5] "cd40 <= 417"      "cd80 <= 680"      "karnof <= 90"

# Considering continuous factors per GRF cuts Only *also* considering drugs and
# symptom per lasso

df.analysis <- within(df.analysis, {
  z1a <- ifelse(age <= 37, 1, 0)
  z1b <- ifelse(age <= median(age), 1, 0)
  z2 <- ifelse(wtkg <= 65, 1, 0)
  z3 <- ifelse(karnof <= 90, 1, 0)
  z4 <- ifelse(cd40 <= 417, 1, 0)
  z5a <- ifelse(cd80 <= 499, 1, 0)
  z5b <- ifelse(cd80 <= 680, 1, 0)
  z5c <- ifelse(cd80 <= 1034, 1, 0)
  # z6<-hemo z7<-homo
  z8 <- drugs
  # z9<-race z10<-gender z11<-oprior
  z12 <- symptom
  # Convert to factors
  v1a <- as.factor(z1a)
  v1b <- as.factor(z1b)
  v2 <- as.factor(z2)

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v3 <- as.factor(z3)
v4 <- as.factor(z4)
v5a <- as.factor(z5a)
v5b <- as.factor(z5b)
v5c <- as.factor(z5c)
v6 <- as.factor(z8)
v7 <- as.factor(z12)
})

FSconfounders.name <- c("v1a", "v1b", "v2", "v3", "v4", "v5a", "v5b", "v5c", "v6",
  "v7")

outcome.name <- c("time_days")
event.name <- c("cens")
id.name <- c("id")
treat.name <- c("treat")

df.confounders <- df.analysis[, FSconfounders.name]
df.confounders <- dummy(df.confounders)

hr.threshold <- 1.5 # Initial candidates
hr.consistency <- 1.25 # Candidates for many splits

pconsistency.threshold <- 0.9
maxk <- 4
# max is max # of covariates in combination Since we want to allow generation
# of intervals for single covariate allowing for 4 can yield v1, v2 (say), and
# v3, v4 with v3 and v4 generating intervals for a single covariate

# Limit timing for forestsearch
max.minutes <- 60
nmin.fs <- 60
# stop.threshold<-0.60 # If any sg meets this, then choose this (stop here);
m1.threshold <- Inf # Turning this off (Default)
stop.threshold <- 1
# =1 will run through all sg's meeting HR criteria
fs.splits <- 1000 # How many times to split for consistency
# vi is % factor is selected in cross-validation --> higher more important
vi.grf.min <- 0.2
# Null, turns off grf screening Set to 5 for this heavily censored data
d.min <- 5 # Min number of events for both arms (d0.min=d1.min=d.min)
# default=5

sg_focus <- "Nsg"
split_method <- "Random"
pstop_futile <- 0
# Stops the consistency evaluation after first subgroup with consistency below
# pstop_futile With idea that since SG's are sorted by hazard ratio estimates,
# once consistency is below pstop_futile it seems unlikely that SG's with lower
# hr's will reach the required consistency criterion

fs.est <- forestsearch(df = df.analysis, confounders.name = FSconfounders.name, df.predict = df.analysis,
  details = TRUE, sg_focus = sg_focus, split_method = split_method, pstop_futile = pstop_futile,
  outcome.name = outcome.name, treat.name = treat.name, event.name = event.name,

```

```

id.name = id.name, n.min = nmin.fs, hr.threshold = hr.threshold, hr.consistency = hr.consistency,
fs.splits = fs.splits, stop.threshold = stop.threshold, d0.min = d.min, d1.min = d.min,
pconsistency.threshold = pconsistency.threshold, max.minutes = max.minutes, maxk = maxk,
plot.sg = FALSE, vi.grf.min = vi.grf.min)

## Confounders per grf screening v2 v1a v7 v3 v6 v5b v5c v1b v5a v4
## Number of possible subgroups= 1048575
## Number of possible subgroups (in millions)= 1.048575
## # of subgroups based on # variables > k.max and excluded 1042380
## k.max= 4
## Events criteria for control,exp= 5 5
## # of subgroups with events less than criteria: control, experimental 3622 3912
## # of subgroups meeting all criteria = 1442
## # of subgroups fitted (Cox model estimable) = 1442
## Minutes= 0.1162667
## Number of criteria not met for subgroup evaluation
## crit.failure
##      0      1      2      3      4
## 1043822    422    3097    484    750
## Number of subgroups meeting HR threshold 92
## Subgroups (1st 10) meeting overall screening thresholds (HR, m1) sorted by focus: (m1,sg_focus)= Inf
##      K   n   E d1  m1  m0  HR L(HR) U(HR) v2.0 v2.1 v1a.0 v1a.1 v7.0 v7.1 v3.0
## 1: 3 225 25 16 Inf Inf 1.61 0.71 3.63 1 0 0 0 0 0 0
## 2: 3 222 51 31 Inf Inf 1.64 0.93 2.87 1 0 1 0 0 0 0
## 3: 4 213 55 28 Inf Inf 1.50 0.88 2.55 1 0 0 0 0 0 0
## 4: 2 212 50 26 Inf Inf 1.58 0.90 2.75 0 0 0 0 0 0 0
## 5: 3 212 50 26 Inf Inf 1.58 0.90 2.75 0 0 0 1 0 0 0
## 6: 3 201 21 13 Inf Inf 1.58 0.65 3.81 1 0 0 0 0 0 0
## 7: 3 195 22 14 Inf Inf 1.55 0.65 3.68 1 0 0 0 0 0 0
## 8: 4 192 20 13 Inf Inf 1.82 0.72 4.56 1 0 0 0 0 0 0
## 9: 3 191 47 26 Inf Inf 1.97 1.11 3.50 0 0 0 0 0 0 0
## 10: 4 191 47 26 Inf Inf 1.97 1.11 3.50 0 0 0 1 0 0 0
##      v3.1 v6.0 v6.1 v5b.0 v5b.1 v5c.0 v5c.1 v1b.0 v1b.1 v5a.0 v5a.1 v4.0 v4.1
## 1: 0 0 0 0 0 0 0 0 0 1 0 1 0
## 2: 0 0 0 1 0 0 0 0 0 0 0 0 0
## 3: 1 1 0 1 0 0 0 0 0 0 0 0 0
## 4: 1 0 0 0 0 0 0 0 1 0 0 0 0
## 5: 1 0 0 0 0 0 0 0 1 0 0 0 0
## 6: 0 1 0 0 0 0 0 0 0 0 0 1 0
## 7: 0 0 0 1 0 0 0 0 0 0 0 1 0
## 8: 0 1 0 0 0 0 0 0 0 1 0 1 0
## 9: 1 1 0 0 0 0 0 0 1 0 0 0 0
## 10: 1 1 0 0 0 0 0 0 1 0 0 0 0
## Consistency 0.075
## Consistency 0.217
## Consistency 0.079
## Consistency 0.141
## Consistency 0.141
## Consistency 0.06
## Consistency 0.058
## Consistency 0.142
## Consistency 0.835
## Consistency 0.835
## Consistency 0.07
## Consistency 0.07

```

```

## Consistency 0.281
## Consistency 0.077
## Consistency 0.077
## Consistency 0.501
## Consistency 0.109
## Consistency 0.17
## Consistency 0.106
## Consistency 0.182
## Consistency 0.182
## Consistency 0.048
## Consistency 0.278
## Consistency 0.404
## Consistency 0.172
## Consistency 0.059
## Consistency 0.06
## Consistency 0.542
## Consistency 0.142
## Consistency 0.076
## Consistency 0.178
## Consistency 0.116
## Consistency 0.174
## Consistency 0.069
## Consistency 0.069
## Consistency 0.149
## Consistency 0.149
## Consistency 0.118
## Consistency 0.913
## Splitting method, # of splits= Random 1000
## Model, % Consistency Met= v1a.0 v5b.0 v5c.1 0.913
## Number of subgroups meeting consistency criteria= 1
##   p.consistency Nsg group.id m.index K   M.1   M.2   M.3 M.4
## 1:           0.913 124         23      39 3 v1a.0 v5b.0 v5c.1
##   p.consistency Nsg group.id m.index K   M.1   M.2   M.3 M.4
## 1:           0.913 124         23      39 3 v1a.0 v5b.0 v5c.1

xx <- fs.est$find.grps$out.found$hr.subgroups
covs.found <- xx[, -c(1:10)]
covs.most <- apply(covs.found, 2, sum)
covs.most <- covs.most[covs.most > 0]
print(covs.most)

##   v2.0 v1a.0 v1a.1 v7.0 v7.1 v3.0 v3.1 v6.0 v5b.0 v5b.1 v5c.0 v5c.1 v1b.0
##   37   22   17   17   1   7   51   32   23   18   19   15   5
## v1b.1 v5a.0 v5a.1 v4.0 v4.1
##   33   12    3   11   16

print(fs.est$grp.consistency$result)

##   p.consistency Nsg group.id m.index K   M.1   M.2   M.3 M.4
## 1:           0.913 124         23      39 3 v1a.0 v5b.0 v5c.1

df0.fs <- subset(fs.est$df.pred, treat.recommend == 0)
df1.fs <- subset(fs.est$df.pred, treat.recommend == 1)

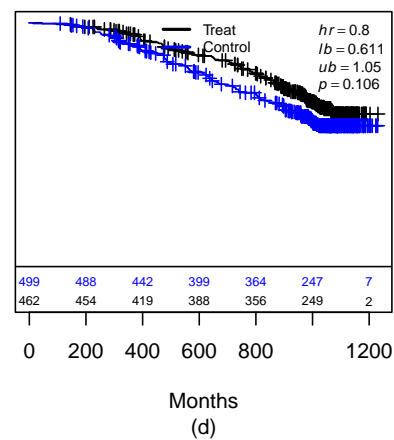
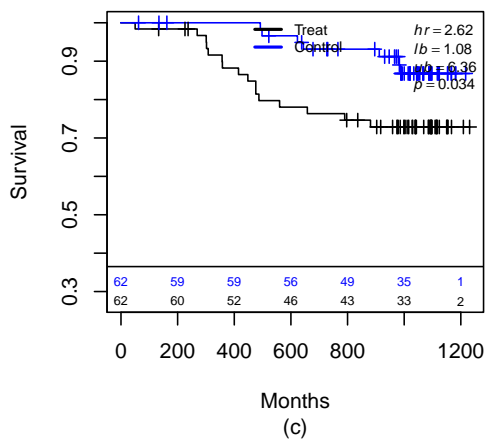
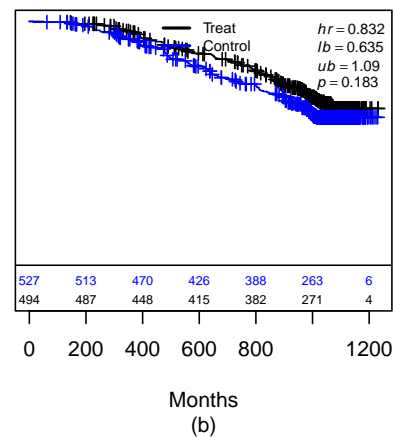
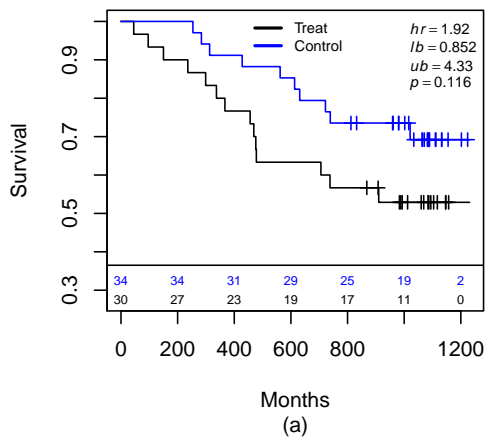
if (!is.null(outfs)) save(fs.est, df.analysis, FSconfounders.name, file = outfs)

```

```
t.done <- proc.time()[3]
t.min <- (t.done - t.start)/60
cat("Minutes and hours for FS estimation", c(t.min, t.min/60), "\n")

## Minutes and hours for FS estimation 0.4666 0.007776667
```

```
# Compare with GRF
layout(matrix(c(1, 2, 3, 4), 2, 2, byrow = TRUE))
plot.subgroup(sub1 = df0.grf, sub1C = df1.grf, tte.name = "time_days", event.name = "cens",
  treat.name = "treat", fix.rows = FALSE, byrisk = 200, show.med = FALSE, ymin = 0.4,
  subtitle1 = "(a)", subtitle2 = "(b)")
plot.subgroup(sub1 = df0.fs, sub1C = df1.fs, tte.name = "time_days", event.name = "cens",
  treat.name = "treat", fix.rows = FALSE, byrisk = 200, show.med = FALSE, ymin = 0.4,
  subtitle1 = "(c)", subtitle2 = "(d)")
```



```
t.start <- proc.time()[3]
# Note, the elements above will need to be re-initiated if running separate
# from above E.g., outcome.names, event.name, ... hr.threshold, etc.
```



```

library(doParallel)
registerDoParallel(parallel::detectCores(logical = FALSE))

cox.formula.boot <- as.formula(paste("Surv(time_days,cens)~treat"))
split_method <- "Random"
est.loghr <- TRUE

confounders.name <- FSconfounders.name
stop.threshold <- 0.99
fs.splits <- 1000
max.minutes <- 6

# Suggest running 50, first ... to get timing estimate
NB <- 2000

df_temp <- fs.est$df.pred[, c("id", "treat.recommend")]
dfa <- merge(df.analysis, df_temp, by = "id")
df_boot_analysis <- dfa

fitH <- get_Cox_sg(df_sg = subset(df_boot_analysis, treat.recommend == 0), cox.formula = cox.formula.boot,
  est.loghr = est.loghr)
H_obs <- fitH$est_obs # log(hr) scale
seH_obs <- fitH$se_obs
# Hc observed estimates
fitHc <- get_Cox_sg(df_sg = subset(df_boot_analysis, treat.recommend == 1), cox.formula = cox.formula.boot,
  est.loghr = est.loghr)
Hc_obs <- fitHc$est_obs
seHc_obs <- fitHc$se_obs
rm("fitH", "fitHc")

Ystar_mat <- bootYstar({
  ystar <- get_Ystar(boot)
}, boots = NB, seed = 8316951, counter = "boot", export = fun_arg_list_boot)
# Check dimension
if (dim(Ystar_mat)[1] != NB | dim(Ystar_mat)[2] != nrow(df_boot_analysis)) stop("Dimension of Ystar_mat")

tB.start <- proc.time()[3]
# Bootstraps
resB <- bootPar({
  ans <- fsboot_forparallel(boot)
}, boots = NB, seed = 8316951, counter = "boot", export = fun_arg_list_boot)
tB.now <- proc.time()[3]
tB.min <- (tB.now - tB.start)/60

doParallel::stopImplicitCluster()

cat("Minutes for Boots", c(NB, tB.min), "\n")

## Minutes for Boots 2000 91.71642

cat("Projection per 100", c(tB.min * (100/NB)), "\n")

## Projection per 100 4.585821

cat("Propn bootstrap subgroups found =", c(sum(!is.na(resB$H_biasadj_1))/NB), "\n")

```

```

## Propn bootstrap subgroups found = 0.9835

# How many timed out
cat("Number timed out=", c(sum(is.na(resB$H_biasadj_1) & resB$tmins_search > max.minutes)),
    "\n")

## Number timed out= 0

H_estimates <- get_dfRes(Hobs = H_obs, seHobs = seH_obs, H1_adj = resB$H_biasadj_1,
    ystar = Ystar_mat, cov_method = "standard", cov_trim = 0.05)

Hc_estimates <- get_dfRes(Hobs = Hc_obs, seHobs = seHc_obs, H1_adj = resB$Hc_biasadj_1,
    ystar = Ystar_mat, cov_method = "standard", cov_trim = 0.05)

print(H_estimates)

##           H0      sdH0 H0_lower H0_upper      H1      sdH1 H1_lower H1_upper
## 1: 2.615041 1.185542 1.075429 6.358799 1.661528 0.1734117 1.354156 2.038668

print(Hc_estimates)

##           H0      sdH0 H0_lower H0_upper      H1      sdH1 H1_lower H1_upper
## 1: 0.8000619 0.110339 0.6105649 1.048372 0.9078549 0.1128085 0.7116191 1.158205

if (!is.null(outfsboot)) save(fs.est, Ystar_mat, resB, H_estimates, Hc_estimates,
    df_boot_analysis, file = outfsboot)

```

```

t.done <- proc.time()[3]
t.min <- (t.done - t.start)/60
cat("Minutes and hours for FS bootstrap", c(t.min, t.min/60), "\n")

## Minutes and hours for FS bootstrap 91.74937 1.529156

```

```

df0.fs <- subset(fs.est$df.pred, treat.recommend == 0)
df1.fs <- subset(fs.est$df.pred, treat.recommend == 1)

# ITT analysis
cox_itt <- summary(coxph(Surv(time_days, cens) ~ treat, data = fs.est$df.pred))$conf.int

# ITT estimates
resITT <- c(round(cox_itt[c(1, 3, 4)], 2), nrow(fs.est$df.pred))

# Forest Search Un-adjusted
Hstat <- c(unlist(H_estimates))[c(1, 3, 4)]
resH_obs <- c(c(Hstat), nrow(df0.fs))
# Bias-corrected
Hstat <- c(unlist(H_estimates))[c(5, 7, 8)]
resH_bc <- c(c(Hstat), nrow(df0.fs))

Hstat2 <- c(unlist(H_estimates))[c(5, 7, 8)]
Hstat2 <- round(Hstat2, 2)
a <- paste0(Hstat2[1], " [")
a <- paste0(a, Hstat2[2])
a <- paste0(a, ",")
a <- paste0(a, Hstat2[3])

```

```

a <- paste0(a, "]")
H_bc2 <- c(a)

# Un-adjusted
Hcstat <- c(unlist(Hc_estimates))[c(1, 3, 4)]
resHc_obs <- c(c(Hcstat), nrow(df1.fs))
# Bias-corrected
Hcstat <- c(unlist(Hc_estimates))[c(5, 7, 8)]
resHc_bc <- c(c(Hcstat), nrow(df1.fs))

Hcstat2 <- c(unlist(Hc_estimates))[c(5, 7, 8)]
Hcstat2 <- round(Hcstat2, 2)
a <- paste0(Hcstat2[1], " [")
a <- paste0(a, Hcstat2[2])
a <- paste0(a, ",")
a <- paste0(a, Hcstat2[3])
a <- paste0(a, "]")
Hc_bc2 <- c(a)

res <- rbind(resITT, resH_obs, resH_bc, resHc_obs, resHc_bc)

resf <- as.data.frame(res)

colnames(resf) <- c("HR Estimate", "Lower", "Upper", "$\\#$ Subjects")

rnH <- c("$\\hat{H}$", "$\\hat{H}_{bc}$")
rnHc <- c("$\\hat{H}^{c}$", "$\\hat{H}^{c}_{bc}$")
rnItt <- c("ITT")
rownames(resf) <- c(rnItt, rnH, rnHc)

```

```

# Resolve conflict with dplyr
library(conflicted)
group_rows <- kableExtra::group_rows

options(knitr.kable.NA = ".", format = "latex")
tab_actg <- kbl(resf, longtable = FALSE, align = "c", format = "latex", booktabs = TRUE,
  escape = F, digits = 3, caption = "\\label{tab:actg} ACTG-175 FS-Nsg Analysis: Cox hazard ratio (HR).
Cox model estimates are based on subgroups: The estimated subgroup $\\hat{H}$; and
the bootstrap ($B=2000$) bias-correction to $\\hat{H}$ estimates, denoted $\\hat{H}_{bc}$. Estimates for
The number of subjects in each population ($\\#$ Subjects) are listed.") %>%
  kable_styling(full_width = FALSE, font_size = 9, latex_options = "hold_position") %>%
  group_rows("ITT", 1, 1) %>%
  group_rows("H subgroup estimates", 2, 3) %>%
  group_rows("H-complement subgroup estimates", 4, 5)

```

```

t.done <- proc.time()[3]
t.min <- (t.done - t.start.all)/60
cat("Minutes and hours to finish", c(t.min, t.min/60), "\\n")

## Minutes and hours to finish 95.13622 1.585604

cat("Machine=", c(Sys.info()[[4]]), "\\n")

```

Table 1: ACTG-175 FS-Nsg Analysis: Cox hazard ratio (HR) estimates for the ITT population and subgroups H and H^c . Cox model estimates are based on subgroups: The estimated subgroup \hat{H} ; and the bootstrap ($B = 2000$) bias-correction to \hat{H} estimates, denoted \hat{H}_{bc} . Estimates for the complement H^c are defined analogously. The number of subjects in each population (# Subjects) are listed.

	HR Estimate	Lower	Upper	# Subjects
ITT				
ITT	0.900	0.690	1.160	1085
H subgroup estimates				
\hat{H}	2.615	1.075	6.359	124
\hat{H}_{bc}	1.662	1.354	2.039	124
H-complement subgroup estimates				
\hat{H}^c	0.800	0.611	1.048	961
\hat{H}_{bc}^c	0.908	0.712	1.158	961

```
## Machine= Mac-Studio-3.local

cat("Number of cores=", c(detectCores(logical = FALSE)), "\n")

## Number of cores= 10
```