# Anchored survival analysis

2024-09-30

### Loading R packages

```
# install.packages("maicplus")
library(maicplus)
```

Additional R packages for this vignette:

```
library(dplyr)
```

### Illustration using example data

This example reads in centered\_ipd\_twt data that was created in calculating\_weights vignette and uses adtte\_twt and pseudo\_ipd\_twt datasets to run survival analysis using the maic\_anchored function by specifying endpoint\_type = "tte".

Set up is very similar to unanchored\_survival vignette, except now that we have a common treatment between two trials. Common treatment has to have same name in the data and we need to specify additional parameter, trt\_common, in maic\_unanchored.

```
data(centered_ipd_twt)
data(adtte_twt)
data(pseudo_ipd_twt)
centered colnames <- c("AGE", "AGE SQUARED", "SEX MALE", "ECOGO", "SMOKE", "N PR THER MEDIAN")
centered_colnames <- pasteO(centered_colnames, "_CENTERED")</pre>
#### derive weights
weighted_data <- estimate_weights(</pre>
 data = centered_ipd_twt,
  centered_colnames = centered_colnames
# inferential result
result <- maic_anchored(</pre>
  weights_object = weighted_data,
  ipd = adtte_twt,
  pseudo_ipd = pseudo_ipd_twt,
  trt_ipd = "A",
  trt_agd = "B",
  trt_common = "C",
```

```
normalize_weight = FALSE,
endpoint_name = "Overall Survival",
endpoint_type = "tte",
eff_measure = "HR",
time_scale = "month",
km_conf_type = "log-log"
)
```

There are two summaries available in the result: descriptive and inferential. In the descriptive section, we have summaries from fitting survfit function. Note that restricted mean (rmean), median, and 95% CI are summarized in the time\_scale specified.

#### result\$descriptive\$summary

```
trt_ind treatment
##
                                    type records
                                                   n.max n.start
## 1
          C
                   C IPD, before matching
                                            500 500.0000 500.0000 500.00000
## 2
          Α
                   A IPD, before matching
                                            500 500.0000 500.0000 190.00000
                     IPD, after matching
          C
                   C
                                            500 199.4265 199.4265 199.42645
## 3
## 4
          Α
                   Α
                      IPD, after matching
                                            500 199.4265 199.4265
                                                                  65.68877
## 5
          С
                   С
                                            500 500.0000 500.0000 500.00000
                           AgD, external
## 6
          В
                   В
                           AgD, external
                                            300 300.0000 300.0000 178.00000
##
      events%
                 rmean se(rmean)
                                    median 0.95LCL
                                                     0.95UCL
## 1 100.00000 2.564797 0.11366994 1.836467 1.644765
                                                   2.045808
## 2 38.00000 8.709690 0.35514766 7.587627 6.278691 10.288538
## 3 100.00000 2.740925 0.18703870 1.815795 1.697526 2.292484
## 4 32.93885 10.166029 0.54999149 11.900015 7.815275 14.873786
## 6 59.33333 4.303551 0.33672602 2.746131 2.261125
# Not shown due to long output
# result$descriptive$survfit_ipd_before
# result$descriptive$survfit_ipd_after
# result$descriptive$survfit_pseudo
```

In the inferential section, we have the fitted models stored (i.e. survfit and coxph) and the results from the coxph models (i.e. hazard ratios and CI). Note that the p-values summarized are from coxph model Wald test and not from a log-rank test. Here is the overall summary.

#### result\$inferential\$summary

```
## case HR LCL UCL pval
## 1 AC 0.2216588 0.1867151 0.2631423 2.136650e-66
## 2 adjusted_AC 0.1761521 0.1288651 0.2407912 1.319486e-27
## 3 BC 0.5718004 0.4811989 0.6794607 2.143660e-10
## 4 AB 0.3876507 0.3039348 0.4944253 2.270430e-14
## 5 adjusted_AB 0.3080657 0.2155705 0.4402481 1.020976e-10
```

Here are models and results before adjustment.

```
result$inferential$fit$km_before
## Call: survfit(formula = Surv(TIME, EVENT) ~ ARM, data = ipd, conf.type = km_conf_type)
##
          n events median 0.95LCL 0.95UCL
## ARM=C 500
                500
                     55.9
                              50.1
                                      62.3
                190 230.9
## ARM=A 500
                             191.1
                                     313.2
result$inferential$fit$model_before
## Call:
## coxph(formula = Surv(TIME, EVENT) ~ ARM, data = ipd)
##
            coef exp(coef) se(coef)
                                      Z
## ARMA -1.50662  0.22166  0.08753 -17.21 <2e-16
## Likelihood ratio test=341.2 on 1 df, p=< 2.2e-16
## n= 1000, number of events= 690
result$inferential$fit$res_AC_unadj
## $est
## [1] -1.506616
## $se
## [1] 0.08752989
##
## $ci_1
## [1] 0.1867151
##
## $ci_u
## [1] 0.2631423
##
## $pval
## [1] 2.13665e-66
result$inferential$fit$res_AB_unadj
##
               result
                                 pvalue
## "0.39[0.30; 0.49]"
                                "<0.001"
Here are models and results after adjustment.
result$inferential$fit$km_after
## Call: survfit(formula = Surv(TIME, EVENT) ~ ARM, data = ipd, weights = ipd$weights,
##
       conf.type = km_conf_type)
##
                 n events median 0.95LCL 0.95UCL
        records
## ARM=C
             500 199 199.4
                            55.3
                                    51.7
                                              69.8
             500 199 65.7 362.2
## ARM=A
                                     237.9
                                             452.7
```

```
result$inferential$fit$model_after
## Call:
## coxph(formula = Surv(TIME, EVENT) ~ ARM, data = ipd, weights = weights,
##
       robust = TRUE)
##
##
           coef exp(coef) se(coef) robust se
## ARMA -1.7364
                   0.1762 0.1475
                                      0.1595 -10.89 <2e-16
## Likelihood ratio test=166.6 on 1 df, p=< 2.2e-16
## n= 1000, number of events= 690
result$inferential$fit$res_AC
## $est
## [1] -1.736407
##
## $se
## [1] 0.1594836
##
## $ci_1
## [1] 0.1288651
##
## $ci_u
## [1] 0.2407912
##
## $pval
## [1] 1.319486e-27
result$inferential$fit$res_AB
               result
                                  pvalue
                                "<0.001"
## "0.31[0.22; 0.44]"
```

## Using bootstrap to calculate standard errors

If bootstrap standard errors are preferred, we need to specify the number of bootstrap iteration (n\_boot\_iteration) in estimate\_weights function and proceed fitting maic\_anchored function. Now, the outputs include bootstrapped CI. Different types of bootstrap CI can be found by using parameter boot\_ci\_type.

```
weighted_data2 <- estimate_weights(
  data = centered_ipd_twt,
  centered_colnames = centered_colnames,
  n_boot_iteration = 100,
  set_seed_boot = 1234
)

result_boot <- maic_anchored(
  weights_object = weighted_data2,</pre>
```

```
ipd = adtte_twt,
pseudo_ipd = pseudo_ipd_twt,
trt_ipd = "A",
trt_agd = "B",
trt_common = "C",
normalize_weight = FALSE,
endpoint_name = "Overall Survival",
endpoint_type = "tte",
eff_measure = "HR",
boot_ci_type = "perc",
time_scale = "month",
km_conf_type = "log-log"
)
```

```
## $est
## [1] 0.3080657
##

## $se
## [1] NA
##

## $ci_1
## [1] 0.2102241
##

## $ci_u
## [1] 0.4148832
##

## $pval
## [1] NA
```