

Example run maicplus

Introduction

This package describes the steps required to perform a matching-adjusted indirect comparison (MAIC) analysis using the `maicplus` package in R where the endpoint of interest is either time-to-event (e.g. overall survival) or binary (e.g. objective tumor response).

The methods described in this document are based on those originally described by Signorovitch et al. 2010 and described in the National Institute for Health and Care Excellence (NICE) Decision Support Unit (DSU) Technical Support Document (TSD) 18. [signorovitch2010; phillippo2016a]

MAIC methods are often required when:

- There is no common comparator treatment to link a clinical trial of a new intervention to clinical trials of other treatments in a given disease area. For example if the only study of a new intervention is a single arm trial with no control group. This is commonly referred to as an unanchored MAIC.
- A common comparator is available to link a clinical trial of a new intervention to a clinical trial of one other treatment in a given disease area but there are substantial differences in patient demographic or disease characteristics that are believed to be treatment effect modifiers. This is commonly referred to as an anchored MAIC.

The premise of MAIC methods is to adjust for between-trial differences in patient demographic or disease characteristics at baseline. When a common treatment comparator or ‘linked network’ are unavailable, a MAIC assumes that differences between absolute outcomes that would be observed in each trial are entirely explained by imbalances in prognostic variables and treatment effect modifiers. Prognostic variables are those that are predictive of disease outcomes, independent of the treatment received. For example, older patients may have increased risk of death compared to younger patients. Treatment effect modifiers are those variables that influence the relative effect of one treatment compared to another. For example patients with a better performance status may experience a larger treatment benefit than those with a worse performance status. Under this assumption, every prognostic variable and every treatment effect modifier that is imbalanced between the two studies must be available. This assumption is generally considered very difficult to meet. [phillippo2016a] There are several ways of identifying prognostic variables/treatment effect modifiers to be used in the MAIC analyses, some of which include:

- Clinical expertise (when available to a project)
- Published papers/previous submissions (what has been identified in the disease area previously)
- Univariable/multivariable regression analyses to identify which covariates have a significant effect on the outcome
- Subgroup analyses of clinical trials may identify interactions between patient characteristics and the relative treatment effect

Theory behind MAIC

We will briefly go over the theory behind MAIC. For detailed information, see Signorovitch et al. 2010.

Let us define t_i to be the treatment patient i received. We assume $t_i = 0$ if the patient received intervention (IPD) and $t_i = 1$ if the patient received comparator treatment. The causal effect of treatment $T = 0$ vs $T = 1$ on the mean of the outcome Y can be estimated as below

$$\frac{\sum_{i=1}^n y_i(1 - t_i)w_i}{\sum_{i=1}^n (1 - t_i)w_i} - \bar{y}_1$$

where $w_i = \frac{Pr(T_i=1|x_i)}{Pr(T_i=0|x_i)}$ is the odds that patient i received treatment $T = 1$ vs $T = 0$ (i.e. enrolls in aggregate data study vs IPD study) given baseline characteristics x_i . Thus, the patients receiving $T = 0$ are re-weighted to match the distribution of patients receiving $T = 1$. Note that this causal effect would be the case when the outcome Y is continuous. If the outcome is binary, Y would be a proportion and we would use a link function such as logit to give us the causal effect in an odds ratio scale. As in propensity score methods, we may assume w_i to follow logistic regression form

$$w_i = \exp(x_i^T \beta)$$

However, in order to estimate β , we cannot use maximum likelihood approach because we do not have IPD for both trials. Instead, we use method of moments. We estimate β such that the weighted averages of the covariates in the IPD exactly matches the aggregate data averages. Mathematically speaking, we want to estimate β such that:

$$0 = \frac{\sum_{i=1}^n x_i \exp(x_i^T \hat{\beta})}{\sum_{i=1}^n \exp(x_i^T \hat{\beta})} - \bar{x}_{agg}$$

If the x_i contains all confounders and the logistic regression for w_i is correctly specified, we obtain a consistent estimate of the causal effect of intervention vs comparator treatment. Above equation is equivalent to

$$0 = \sum_{i=1}^n (x_i - \bar{x}_{agg}) \exp(x_i^T \hat{\beta})$$

We could transform transform IPD by subtracting the aggregate data means (this is why centering is needed when preprocessing).

$$0 = \sum_{i=1}^n x_i \exp(x_i^T \hat{\beta})$$

Note that this is the first derivative of

$$Q(\beta) = \sum_{i=1}^n \exp(x_i^T \hat{\beta})$$

which has second derivative

$$Q''(\beta) = \sum_{i=1}^n x_i x_i^T \exp(x_i^T \hat{\beta})$$

Since $Q''(\beta)$ is positive-definite for all β , $Q(\beta)$ is convex and any finite solution from the equation is unique and corresponds to the global minimum of $Q(\beta)$. Thus, we can use optimization methods to calculate β .

Example scenario

We present an unanchored MAIC of two treatments in lung cancer. The two endpoints being compared are overall survival (a time to event outcome) and objective response (a binary outcome). The data available are:

- Individual patient data from a single arm study
- Aggregate summary data for the comparator study
- Psuedo patient data from the comparator study. This is not required for the matching process but is needed to derive the relative treatment effects between the internal treatment and comparator treatment.

Preprocessing

Package load

```
# change directory
setwd("~/GitHub/maicplus")
devtools::load_all()

# devtools::install_github('hta-pharma/maicplus') library(maicplus)

library(dplyr) # this is used for data merging/cleaning. Package itself does not depend on dplyr

library(clubSandwich) # For robust standard error in logistic regression
library(sandwich)

library(survminer) # for ggsurvplot
library(ggplot2) # for ggplot functions
library(boot) # for bootstrapping
```

Preprocessing IPD

In this example scenario, age, sex, the Eastern Cooperative Oncology Group (ECOG) performance status, smoking status, and number of previous treatments have been identified as imbalanced prognostic variables/treatment effect modifiers.

This example reads in and combines data from three standard simulated data sets (adsl, adrs and adtte) which are saved as 'csv' files.

```
adsl <- read.csv(system.file("extdata", "adsl.csv", package = "maicplus", mustWork = TRUE))
adrs <- read.csv(system.file("extdata", "adrs.csv", package = "maicplus", mustWork = TRUE))
adtte <- read.csv(system.file("extdata", "adtte.csv", package = "maicplus", mustWork = TRUE))

# Data containing the matching variables
adsl <- adsl %>%
  mutate(SEX_MALE = ifelse(SEX == "Male", 1, 0)) %>%
  mutate(AGE_SQUARED = AGE^2)

# Could use built-in function for dummizing variables adsl <- dummize_ipd(adsl,
```

```

# dummize_cols=c('SEX'), dummize_ref_level=c('Female'))

# Response data
adrs <- adrs %>%
  filter(PARAM == "Response") %>%
  transmute(USUBJID, ARM, RESPONSE = AVAL)

# Time to event data (overall survival)
adtte <- adtte %>%
  filter(PARAMCD == "OS") %>%
  mutate(EVENT = 1 - CNSR) %>%
  transmute(USUBJID, ARM, TIME = AVAL, EVENT)

# Combine all ipd data
ipd <- adsl %>%
  full_join(adrs, by = c("USUBJID", "ARM")) %>%
  full_join(adtte, by = c("USUBJID", "ARM"))
head(ipd)

```

```

##      X USUBJID ARM AGE      SEX SMOKE ECOGO N_PR_THER SEX_MALE AGE_SQUARED RESPONSE
## 1 1      1    A  45   Male      0      0          4         1       2025         0
## 2 2      2    A  71   Male      0      0          3         1       5041         1
## 3 3      3    A  58   Male      1      1          2         1       3364         1
## 4 4      4    A  48 Female      0      1          4         0       2304         1
## 5 5      5    A  69   Male      0      1          4         1       4761         0
## 6 6      6    A  48 Female      0      1          4         0       2304         0
##      TIME EVENT
## 1 281.5195     0
## 2 500.0000     0
## 3 304.6406     0
## 4 102.4731     0
## 5 101.6632     0
## 6 237.0593     1

```

Preprocessing aggregate data

There are two ways of specifying aggregate data. One approach is to read in aggregate data using an excel spreadsheet. In the spreadsheet, possible variable types include mean, median, or standard deviation for continuous variables and count or proportion for binary variables. The naming should be followed by these suffixes accordingly: `_COUNT`, `_MEAN`, `_MEDIAN`, `_SD`, `_PROP`. Then, `process_agd` will convert the count into proportions.

Other way is to define data frame of aggregate data in R. If you do it this way, `_COUNT` prefix should not be specified and only proportion is allowed for binary variables. Other suffix names would be the same as the first approach.

Possible missingness in the binary variables should be accounted for by subtracting the denominator by the missing count i.e. $\text{proportion} = \text{count} / (N - \text{missing})$.

```

# Through excel spreadsheet target_pop <-
# read.csv(system.file('extdata', 'aggregate_data_example_1.csv', package =
# 'maicplus', mustWork = TRUE)) agd <- process_agd(target_pop)

```

```
# Second approach by defining a data frame in R
agd <- data.frame(STUDY = "Lung study", ARM = "Total", N = 300, AGE_MEAN = 51, AGE_MEDIAN = 49,
  AGE_SD = 3.25, SEX_MALE_PROP = 147/300, ECOGO_PROP = 0.4, SMOKE_PROP = 58/(300 -
    5), N_PR_THER_MEDIAN = 2)
```

Preprocessing aggregate data

```
#### prepare data
ipd_centered <- center_ipd(ipd = ipd, agd = agd)
head(ipd_centered)
```

```
##      X USUBJID ARM AGE      SEX SMOKE ECOGO N_PR_THER SEX_MALE AGE_SQUARED RESPONSE
## 1 1      1      A 45      Male      0      0          4          1      2025          0
## 2 2      2      A 71      Male      0      0          3          1      5041          1
## 3 3      3      A 58      Male      1      1          2          1      3364          1
## 4 4      4      A 48 Female      0      1          4          0      2304          1
## 5 5      5      A 69      Male      0      1          4          1      4761          0
## 6 6      6      A 48 Female      0      1          4          0      2304          0
##      TIME EVENT AGE_CENTERED AGE_MEDIAN_CENTERED AGE_SQUARED_CENTERED
## 1 281.5195      0          -6          -0.5          -586.5625
## 2 500.0000      0          20           0.5          2429.4375
## 3 304.6406      0           7           0.5           752.4375
## 4 102.4731      0          -3          -0.5          -307.5625
## 5 101.6632      0          18           0.5          2149.4375
## 6 237.0593      1          -3          -0.5          -307.5625
##      SEX_MALE_CENTERED ECOGO_CENTERED SMOKE_CENTERED N_PR_THER_MEDIAN_CENTERED
## 1              0.51          -0.4      -0.1966102              0.5
## 2              0.51          -0.4      -0.1966102              0.5
## 3              0.51           0.6       0.8033898             -0.5
## 4             -0.49           0.6      -0.1966102              0.5
## 5              0.51           0.6      -0.1966102              0.5
## 6             -0.49           0.6      -0.1966102              0.5
```

How to handle standard deviation aggregate summary

As described by Phillippo et al. 2016, balancing on both mean and standard deviation for continuous variables (where possible) may be considered in some cases. If a standard deviation is provided in the comparator population, preprocessing is done so that in the target population, $E(X^2)$ is calculated using the variance formula $Var(X) = E(X^2) - E(X)^2$. This $E(X^2)$ in the target population is matched with the IPD level data, which is why X^2 was calculated during the preprocessing stage of IPD.

How to handle median aggregate summary

If a median is provided, IPD is preprocessed to categorize the variable into a binary variable. All the values in the IPD that are higher than the comparator population median is assigned a value of 1. Conversely, all values that are lower are assigned a value of 0. Comparator population median is replaced by 0.5 to adjust to the categorization in the IPD data. The newly created IPD binary variable is matched so that the proportion is 0.5.

Calculating weights

```
# list variables that are going to be used to match
centered_colnames <- c("AGE", "AGE_SQUARED", "SEX_MALE", "ECOGO", "SMOKE", "N_PR_THER_MEDIAN")
centered_colnames <- paste0(centered_colnames, "_CENTERED")

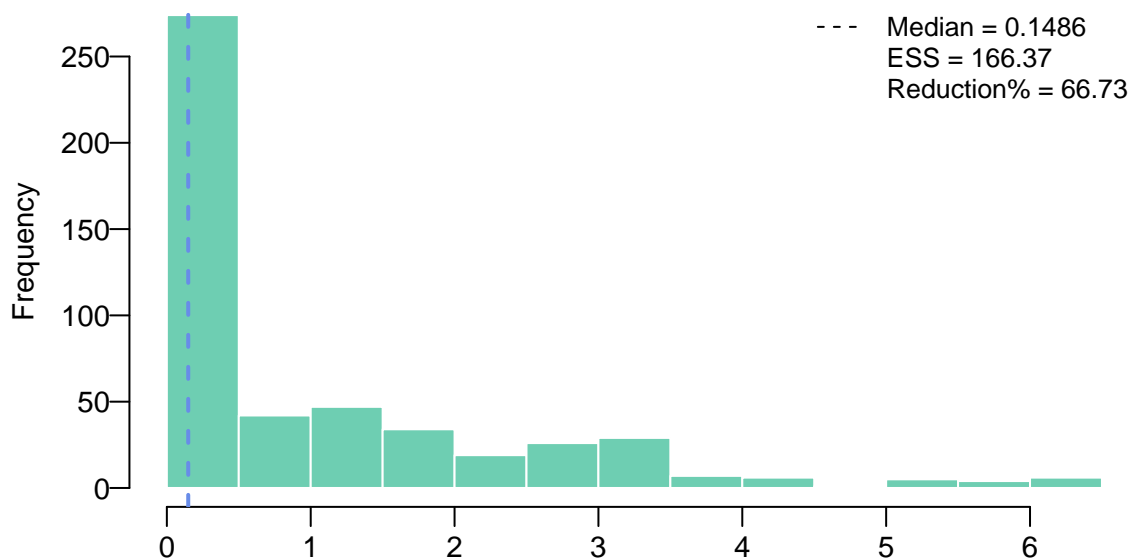
weighted_data <- estimate_weights(data = ipd_centered, centered_colnames = centered_colnames)

## initial value 500.000000
## iter 10 value 215.753747
## iter 20 value 199.844445
## final value 199.842237
## converged

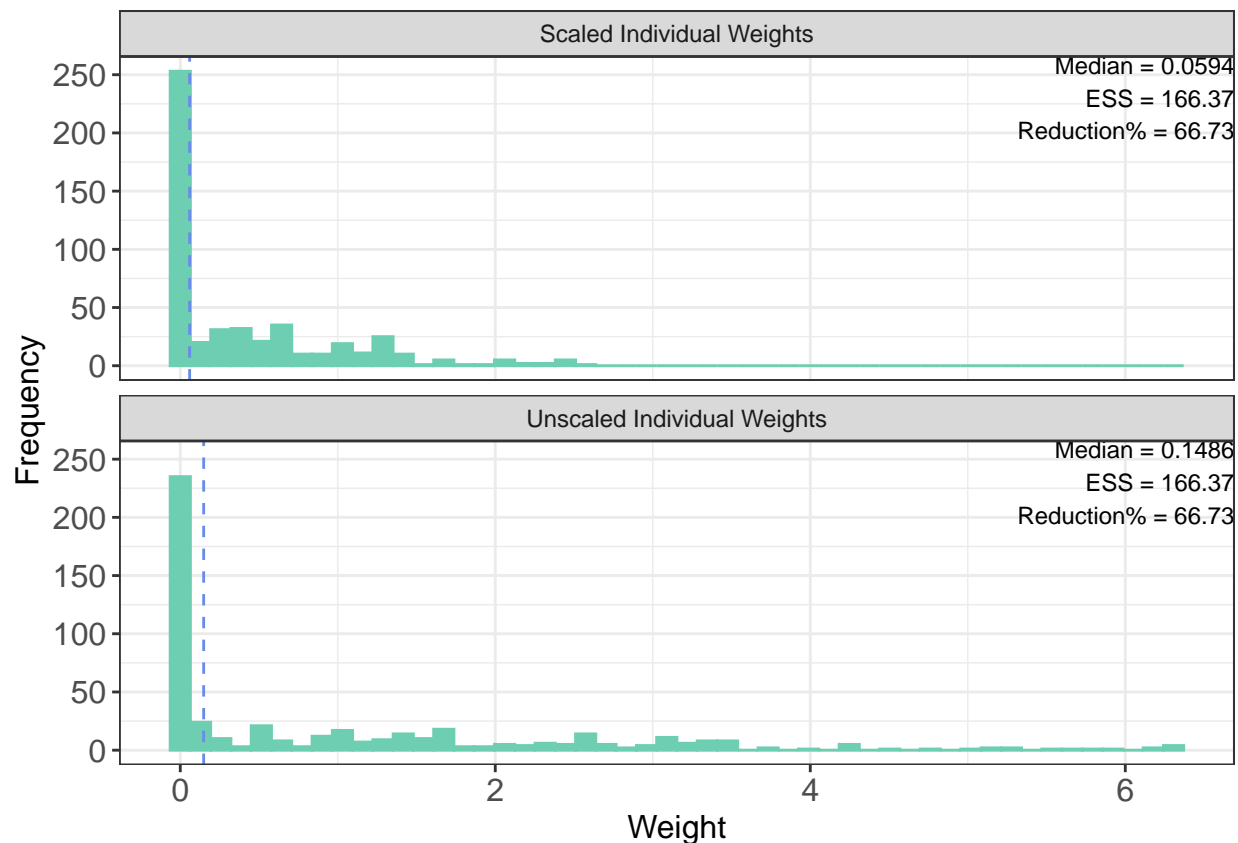
# Alternatively, you can specify the numeric column locations for
# centered_colnames weighted_data <- estimate_weights(ipd_centered,
# centered_colnames = c(14, 16:20))

# Two options to plot weights plot using base R or ggplot
plot(weighted_data)
```

Scaled Individual Weights



```
plot(weighted_data, ggplot = TRUE)
```



Another check after the weights are calculated is to look at how the weighted covariates match with the aggregate data summary.

```
outdata <- check_weights(weighted_data, agd)
outdata
```

```
##   covariate match_stat internal_trial internal_trial_after_weighted
## 1      AGE      Mean      59.850      51.00
## 2      AGE      SD       9.011       3.25
## 3  SEX_MALE      Prop       0.380       0.49
## 4    ECOGO      Prop       0.410       0.40
## 5    SMOKE      Prop       0.320       0.20
## 6  N_PR_THER      Median      3.000       2.00
##   external_trial sum_centered_IPD_with_weights
## 1          51.00          0.0001
## 2           3.25          0.0125
## 3           0.49          0.0000
## 4           0.40          0.0000
## 5           0.20          0.0000
## 6           2.00          0.0000
```

Time to event analysis

We first need to combine internal IPD data with pseudo comparator IPD. To obtain pseudo comparator IPD, we would digitize Kaplan Meier curves from the comparator study.

```

pseudo_ipd <- read.csv(system.file("extdata", "psuedo_IPD.csv", package = "maicplus",
  mustWork = TRUE))
ipd_matched <- weighted_data$data

# Need to specify pseudo_ipd ARM if not specified
pseudo_ipd$ARM <- "B" #Need to specify ARM for pseudo ipd

# Need to specify weights for pseudo_ipd which is 1
pseudo_ipd$weights <- 1

# make sure pseudo_ipd name has same name compared with ipd_matched for time,
# event, arm
colnames(pseudo_ipd) <- c("TIME", "EVENT", "ARM", "weights")

combined_data_tte <- rbind(ipd_matched[, colnames(pseudo_ipd)], pseudo_ipd)
combined_data_tte

```

##	TIME	EVENT	ARM	weights
## 1	281.5194863	0	A	6.884028e-01
## 2	500.0000000	0	A	5.669105e-08
## 3	304.6405555	0	A	1.146355e-01
## 4	102.4731386	0	A	1.178307e+00
## 5	101.6631927	0	A	1.605203e-06
## 6	237.0593233	1	A	1.178307e+00
## 7	337.3663345	0	A	7.020419e-01
## 8	180.6996302	1	A	1.076517e-02
## 9	156.3530945	0	A	4.281036e-01
## 10	126.0500878	0	A	1.794858e-01
## 11	2.9969434	0	A	1.887615e-03
## 12	189.3613424	0	A	1.315199e+00
## 13	137.1939184	1	A	4.172768e-01
## 14	0.4303082	1	A	2.829799e-03
## 15	238.4480442	0	A	2.447849e-01
## 16	64.6872731	0	A	9.795904e-05
## 17	62.6283981	0	A	1.831411e-11
## 18	61.8689337	1	A	8.304939e-01
## 19	172.9990508	0	A	3.727682e-01
## 20	500.0000000	0	A	1.320416e+00
## 21	404.9665031	1	A	4.664021e-01
## 22	8.6078129	1	A	1.222983e-03
## 23	2.6752029	1	A	4.966403e-01
## 24	37.1862175	1	A	1.146355e-01
## 25	72.3471050	1	A	1.409553e+00
## 26	149.0394051	0	A	1.452911e-02
## 27	271.3474961	0	A	1.375440e+00
## 28	132.7882079	0	A	5.493376e-01
## 29	124.8525835	1	A	6.432655e-05
## 30	115.1863723	0	A	2.321810e-01
## 31	391.6005114	0	A	2.344667e+00
## 32	53.9968261	0	A	2.180362e-02
## 33	125.7206051	0	A	4.878947e-05
## 34	500.0000000	0	A	6.854063e-01
## 35	313.1573766	1	A	3.446106e-02

## 36	198.6208194	1	A 6.991433e-11
## 37	168.8770094	1	A 9.458694e-10
## 38	97.4835043	1	A 2.690322e-10
## 39	120.7169260	0	A 1.314668e+00
## 40	87.4381573	1	A 6.724802e-02
## 41	117.0809444	1	A 1.431773e-02
## 42	7.4378994	1	A 4.590016e-01
## 43	53.9061795	0	A 5.227680e-10
## 44	42.4329399	0	A 6.346509e-06
## 45	22.8324762	1	A 1.228729e+00
## 46	152.6837825	0	A 3.311161e-08
## 47	5.1546502	1	A 3.325765e-07
## 48	13.8523925	0	A 2.527960e-03
## 49	317.5266710	0	A 2.085457e+00
## 50	222.4007682	0	A 1.403734e-10
## 51	7.2337488	1	A 6.755100e-01
## 52	60.2611923	0	A 1.854286e-06
## 53	176.9610656	1	A 5.079003e-01
## 54	12.6413833	1	A 1.074351e-11
## 55	63.5048707	0	A 8.304939e-01
## 56	329.3894821	0	A 6.906663e-01
## 57	54.6861744	0	A 5.844263e-09
## 58	187.3284384	0	A 2.069241e-01
## 59	108.2199961	0	A 1.024216e+00
## 60	16.0028888	0	A 2.000419e-01
## 61	59.6044136	0	A 1.797056e-09
## 62	176.6590842	1	A 1.633499e-02
## 63	49.6663522	0	A 3.284876e-11
## 64	87.2997415	1	A 4.649248e-07
## 65	326.3333469	1	A 9.256083e-01
## 66	173.9223130	1	A 2.403360e-10
## 67	59.3667629	0	A 3.706514e-08
## 68	500.0000000	0	A 6.791004e-01
## 69	101.2849073	0	A 6.374256e-06
## 70	500.0000000	0	A 2.334461e+00
## 71	12.7575511	1	A 3.311289e-07
## 72	170.4704706	0	A 4.020763e-01
## 73	379.0575377	0	A 9.296550e-01
## 74	295.6642687	0	A 2.321810e-01
## 75	180.0471671	1	A 1.375440e+00
## 76	88.3276166	0	A 3.723019e-06
## 77	230.9483853	1	A 5.016332e-02
## 78	19.5843537	0	A 1.993864e-01
## 79	67.6855902	0	A 2.177232e-01
## 80	187.2930109	1	A 1.472234e+00
## 81	205.1596244	0	A 3.601956e-03
## 82	133.9676829	0	A 8.268788e-01
## 83	99.3645367	0	A 4.185769e-06
## 84	152.3036359	1	A 2.229472e+00
## 85	158.5194710	1	A 4.994496e-02
## 86	203.4020672	1	A 5.913878e-01
## 87	336.8420868	1	A 7.925421e-07
## 88	25.6490953	0	A 1.950976e-07
## 89	352.4383084	0	A 9.919157e-09

## 90	33.8799882	0	A 6.725696e-01
## 91	15.8860250	0	A 1.105577e+00
## 92	245.3458498	1	A 9.375528e-07
## 93	425.2838139	0	A 9.795904e-05
## 94	28.5374060	0	A 1.797056e-09
## 95	94.0876845	1	A 4.690489e-10
## 96	109.4524597	0	A 5.706485e-03
## 97	313.3722027	0	A 5.517393e-01
## 98	50.3150662	1	A 1.294041e-05
## 99	52.4467296	1	A 3.841122e-01
## 100	10.2701408	0	A 6.619996e-01
## 101	6.8633253	0	A 3.711455e-01
## 102	11.1663130	1	A 1.213868e-01
## 103	208.5440529	0	A 3.727682e-01
## 104	453.8755271	0	A 8.460560e-06
## 105	13.7869996	0	A 8.460560e-06
## 106	350.2207221	1	A 7.792145e-11
## 107	89.6167692	1	A 2.885507e-09
## 108	0.2046028	0	A 9.458694e-10
## 109	30.8717178	1	A 2.186750e-01
## 110	280.3909651	0	A 4.153338e-07
## 111	84.7166775	0	A 9.364378e-01
## 112	8.3998372	0	A 1.409871e-10
## 113	135.1019149	0	A 3.739296e-06
## 114	126.7874323	0	A 1.699809e+00
## 115	174.5461325	1	A 1.427743e-06
## 116	161.5846889	1	A 7.104283e-06
## 117	66.0390115	0	A 2.065127e-01
## 118	104.5408470	0	A 6.409077e-04
## 119	209.6796639	1	A 5.644428e-08
## 120	1.2808132	0	A 9.375528e-07
## 121	45.4720260	0	A 3.178209e-04
## 122	43.6389358	0	A 5.394206e-04
## 123	13.1747627	0	A 1.052832e+00
## 124	204.8322250	1	A 2.403360e-10
## 125	76.2621398	1	A 2.520641e+00
## 126	179.5550296	0	A 7.104283e-06
## 127	153.0189691	0	A 4.994496e-02
## 128	2.0300958	0	A 6.235207e-02
## 129	168.2281259	1	A 1.649156e-08
## 130	55.0706664	0	A 1.605203e-06
## 131	31.4891944	0	A 4.033983e-01
## 132	168.4294215	0	A 2.495671e+00
## 133	213.0554394	1	A 3.807629e-04
## 134	58.1487885	1	A 3.821334e-01
## 135	139.0211403	0	A 1.223381e+00
## 136	104.1193509	0	A 6.991433e-11
## 137	46.1566080	0	A 1.846066e-08
## 138	158.4800477	0	A 3.401490e-04
## 139	295.1617767	1	A 1.524147e-05
## 140	42.5864914	0	A 1.052623e+00
## 141	127.9743928	0	A 1.950976e-07
## 142	34.0826279	0	A 5.818823e-09
## 143	93.3136053	0	A 9.476914e-01

## 144	39.6943191	0	A 1.854286e-06
## 145	418.5750209	1	A 3.807629e-04
## 146	108.9082910	0	A 9.674732e-08
## 147	105.0762188	1	A 2.065127e-01
## 148	56.6565761	1	A 4.185769e-06
## 149	80.5380440	1	A 7.745887e-01
## 150	142.4839370	0	A 1.074351e-11
## 151	189.7859562	1	A 6.820694e-01
## 152	44.5140716	0	A 5.016332e-02
## 153	30.8273271	1	A 2.002581e-01
## 154	10.2380585	1	A 4.690489e-10
## 155	214.0049455	0	A 3.722719e-08
## 156	12.6075825	0	A 9.458694e-10
## 157	185.7438835	0	A 1.216751e-01
## 158	210.5303223	0	A 6.949310e-02
## 159	35.8691523	1	A 2.157072e-11
## 160	28.2886213	0	A 3.401490e-04
## 161	42.1096005	1	A 8.859415e-01
## 162	132.0808389	0	A 2.103799e-03
## 163	158.7392013	0	A 1.409871e-10
## 164	208.5095081	1	A 6.409077e-04
## 165	124.8827926	1	A 1.223381e+00
## 166	66.0733700	0	A 4.051619e-01
## 167	18.0631542	0	A 4.033983e-01
## 168	35.7879285	0	A 1.048041e+00
## 169	35.6976157	1	A 3.824275e-04
## 170	344.6852715	0	A 1.001509e+00
## 171	130.7031601	0	A 9.919157e-09
## 172	75.4758943	1	A 9.597560e-12
## 173	79.9076509	0	A 1.942484e-07
## 174	3.8751813	0	A 4.944784e-01
## 175	56.6804001	0	A 2.241689e-01
## 176	88.0871919	0	A 5.559392e-01
## 177	40.1599769	0	A 1.329157e+00
## 178	11.3527364	1	A 6.342725e-03
## 179	8.7321192	0	A 2.971024e-07
## 180	81.6143745	1	A 1.216751e-01
## 181	48.3479226	0	A 1.314668e+00
## 182	62.6601429	0	A 1.699809e+00
## 183	187.8449785	0	A 2.392899e-10
## 184	114.1935322	1	A 1.222983e-03
## 185	500.0000000	0	A 2.024093e+00
## 186	151.8747627	1	A 9.458694e-10
## 187	43.0372554	0	A 2.736030e-01
## 188	58.9000652	0	A 3.325637e-08
## 189	44.1549084	1	A 1.084392e-01
## 190	39.9270162	1	A 6.066646e-01
## 191	10.3717562	1	A 1.433985e-06
## 192	25.5091635	1	A 6.961000e-11
## 193	500.0000000	0	A 6.235207e-02
## 194	108.9450103	0	A 1.707240e+00
## 195	101.7250316	0	A 1.334968e+00
## 196	56.4060157	0	A 4.590016e-01
## 197	129.6704036	1	A 1.279054e-02

## 198	47.0546355	0	A 1.302170e+00
## 199	169.4244480	1	A 2.527960e-03
## 200	20.9988640	0	A 3.078529e-02
## 201	6.5182421	0	A 2.065127e-01
## 202	66.0441764	0	A 1.431773e-02
## 203	329.8200403	0	A 4.020763e-01
## 204	130.9970045	1	A 5.874464e-02
## 205	32.8199139	0	A 6.007505e-02
## 206	111.9904588	1	A 2.598163e-05
## 207	259.3829166	0	A 6.457357e-01
## 208	48.0823337	0	A 3.538358e-06
## 209	373.8745493	0	A 4.944784e-01
## 210	500.0000000	0	A 5.417789e-04
## 211	25.5794699	1	A 2.430073e-02
## 212	362.2067038	1	A 1.003731e+00
## 213	49.2037680	1	A 2.447849e-01
## 214	12.3885075	0	A 1.079671e-01
## 215	71.2672138	0	A 1.228729e+00
## 216	3.3942755	1	A 1.237583e+00
## 217	34.0987472	0	A 2.929895e-02
## 218	91.9824456	1	A 1.452911e-02
## 219	320.7036093	1	A 3.325637e-08
## 220	178.5031223	0	A 7.712169e-01
## 221	116.0163469	0	A 1.100765e+00
## 222	134.5847123	0	A 6.345997e-08
## 223	246.1299544	0	A 1.409553e+00
## 224	132.8690671	0	A 3.401490e-04
## 225	25.3781343	0	A 9.971498e-01
## 226	180.2837518	0	A 3.603700e-01
## 227	12.8976681	1	A 1.105577e+00
## 228	48.7539111	1	A 3.723019e-06
## 229	254.5446271	1	A 2.157072e-11
## 230	8.3675931	1	A 1.223381e+00
## 231	30.4157094	1	A 1.186619e-10
## 232	32.3195134	0	A 5.746520e-05
## 233	5.8283381	1	A 1.403734e-10
## 234	409.5208072	0	A 5.706485e-03
## 235	80.7172811	0	A 9.971498e-01
## 236	29.5736758	0	A 5.706485e-03
## 237	88.3243550	1	A 8.642782e-08
## 238	16.6777043	1	A 1.452911e-02
## 239	201.8084701	1	A 9.919157e-09
## 240	310.0655345	0	A 6.991433e-11
## 241	4.0793628	0	A 4.118352e-01
## 242	1.2688996	1	A 8.670747e-01
## 243	33.3162513	0	A 2.233649e-04
## 244	70.2602449	0	A 2.678611e-10
## 245	5.4278376	0	A 2.430073e-02
## 246	50.1248807	0	A 3.841122e-01
## 247	85.1873869	0	A 3.416361e-04
## 248	464.9161960	1	A 2.898122e-09
## 249	26.3512119	0	A 1.838030e-08
## 250	23.2462453	1	A 3.416361e-04
## 251	54.6123914	0	A 2.311704e-01

##	252	204.7131962	0	A	1.024216e+00
##	253	221.0842591	1	A	4.966403e-01
##	254	126.8931381	0	A	1.649156e-08
##	255	6.8416124	1	A	1.584752e+00
##	256	39.5099966	0	A	6.854063e-01
##	257	303.3503769	0	A	2.251778e+00
##	258	103.3599337	0	A	7.591163e-06
##	259	73.0774123	0	A	4.918829e-09
##	260	15.2886098	0	A	4.500843e-01
##	261	144.5084460	1	A	9.555783e-12
##	262	227.9757161	0	A	3.416361e-04
##	263	233.3291179	0	A	3.294064e-02
##	264	10.9352310	0	A	2.166503e-11
##	265	284.9961410	0	A	1.459263e-02
##	266	119.6814391	0	A	6.066646e-01
##	267	153.7818843	0	A	1.356103e-01
##	268	41.5788383	0	A	2.069241e-01
##	269	17.1922456	0	A	7.080060e-07
##	270	12.1850070	0	A	2.484808e+00
##	271	301.7347889	0	A	3.841122e-01
##	272	93.7104093	0	A	1.052832e+00
##	273	414.9602508	1	A	1.228729e+00
##	274	203.2206009	0	A	6.961000e-11
##	275	81.0661957	0	A	4.643719e-01
##	276	135.8094446	1	A	5.888135e-01
##	277	113.1377720	0	A	3.401490e-04
##	278	406.0771660	0	A	8.605161e-08
##	279	136.1992022	1	A	3.189901e-05
##	280	110.6752035	0	A	2.112996e-03
##	281	282.6318510	0	A	1.431773e-02
##	282	245.5501089	0	A	3.807629e-04
##	283	101.3714715	0	A	1.605374e-09
##	284	14.6109023	1	A	3.062712e-01
##	285	3.2894058	0	A	2.009165e-01
##	286	20.4779808	0	A	4.167548e-06
##	287	0.3321626	1	A	6.991433e-11
##	288	178.9681939	0	A	1.524147e-05
##	289	27.2088851	0	A	1.101348e-04
##	290	211.4006422	0	A	1.052623e+00
##	291	30.7223985	1	A	6.820694e-01
##	292	60.0808303	0	A	1.626389e-02
##	293	99.6052279	0	A	9.416517e-07
##	294	86.9340820	0	A	1.362031e-01
##	295	191.1076682	1	A	2.241689e-01
##	296	311.8106687	1	A	1.369453e+00
##	297	55.6752080	1	A	7.591163e-06
##	298	20.9775017	1	A	3.217755e-03
##	299	89.1750066	0	A	1.315199e+00
##	300	39.8458329	0	A	4.185769e-06
##	301	204.6085827	0	A	1.902766e+00
##	302	34.5820833	0	A	3.586277e-03
##	303	37.8814246	0	A	2.074156e-01
##	304	88.6145506	0	A	1.950976e-07
##	305	98.5382896	1	A	3.603700e-01

## 306	237.8774307	1	A	6.906663e-01
## 307	76.6524844	1	A	1.279054e-02
## 308	91.8647559	0	A	9.919157e-09
## 309	51.6937890	0	A	2.484808e+00
## 310	29.5678669	0	A	9.962523e-09
## 311	71.2587985	1	A	6.409077e-04
## 312	145.2570428	1	A	1.058269e-01
## 313	249.9233069	0	A	1.935414e-11
## 314	131.4908055	1	A	1.926989e-11
## 315	312.7128096	1	A	2.392899e-10
## 316	22.6567004	1	A	1.478074e+00
## 317	96.7897325	0	A	5.517393e-01
## 318	103.3858997	1	A	5.888135e-01
## 319	34.5806822	1	A	6.725696e-01
## 320	56.7837124	0	A	1.699809e+00
## 321	311.0184998	0	A	8.633004e-01
## 322	63.9452407	0	A	5.097806e-03
## 323	173.7507167	0	A	6.547835e-01
## 324	4.6245131	0	A	3.619456e-01
## 325	52.2469200	1	A	1.048041e+00
## 326	93.2408592	0	A	1.329157e+00
## 327	101.6701105	0	A	6.176170e-01
## 328	247.7760192	0	A	8.375493e-07
## 329	43.3221132	0	A	1.048041e+00
## 330	130.9639163	0	A	5.843128e-01
## 331	89.7755695	1	A	5.016332e-02
## 332	37.7626359	1	A	1.571340e-10
## 333	236.1039880	0	A	4.020763e-01
## 334	5.5735189	0	A	5.394206e-04
## 335	15.9789179	0	A	1.074351e-11
## 336	219.5385758	0	A	5.120093e-03
## 337	122.1766793	0	A	5.669105e-08
## 338	85.2629108	1	A	5.843128e-01
## 339	72.1670941	1	A	9.971498e-01
## 340	49.3435304	1	A	8.728055e-03
## 341	84.3199651	0	A	8.375493e-07
## 342	102.0646836	0	A	5.818823e-09
## 343	99.9203054	0	A	1.273487e-02
## 344	105.9591180	0	A	1.409553e+00
## 345	341.3657643	0	A	2.311704e-01
## 346	61.1170188	1	A	1.192574e+00
## 347	273.1257002	0	A	1.228729e+00
## 348	83.7537322	0	A	1.302170e+00
## 349	287.8308610	0	A	7.228367e-01
## 350	85.1705400	0	A	9.962523e-09
## 351	500.0000000	0	A	6.374256e-06
## 352	60.6304562	0	A	1.228729e+00
## 353	405.1024439	0	A	4.038341e-01
## 354	10.3618326	0	A	1.228729e+00
## 355	13.8586577	0	A	3.807629e-04
## 356	222.7575312	0	A	6.143110e-01
## 357	12.9398765	0	A	2.231931e-01
## 358	71.8214219	0	A	1.840480e-01
## 359	28.0451023	1	A	9.435662e-01

## 360	217.0832170	1	A	1.995398e-04
## 361	30.4968240	1	A	4.172768e-01
## 362	37.0950110	0	A	6.176170e-01
## 363	15.8151577	0	A	4.154604e-01
## 364	9.1691822	0	A	6.755100e-01
## 365	128.8321170	1	A	9.375528e-07
## 366	68.7223284	0	A	1.713589e-05
## 367	23.2247571	0	A	9.364378e-01
## 368	500.0000000	0	A	1.121090e+00
## 369	12.0051551	1	A	6.034572e-01
## 370	70.5995378	0	A	5.669105e-08
## 371	128.1287128	0	A	7.104283e-06
## 372	173.8815563	0	A	1.375440e+00
## 373	147.5909236	1	A	1.307863e+00
## 374	106.7080111	0	A	1.112491e-04
## 375	72.1695415	1	A	5.517393e-01
## 376	100.0319960	0	A	1.707240e+00
## 377	21.5799492	1	A	2.243415e-04
## 378	129.3533244	0	A	3.244159e-09
## 379	1.9459751	1	A	2.430073e-02
## 380	50.8566442	1	A	9.417521e-10
## 381	169.4422522	1	A	2.829799e-03
## 382	141.6016337	0	A	1.024216e+00
## 383	500.0000000	0	A	2.495671e+00
## 384	67.3416893	1	A	2.784573e-02
## 385	293.6815759	1	A	4.051619e-01
## 386	170.5776237	1	A	9.375528e-07
## 387	74.4971040	0	A	6.724802e-02
## 388	252.7425757	0	A	6.754202e-02
## 389	370.3157123	1	A	1.116210e+00
## 390	18.4767328	0	A	8.268788e-01
## 391	242.3122311	0	A	1.184626e-01
## 392	108.6286686	0	A	8.304939e-01
## 393	135.1588000	1	A	1.459263e-02
## 394	13.4000154	1	A	9.458694e-10
## 395	50.6666237	1	A	4.994496e-02
## 396	181.3283312	0	A	3.299237e-11
## 397	13.0073322	0	A	2.004122e-04
## 398	357.7553493	0	A	6.346509e-06
## 399	180.9009377	1	A	5.517393e-01
## 400	242.1178978	0	A	2.992495e-01
## 401	60.2893293	0	A	4.500843e-01
## 402	93.4905863	0	A	1.649220e-07
## 403	52.7997845	1	A	4.051619e-01
## 404	350.2654152	0	A	5.120093e-03
## 405	241.1774392	0	A	2.094575e+00
## 406	8.7683064	0	A	1.192574e+00
## 407	330.7110893	0	A	1.713589e-05
## 408	48.4040249	0	A	7.300688e-01
## 409	77.9263829	0	A	2.066653e-06
## 410	16.1304526	0	A	7.745887e-01
## 411	9.3282041	0	A	3.416361e-04
## 412	164.7372721	1	A	6.149286e-01
## 413	366.6874542	1	A	5.559392e-01

## 414	38.5668907	0	A 3.311161e-08
## 415	21.8873529	0	A 1.786562e+00
## 416	20.9492488	0	A 8.670747e-01
## 417	174.2766212	1	A 1.636065e-11
## 418	57.1719156	0	A 9.971498e-01
## 419	41.6267738	1	A 6.550478e-01
## 420	15.8302898	1	A 3.164374e-04
## 421	86.8743175	1	A 1.995398e-04
## 422	350.3644114	0	A 2.243415e-04
## 423	241.5604544	1	A 1.452911e-02
## 424	318.7833017	1	A 8.642782e-08
## 425	359.1658176	0	A 1.302170e+00
## 426	14.1516358	1	A 4.500843e-01
## 427	104.8671198	0	A 9.555783e-12
## 428	158.0674152	0	A 5.888135e-01
## 429	53.4114635	1	A 2.971024e-07
## 430	52.6613128	1	A 4.669574e-07
## 431	402.2578995	0	A 6.381179e-04
## 432	2.4121713	0	A 1.846215e-06
## 433	189.4981770	1	A 1.100765e+00
## 434	4.2866692	0	A 6.949310e-02
## 435	256.4404196	0	A 2.177232e-01
## 436	452.7208595	1	A 1.409553e+00
## 437	31.7437313	0	A 3.807629e-04
## 438	370.0496553	0	A 3.807629e-04
## 439	299.0591141	0	A 3.401490e-04
## 440	134.9211996	0	A 1.024216e+00
## 441	34.0150132	1	A 6.409077e-04
## 442	36.3408479	1	A 2.447849e-01
## 443	133.8500312	0	A 1.713589e-05
## 444	332.3420058	0	A 6.342725e-03
## 445	23.7400288	0	A 6.169967e-01
## 446	343.7001138	1	A 2.032942e+00
## 447	222.9677203	0	A 7.826211e-11
## 448	76.9672003	1	A 3.693166e-11
## 449	389.5516777	1	A 2.321810e-01
## 450	174.7162274	0	A 2.447849e-01
## 451	363.8263817	1	A 5.493376e-01
## 452	19.6747055	1	A 4.944784e-01
## 453	19.9823259	0	A 1.636065e-11
## 454	10.2292442	0	A 2.243415e-04
## 455	326.7511055	0	A 2.004122e-04
## 456	20.0770245	1	A 2.074156e-01
## 457	36.0369583	1	A 3.325637e-08
## 458	184.0466008	1	A 5.669105e-08
## 459	76.6013852	1	A 5.270811e-02
## 460	207.4070734	0	A 5.101208e-01
## 461	154.3107802	0	A 1.307863e+00
## 462	106.6420898	1	A 4.051619e-01
## 463	205.0363326	1	A 5.746520e-05
## 464	20.9126041	1	A 3.078529e-02
## 465	18.6336849	0	A 5.197152e-01
## 466	136.3800132	1	A 3.739296e-06
## 467	316.3884586	0	A 2.186750e-01

## 468	141.3017821	0	A	3.217755e-03
## 469	13.2112969	0	A	9.770186e-03
## 470	99.6448581	0	A	1.742876e-07
## 471	135.2069709	1	A	6.149286e-01
## 472	61.6891086	0	A	3.059637e-01
## 473	101.1286638	0	A	1.100765e+00
## 474	166.2426128	1	A	1.307863e+00
## 475	79.8316941	0	A	3.349799e-01
## 476	234.7546470	0	A	2.032942e+00
## 477	94.7052270	0	A	6.345997e-08
## 478	168.1161018	1	A	6.547835e-01
## 479	146.5126322	0	A	1.048249e+00
## 480	500.0000000	0	A	6.034572e-01
## 481	130.1803275	0	A	1.735290e-07
## 482	39.2364700	1	A	4.185769e-06
## 483	67.4707314	1	A	2.509669e+00
## 484	89.4307290	1	A	4.020763e-01
## 485	101.4314849	0	A	6.346509e-06
## 486	245.8857517	0	A	6.876598e-01
## 487	117.1680451	1	A	1.189805e-01
## 488	143.3116393	1	A	1.232196e+00
## 489	382.6979071	1	A	6.342725e-03
## 490	33.8249243	0	A	3.294064e-02
## 491	157.0907872	0	A	1.846215e-06
## 492	15.7821636	1	A	1.448549e-05
## 493	87.0820950	1	A	3.804700e-01
## 494	190.6912802	1	A	3.706514e-08
## 495	49.8173522	0	A	1.052832e+00
## 496	215.4027340	1	A	5.844263e-09
## 497	111.1416159	1	A	5.219874e-01
## 498	17.0752816	1	A	1.846215e-06
## 499	98.2021703	1	A	4.020763e-01
## 500	97.5095606	1	A	6.754202e-02
## 501	20.2311676	1	B	1.000000e+00
## 502	28.7679537	1	B	1.000000e+00
## 503	41.0662129	0	B	1.000000e+00
## 504	0.8492261	1	B	1.000000e+00
## 505	9.0521882	0	B	1.000000e+00
## 506	3.4450075	1	B	1.000000e+00
## 507	88.7049039	0	B	1.000000e+00
## 508	75.5205919	0	B	1.000000e+00
## 509	102.0480708	0	B	1.000000e+00
## 510	61.1832674	0	B	1.000000e+00
## 511	44.6248777	1	B	1.000000e+00
## 512	417.7060892	0	B	1.000000e+00
## 513	188.0853029	1	B	1.000000e+00
## 514	135.4086771	1	B	1.000000e+00
## 515	14.4693075	1	B	1.000000e+00
## 516	19.2886739	1	B	1.000000e+00
## 517	253.9413828	0	B	1.000000e+00
## 518	18.8265045	1	B	1.000000e+00
## 519	42.5311133	0	B	1.000000e+00
## 520	203.2845550	0	B	1.000000e+00
## 521	32.2845542	1	B	1.000000e+00

## 522	3.0685160	1	B 1.000000e+00
## 523	53.3559798	1	B 1.000000e+00
## 524	69.5240787	0	B 1.000000e+00
## 525	38.8236166	1	B 1.000000e+00
## 526	204.6022754	0	B 1.000000e+00
## 527	184.5103590	0	B 1.000000e+00
## 528	83.5830935	0	B 1.000000e+00
## 529	114.7067767	1	B 1.000000e+00
## 530	31.4008382	1	B 1.000000e+00
## 531	65.7530859	0	B 1.000000e+00
## 532	163.6438166	1	B 1.000000e+00
## 533	103.4746398	0	B 1.000000e+00
## 534	115.6529216	0	B 1.000000e+00
## 535	119.8663712	1	B 1.000000e+00
## 536	39.7824824	0	B 1.000000e+00
## 537	26.2260987	1	B 1.000000e+00
## 538	168.2133266	1	B 1.000000e+00
## 539	77.4276997	0	B 1.000000e+00
## 540	113.1300571	0	B 1.000000e+00
## 541	341.8226476	0	B 1.000000e+00
## 542	4.6203917	1	B 1.000000e+00
## 543	76.1546928	1	B 1.000000e+00
## 544	31.3239259	1	B 1.000000e+00
## 545	139.8137748	1	B 1.000000e+00
## 546	26.2748075	1	B 1.000000e+00
## 547	78.8443008	0	B 1.000000e+00
## 548	150.1996343	0	B 1.000000e+00
## 549	7.5020884	1	B 1.000000e+00
## 550	27.0121949	1	B 1.000000e+00
## 551	157.8603589	1	B 1.000000e+00
## 552	196.4246807	0	B 1.000000e+00
## 553	21.6935437	0	B 1.000000e+00
## 554	140.2541753	1	B 1.000000e+00
## 555	12.1075238	0	B 1.000000e+00
## 556	107.3694875	1	B 1.000000e+00
## 557	37.8779261	1	B 1.000000e+00
## 558	121.0960158	0	B 1.000000e+00
## 559	20.3595135	1	B 1.000000e+00
## 560	41.0376828	0	B 1.000000e+00
## 561	27.4099098	1	B 1.000000e+00
## 562	14.2204744	1	B 1.000000e+00
## 563	49.0816396	1	B 1.000000e+00
## 564	91.8865159	1	B 1.000000e+00
## 565	20.8240812	0	B 1.000000e+00
## 566	19.7480647	1	B 1.000000e+00
## 567	13.4869944	0	B 1.000000e+00
## 568	297.0789867	1	B 1.000000e+00
## 569	35.3155408	1	B 1.000000e+00
## 570	61.3301293	1	B 1.000000e+00
## 571	236.3826316	0	B 1.000000e+00
## 572	37.6872463	1	B 1.000000e+00
## 573	12.4915818	0	B 1.000000e+00
## 574	117.1516860	1	B 1.000000e+00
## 575	74.0347874	1	B 1.000000e+00

## 576	31.8360820	1	B	1.000000e+00
## 577	6.1533491	0	B	1.000000e+00
## 578	58.6084245	1	B	1.000000e+00
## 579	3.7608198	0	B	1.000000e+00
## 580	32.1776180	1	B	1.000000e+00
## 581	123.7513692	1	B	1.000000e+00
## 582	191.6321564	1	B	1.000000e+00
## 583	49.7949898	0	B	1.000000e+00
## 584	95.9720009	0	B	1.000000e+00
## 585	35.3873079	0	B	1.000000e+00
## 586	93.7520019	1	B	1.000000e+00
## 587	8.2221920	1	B	1.000000e+00
## 588	69.4935935	1	B	1.000000e+00
## 589	115.3801046	0	B	1.000000e+00
## 590	201.1106058	0	B	1.000000e+00
## 591	101.8512269	1	B	1.000000e+00
## 592	16.3430735	0	B	1.000000e+00
## 593	73.2620925	1	B	1.000000e+00
## 594	20.9476736	0	B	1.000000e+00
## 595	13.2074189	1	B	1.000000e+00
## 596	133.1594500	0	B	1.000000e+00
## 597	6.7140516	1	B	1.000000e+00
## 598	2.0758651	0	B	1.000000e+00
## 599	155.7676131	1	B	1.000000e+00
## 600	324.6217046	0	B	1.000000e+00
## 601	57.1030595	1	B	1.000000e+00
## 602	3.6143976	1	B	1.000000e+00
## 603	35.3912534	0	B	1.000000e+00
## 604	48.2754867	1	B	1.000000e+00
## 605	24.2416986	0	B	1.000000e+00
## 606	3.2412819	1	B	1.000000e+00
## 607	77.1943697	0	B	1.000000e+00
## 608	401.8506175	1	B	1.000000e+00
## 609	52.2920989	0	B	1.000000e+00
## 610	14.2519825	0	B	1.000000e+00
## 611	195.5002523	1	B	1.000000e+00
## 612	3.1712902	1	B	1.000000e+00
## 613	58.4270646	1	B	1.000000e+00
## 614	18.5735263	1	B	1.000000e+00
## 615	59.6546380	1	B	1.000000e+00
## 616	6.4806603	1	B	1.000000e+00
## 617	75.1656036	1	B	1.000000e+00
## 618	1.7198339	1	B	1.000000e+00
## 619	84.2445319	0	B	1.000000e+00
## 620	18.3219669	0	B	1.000000e+00
## 621	27.3660973	0	B	1.000000e+00
## 622	23.8855711	0	B	1.000000e+00
## 623	68.8229804	1	B	1.000000e+00
## 624	18.9849356	1	B	1.000000e+00
## 625	37.3202892	1	B	1.000000e+00
## 626	48.0896160	1	B	1.000000e+00
## 627	78.4347848	1	B	1.000000e+00
## 628	128.6077718	0	B	1.000000e+00
## 629	91.3637782	1	B	1.000000e+00

## 630	56.9334980	1	B	1.000000e+00
## 631	13.9279249	1	B	1.000000e+00
## 632	3.0113133	1	B	1.000000e+00
## 633	53.6840931	0	B	1.000000e+00
## 634	109.4392228	1	B	1.000000e+00
## 635	27.8727602	0	B	1.000000e+00
## 636	31.3737925	1	B	1.000000e+00
## 637	36.6028967	0	B	1.000000e+00
## 638	34.0285658	1	B	1.000000e+00
## 639	49.9062966	1	B	1.000000e+00
## 640	47.1405277	0	B	1.000000e+00
## 641	101.0785894	1	B	1.000000e+00
## 642	93.6487147	1	B	1.000000e+00
## 643	20.8436242	1	B	1.000000e+00
## 644	3.4515079	1	B	1.000000e+00
## 645	29.8875161	1	B	1.000000e+00
## 646	63.3996256	0	B	1.000000e+00
## 647	230.9729773	1	B	1.000000e+00
## 648	364.3259341	1	B	1.000000e+00
## 649	12.2323488	1	B	1.000000e+00
## 650	159.8315468	0	B	1.000000e+00
## 651	258.5498424	1	B	1.000000e+00
## 652	24.9889490	0	B	1.000000e+00
## 653	63.0700888	1	B	1.000000e+00
## 654	320.4212314	1	B	1.000000e+00
## 655	90.6121802	1	B	1.000000e+00
## 656	160.7520774	0	B	1.000000e+00
## 657	28.8516511	0	B	1.000000e+00
## 658	8.7919587	0	B	1.000000e+00
## 659	27.1385849	1	B	1.000000e+00
## 660	38.2870764	1	B	1.000000e+00
## 661	7.4210626	0	B	1.000000e+00
## 662	13.6943879	1	B	1.000000e+00
## 663	139.8042160	1	B	1.000000e+00
## 664	170.6566002	0	B	1.000000e+00
## 665	114.2058151	1	B	1.000000e+00
## 666	172.4208727	0	B	1.000000e+00
## 667	39.0678457	1	B	1.000000e+00
## 668	16.0775600	0	B	1.000000e+00
## 669	62.4040822	1	B	1.000000e+00
## 670	95.9224128	1	B	1.000000e+00
## 671	31.0753223	1	B	1.000000e+00
## 672	7.3859528	1	B	1.000000e+00
## 673	13.5637730	0	B	1.000000e+00
## 674	25.3284722	0	B	1.000000e+00
## 675	215.0981459	1	B	1.000000e+00
## 676	13.9126408	1	B	1.000000e+00
## 677	220.6392416	1	B	1.000000e+00
## 678	82.5469181	0	B	1.000000e+00
## 679	10.3249249	0	B	1.000000e+00
## 680	114.4152727	0	B	1.000000e+00
## 681	67.4200893	1	B	1.000000e+00
## 682	16.5377021	1	B	1.000000e+00
## 683	21.4476172	0	B	1.000000e+00

## 684	163.3827108	1	B	1.000000e+00
## 685	114.8396735	0	B	1.000000e+00
## 686	33.7408843	1	B	1.000000e+00
## 687	72.9266499	1	B	1.000000e+00
## 688	85.2637815	1	B	1.000000e+00
## 689	12.7049720	0	B	1.000000e+00
## 690	33.5083467	1	B	1.000000e+00
## 691	64.9965467	1	B	1.000000e+00
## 692	62.4816013	1	B	1.000000e+00
## 693	32.6268562	1	B	1.000000e+00
## 694	230.5868701	1	B	1.000000e+00
## 695	40.2919970	0	B	1.000000e+00
## 696	38.4803842	1	B	1.000000e+00
## 697	116.5770227	1	B	1.000000e+00
## 698	11.9051673	1	B	1.000000e+00
## 699	34.7955872	1	B	1.000000e+00
## 700	48.1972482	1	B	1.000000e+00
## 701	84.6593786	0	B	1.000000e+00
## 702	210.0548161	0	B	1.000000e+00
## 703	32.3201275	0	B	1.000000e+00
## 704	47.8891543	1	B	1.000000e+00
## 705	94.4459064	1	B	1.000000e+00
## 706	27.1427844	1	B	1.000000e+00
## 707	75.4571413	0	B	1.000000e+00
## 708	13.0554772	1	B	1.000000e+00
## 709	1.4030134	1	B	1.000000e+00
## 710	150.6582394	1	B	1.000000e+00
## 711	80.4921978	0	B	1.000000e+00
## 712	102.1683344	1	B	1.000000e+00
## 713	44.9419892	0	B	1.000000e+00
## 714	232.5020784	0	B	1.000000e+00
## 715	2.7979480	0	B	1.000000e+00
## 716	64.5608166	0	B	1.000000e+00
## 717	67.5251343	1	B	1.000000e+00
## 718	129.1025209	1	B	1.000000e+00
## 719	500.0000000	0	B	1.000000e+00
## 720	19.5837178	0	B	1.000000e+00
## 721	70.1227875	0	B	1.000000e+00
## 722	22.5998941	1	B	1.000000e+00
## 723	83.5853505	1	B	1.000000e+00
## 724	8.6680839	1	B	1.000000e+00
## 725	129.7187580	1	B	1.000000e+00
## 726	19.3144386	0	B	1.000000e+00
## 727	333.8879947	1	B	1.000000e+00
## 728	51.2082623	1	B	1.000000e+00
## 729	46.6101451	0	B	1.000000e+00
## 730	73.6926698	1	B	1.000000e+00
## 731	34.3307012	0	B	1.000000e+00
## 732	76.4192775	1	B	1.000000e+00
## 733	2.9805455	0	B	1.000000e+00
## 734	127.4336784	0	B	1.000000e+00
## 735	3.4211613	0	B	1.000000e+00
## 736	54.9236065	1	B	1.000000e+00
## 737	294.1386975	1	B	1.000000e+00

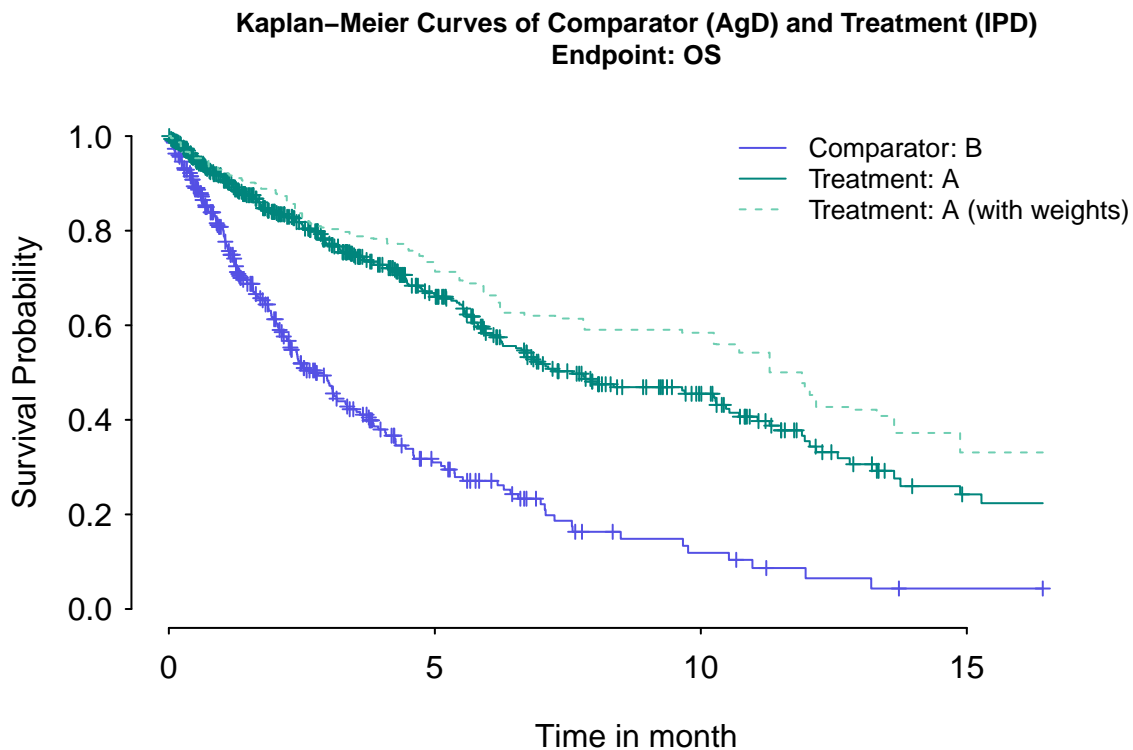
## 738	15.2915139	0	B 1.000000e+00
## 739	56.8481500	1	B 1.000000e+00
## 740	55.3458512	0	B 1.000000e+00
## 741	7.7622930	1	B 1.000000e+00
## 742	93.8619589	0	B 1.000000e+00
## 743	177.5091814	0	B 1.000000e+00
## 744	70.2628625	0	B 1.000000e+00
## 745	41.2949253	1	B 1.000000e+00
## 746	129.7250459	1	B 1.000000e+00
## 747	5.5211413	0	B 1.000000e+00
## 748	38.4697339	1	B 1.000000e+00
## 749	38.4278985	0	B 1.000000e+00
## 750	37.9046463	1	B 1.000000e+00
## 751	29.7580207	0	B 1.000000e+00
## 752	37.3557166	0	B 1.000000e+00
## 753	2.3393342	1	B 1.000000e+00
## 754	116.2388631	0	B 1.000000e+00
## 755	37.1140694	1	B 1.000000e+00
## 756	93.2119835	1	B 1.000000e+00
## 757	16.7345687	0	B 1.000000e+00
## 758	28.7863941	0	B 1.000000e+00
## 759	17.0540489	1	B 1.000000e+00
## 760	60.2527239	0	B 1.000000e+00
## 761	56.7171853	0	B 1.000000e+00
## 762	22.2428646	1	B 1.000000e+00
## 763	75.5904943	0	B 1.000000e+00
## 764	32.8579123	1	B 1.000000e+00
## 765	105.5323827	0	B 1.000000e+00
## 766	124.2150196	1	B 1.000000e+00
## 767	90.5420118	1	B 1.000000e+00
## 768	55.0154610	1	B 1.000000e+00
## 769	215.5597419	1	B 1.000000e+00
## 770	5.5773040	1	B 1.000000e+00
## 771	144.2521772	0	B 1.000000e+00
## 772	69.0486551	1	B 1.000000e+00
## 773	212.7464896	1	B 1.000000e+00
## 774	128.9828791	0	B 1.000000e+00
## 775	26.6127303	1	B 1.000000e+00
## 776	12.2191633	1	B 1.000000e+00
## 777	18.6707015	0	B 1.000000e+00
## 778	175.4929594	0	B 1.000000e+00
## 779	40.8238759	1	B 1.000000e+00
## 780	69.7451992	1	B 1.000000e+00
## 781	47.8510476	0	B 1.000000e+00
## 782	18.9679808	0	B 1.000000e+00
## 783	61.2068279	1	B 1.000000e+00
## 784	44.8460398	1	B 1.000000e+00
## 785	199.8426419	1	B 1.000000e+00
## 786	58.7730149	1	B 1.000000e+00
## 787	64.6149696	1	B 1.000000e+00
## 788	38.9656553	0	B 1.000000e+00
## 789	17.7346078	1	B 1.000000e+00
## 790	64.0457781	1	B 1.000000e+00
## 791	40.1446851	1	B 1.000000e+00

```
## 792 73.5593273      1 B 1.000000e+00
## 793 68.5812580      0 B 1.000000e+00
## 794 96.2560394      1 B 1.000000e+00
## 795 10.5896188      1 B 1.000000e+00
## 796 111.0420553     0 B 1.000000e+00
## 797 22.4233793      1 B 1.000000e+00
## 798  9.0396962      1 B 1.000000e+00
## 799 143.5751793     0 B 1.000000e+00
## 800 15.1259399      0 B 1.000000e+00
```

Report 1: Kaplan-Meier plot

```
kmobj <- survfit(Surv(TIME, EVENT) ~ ARM, combined_data_tte, conf.type = "log-log")
kmobj_adj <- survfit(Surv(TIME, EVENT) ~ ARM, combined_data_tte, weights = combined_data_tte$weights,
  conf.type = "log-log")

par(cex.main = 0.85)
km_plot(kmobj, kmobj_adj, time_scale = "month", trt = "A", trt_ext = "B", endpoint_name = "OS")
```



There is also a ggplot option for Kaplan-Meier curves using `survminer` R package.

```
# km_plot2(combined_data_tte, trt = 'A', trt_ext = 'B', censor = TRUE,
# risk.table = TRUE)
```

Report 2: Analysis table (Cox model) before and after matching, incl Median Survival Time

We can then fit a cox regression model using the combined dataset. For the weight adjusted cox regression, we fit the model with robust standard errors. Along with the hazard ratios, we can also find median survival time using `medSurv_makeup` function. Then, `report_table` function nicely combines the information together and create a result table.

```
# Fit a Cox model with/without weights to estimate the HR
unweighted_cox <- coxph(Surv(TIME, EVENT == 1) ~ ARM, data = combined_data_tte)
weighted_cox <- coxph(Surv(TIME, EVENT == 1) ~ ARM, data = combined_data_tte, weights = combined_data_tte$weight,
  robust = TRUE)

# Derive median survival time
medSurv <- medSurv_makeup(kmobj, legend = "before matching", time_scale = "day")
medSurv_adj <- medSurv_makeup(kmobj_adj, legend = "after matching", time_scale = "day")
medSurv_out <- rbind(medSurv, medSurv_adj)
medSurv_out
```

```
##      treatment      type records    n.max  n.start    events    rmean
## 1    ARM=A before matching    500 500.0000 500.0000 190.00000 265.1012
## 2    ARM=B before matching    300 300.0000 300.0000 178.00000 130.9893
## 3    ARM=A after matching    500 199.8422 199.8422  66.84953 307.7223
## 4    ARM=B after matching    300 300.0000 300.0000 178.00000 130.9893
##      se(rmean)   median  0.95LCL  0.95UCL
## 1  10.80981 230.94839 191.10767 313.1574
## 2  10.24910  83.58535  68.82298 101.0786
## 3  16.71338 362.20670 237.05932 452.7209
## 4  10.24910  83.58535  68.82298 101.0786
```

```
rbind(report_table(unweighted_cox, medSurv, tag = paste0("Before/", "Overall survival")),
  report_table(weighted_cox, medSurv_adj, tag = paste0("After/", "Overall survival")))
```

```
##      Matching treatment    N n.events(%)    median[95% CI]
## 2 Before/Overall survival  ARM=B 300.0    178(59.3)  83.6[ 68.8;101.1]
## 1 Before/Overall survival  ARM=A 500.0    190(38.0) 230.9[191.1;313.2]
## 21 After/Overall survival  ARM=B 300.0    178(59.3)  83.6[ 68.8;101.1]
## 11 After/Overall survival  ARM=A 199.8    66.8(33.5) 362.2[237.1;452.7]
##      HR[95% CI] WaldTest
## 2  2.67[2.16;3.29]    <0.001
## 1
## 21 3.46[2.53;4.74]    <0.001
## 11
```

Report 3: Bootstrap result

```
set.seed(1)
HR_bootstraps <- boot(data = ipd_centered, statistic = bootstrap_HR, centered_colnames = centered_colnames,
  pseudo_ipd = pseudo_ipd, model = Surv(TIME, EVENT == 1) ~ ARM, ref_treat = "B",
  R = 1000)
```



```

# Median of the bootstrap samples
HR_median <- median(HR_bootstraps$t)

# Bootstrap CI - Percentile CI
boot_ci_HR <- boot.ci(boot.out = HR_bootstraps, index = 1, type = "perc")

# Bootstrap CI - BCa CI
boot_ci_HR_BCA <- boot.ci(boot.out = HR_bootstraps, index = 1, type = "bca")

HR_median

```

```
## [1] 0.2858165
```

```
boot_ci_HR
```

```

## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 1000 bootstrap replicates
##
## CALL :
## boot.ci(boot.out = HR_bootstraps, type = "perc", index = 1)
##
## Intervals :
## Level      Percentile
## 95%      ( 0.2236,  0.3689 )
## Calculations and Intervals on Original Scale

```

```
boot_ci_HR_BCA
```

```

## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 1000 bootstrap replicates
##
## CALL :
## boot.ci(boot.out = HR_bootstraps, type = "bca", index = 1)
##
## Intervals :
## Level      BCa
## 95%      ( 0.2296,  0.3789 )
## Calculations and Intervals on Original Scale

```

Report 4: Diagnosis Plot

```

# grambsch & theanew ph test
coxdiag <- cox.zph(unweighted_cox, global = F, transform = "log")
coxdiag_adj <- cox.zph(weighted_cox, global = F, transform = "log")

coxdiag

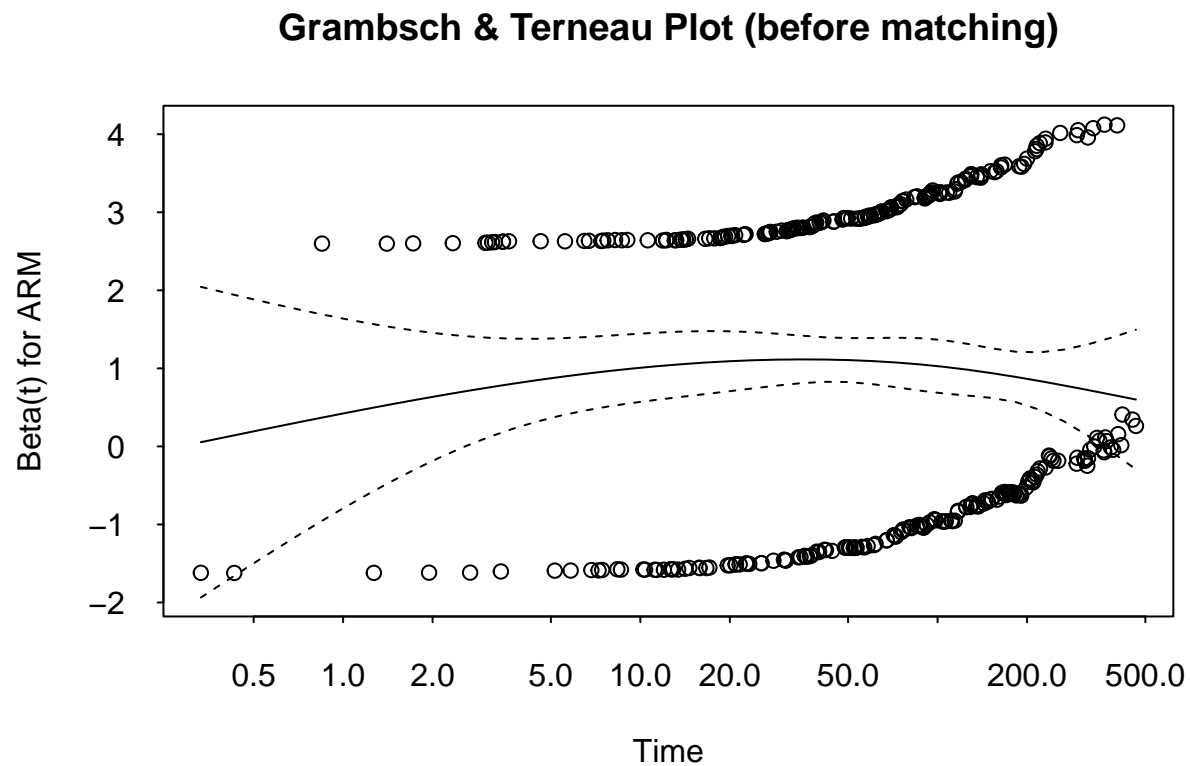
```

```

##          chisq df    p
## ARM 0.00996  1 0.92

```

```
par(mfrow = c(1, 1), tcl = -0.15)
plot(coxdiag, yaxt = "n", main = "Grambsch & Terneau Plot (before matching)")
axis(2, las = 1)
```

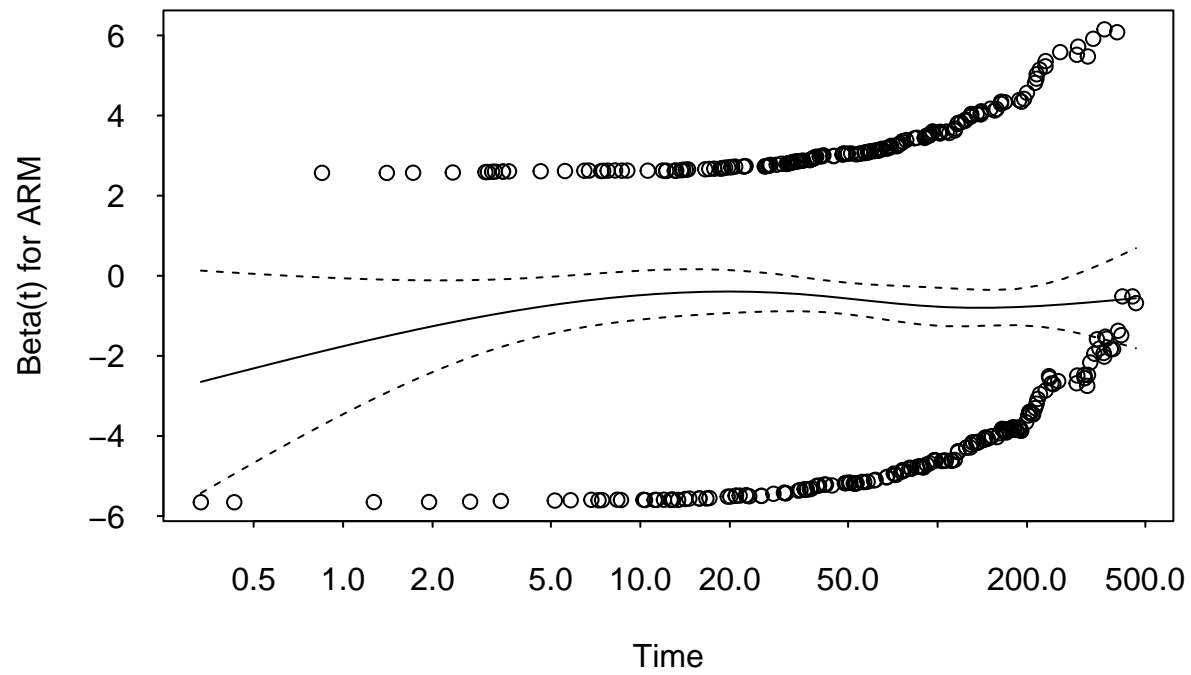


```
coxdiag_adj
```

```
##      chisq df    p
## ARM 0.0438  1 0.83
```

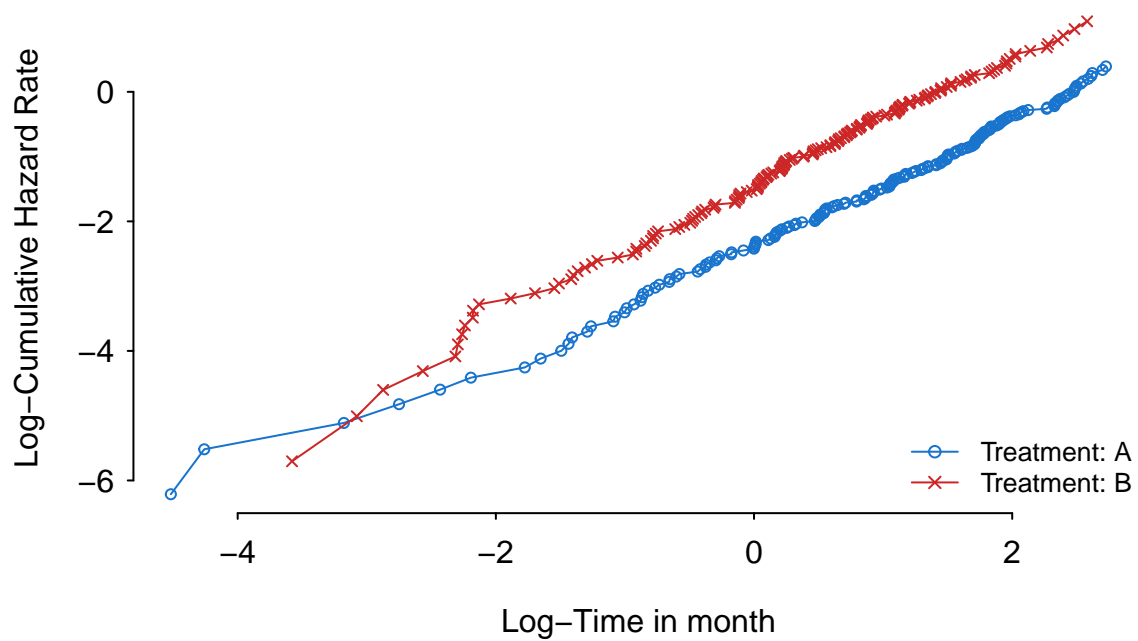
```
par(mfrow = c(1, 1), tcl = -0.15)
plot(coxdiag_adj, yaxt = "n", main = "Grambsch & Terneau Plot (after matching)")
axis(2, las = 1)
```

Grambsch & Terneau Plot (after matching)



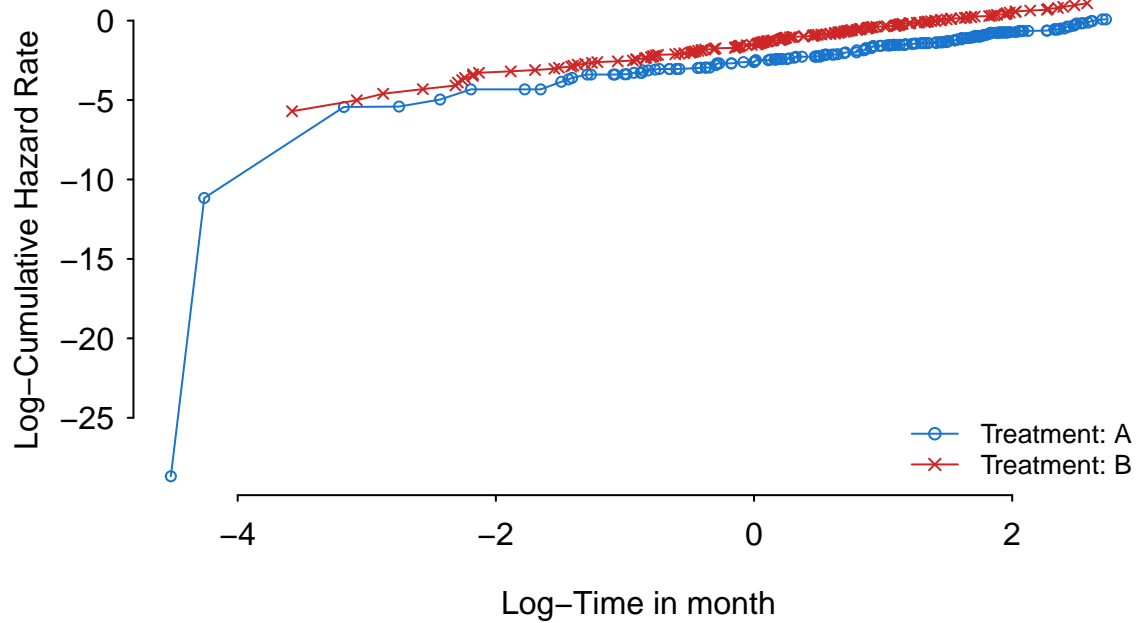
```
# log-cumulative hazard plot
log_cum_haz_plot(kmobj, time_scale = "month", log_time = TRUE, endpoint_name = "OS",
  subtitle = "(Before Matching)")
```

Diagnosis plot for Proportional Hazard assumption
Endpoint: OS
(Before Matching)



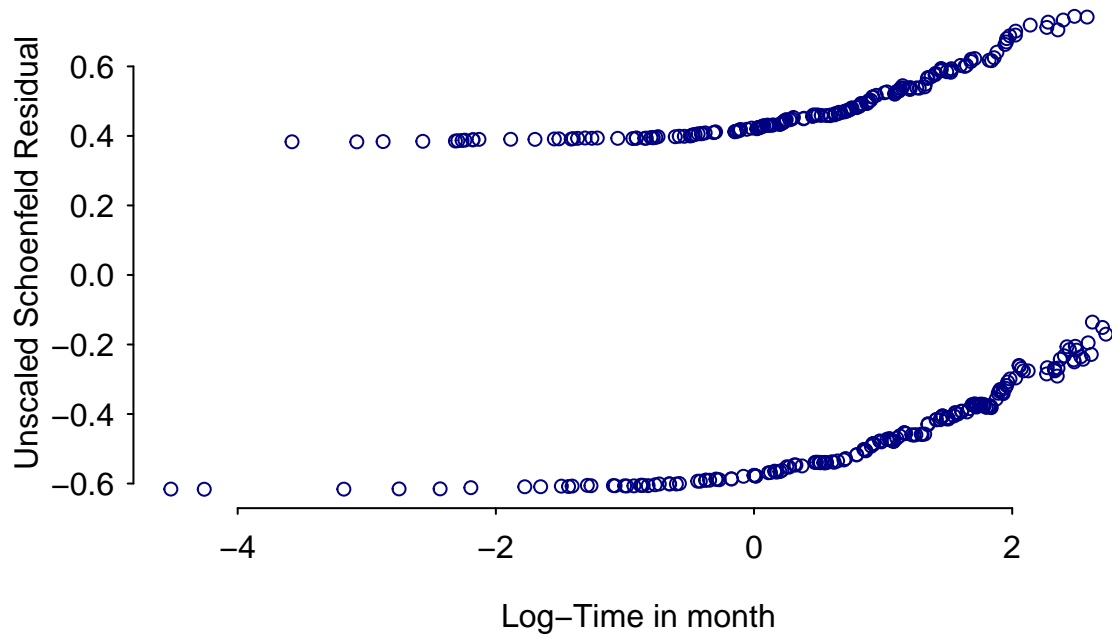
```
log_cum_haz_plot(kmobj_adj, time_scale = "month", log_time = TRUE, endpoint_name = "OS",  
  subtitle = "(After Matching)")
```

Diagnosis plot for Proportional Hazard assumption
Endpoint: OS
(After Matching)



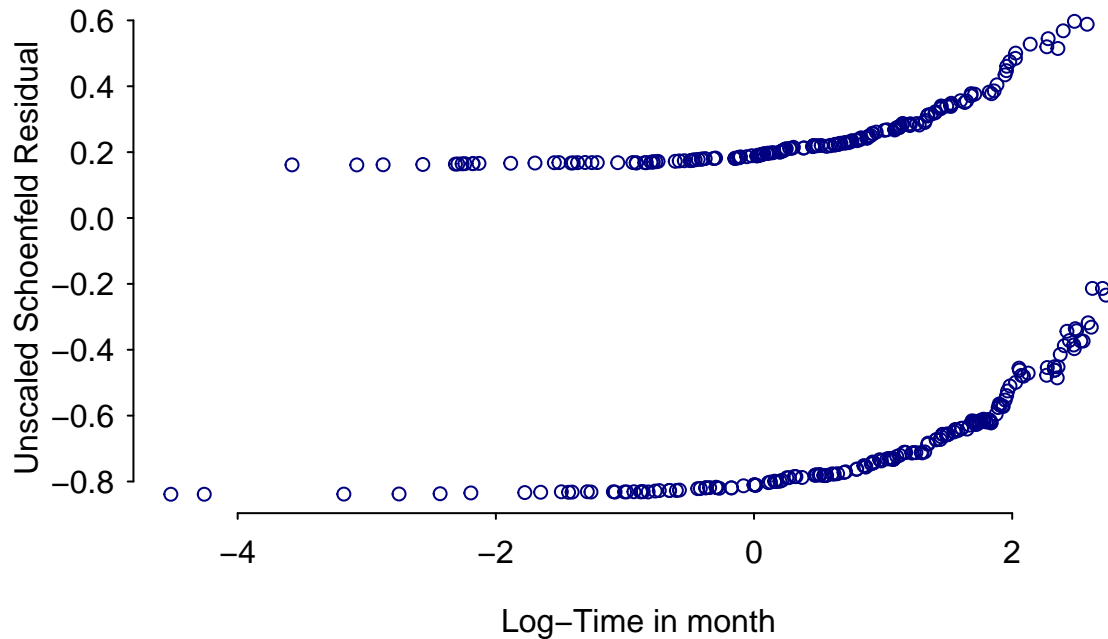
```
# schoenfeld residual plot  
resid_plot(unweighted_cox, time_scale = "month", log_time = TRUE, endpoint_name = "OS",  
           subtitle = "(Before Matching)")
```

Diagnostic Plot: Unscaled Schoenfeld Residual
Endpoint: OS
(Before Matching)



```
resid_plot(weighted_cox, time_scale = "month", log_time = TRUE, endpoint_name = "OS",  
           subtitle = "(After Matching)")
```

Diagnostic Plot: Unscaled Schoenfeld Residual Endpoint: OS (After Matching)



Analysis using a built-in wrapper

One can do all this analysis in a wrapper

```
# put in wrapper code
```

Binary outcome analysis (TODO)

```
# Simulate response data based on the known proportion of responders
comparator_prop_events <- 0.4

# Calculate number with event. Use round() to ensure we end up with a whole
# number of people. number without an event = Total N - number with event to
# ensure we keep the same number of patients
n_with_event <- round(agd$N * comparator_prop_events, digits = 0)
comparator_binary <- data.frame(RESPONSE = c(rep(1, n_with_event), rep(0, agd$N -
  n_with_event)))
comparator_binary$ARM <- "B" # need to specify ARM for comparator data
ipd_matched <- weighted_data$data

combined_data_binary <- merge_two_data(comparator_binary, ipd_matched, internal_response_name = "RESPONSE")
```

```

unweighted_OR <- glm(formula = RESPONSE ~ ARM, family = binomial(link = "logit"),
  data = combined_data_binary)

# Log odds ratio
log_OR_CI <- cbind(coef(unweighted_OR), confint.default(unweighted_OR, level = 0.95))[2,
]

# Odds ratio
OR_CI <- exp(log_OR_CI)
names(OR_CI) <- c("OR", "OR_low_CI", "OR_upp_CI")
OR_CI

# Fit a logistic regression model with weights to estimate the weighted OR
weighted_OR <- suppressWarnings(glm(formula = RESPONSE ~ ARM, family = binomial(link = "logit"),
  data = combined_data_binary, weight = weights))

# Weighted log odds ratio
log_OR_CI_wtd <- cbind(coef(weighted_OR), confint.default(weighted_OR, level = 0.95))[2,
]

# Weighted odds ratio
OR_CI_wtd <- exp(log_OR_CI_wtd)
names(OR_CI_wtd) <- c("OR", "OR_low_CI", "OR_upp_CI")
OR_CI_wtd

# Robust standard error
vmod <- clubSandwich::vcovCR(weighted_OR, cluster = 1:dim(combined_data_binary)[1],
  type = "CR2")
coef_res <- clubSandwich::conf_int(weighted_OR, vmod, coef = 2)

OR_CI_robust <- exp(with(coef_res, c(beta, CI_L, CI_U)))
names(OR_CI_robust) <- c("Estimate", "Lower 95% CI", "Upper 95% CI")
OR_CI_robust

# Using sandwich package
V.sw <- sandwich::vcovHC(weighted_OR) #white's estimator
SD <- sqrt(V.sw[2, 2])
Estimate <- coef(weighted_OR)[2]
OR_CI_robust2 <- exp(c(Estimate, Estimate - 1.96 * SD, Estimate + 1.96 * SD))
names(OR_CI_robust2) <- c("Estimate", "Lower 95% CI", "Upper 95% CI")
OR_CI_robust2

```