Package 'ICHe9r1'

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Type Package

Title Treatment effect estimation for time-to-event data under ICH E9 (R1)

Version 1.0.0

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Description Estimation and inference for the cumulative incidence function for time-to-event outcomes with intercurrent events under ICH E9 (R1).

URL https://github.com/mephas/ICHe9r1

Reference Deng, Y., Han, S., & Zhou, X. H. (2025). Inference for Cumulative Incidences and Treatment Effects in Randomized Controlled Trials With Time-to-Event Outcomes Under ICH E9 (R1). Statistics in Medicine. https://doi.org/10.1002/sim.70091

License GPL (>= 3)

Encoding UTF-8

LazyData True

RoxygenNote 7.3.2

Imports cmprsk,
MASS,
survival

Depends shiny,
shinythemes,
shinyWidgets,
DT,
R (>= 3.5),
psych

Suggests knitr,
rmarkdown

VignetteBuilder knitr

Contents

`bmt` *Data from Section 1.3 of Klein and Moeschberger (1997)*

Description

The `bmt` data frame has 137 rows and 22 columns.

Usage

```
bmt
```

Format

This data frame contains the following columns:

group Disease Group 1-ALL, 2-AML Low Risk, 3-AML High Risk

t1 Time To Death Or On Study Time

t2 Disease Free Survival Time (Time To Relapse, Death Or End Of Study)

d1 Death Indicator 1-Dead 0-Alive

d2 Relapse Indicator 1-Relapsed, 0-Disease Free

d3 Disease Free Survival Indicator 1-Dead Or Relapsed, 0-Alive Disease Free)

ta Time To Acute Graft-Versus-Host Disease

da Acute GVHDIndicator 1-Developed Acute GVHD 0-Never Developed Acute GVHD)

tc Time To Chronic Graft-Versus-Host Disease

dc Chronic GVHD Indicator 1-Developed Chronic GVHD 0-Never Developed Chronic GVHD

tp Time To Chronic Graft-Versus-Host Disease

dp Platelet Recovery Indicator 1-Platelets Returned To Normal, 0-Platelets Never Returned to Normal

z1 Patient Age In Years

z2 Donor Age In Years

z3 Patient Sex: 1-Male, 0-Female

z4 Donor Sex: 1-Male, 0-Female

z5 Patient CMV Status: 1-CMV Positive, 0-CMV Negative

z6 Donor CMVStatus: 1-CMV Positive, 0-CMV Negative

z7 Waiting Time to Transplant In Days

z8 FAB: 1-FAB Grade 4 Or 5 and AML, 0-Otherwise

z9 Hospital: 1-The Ohio State University, 2-Alferd, 3-St. Vincent, 4-Hahnemann

z10 MTX used as a Graft-Versus-Host-Prophylactic: 1-Yes 0-No

Source

Klein and Moeschberger (1997) Survival Analysis Techniques for Censored and Truncated Data, Springer.

Examples

```
## data(bmt)
```

`ICHe9r1Shiny` *Shiny for ICHe9r1*

Description

This function opens the Rshiny app for ICHe9r1

Usage

```
ICHe9r1Shiny()
```

Value

Rshiny inteface

Examples

```
if(interactive()){
  ICHe9r1Shiny()
}
```

plot.ICH *Plotting the estimated function*

Description

This function plots the estimated potential cumulative incidence function with pointwise confidence intervals.

Usage

```
## S3 method for class 'ICH'
plot(
  x,
  type = c("ate", "inc")[1],
  decrease = FALSE,
  conf.int = 0.95,
  nboot = 0,
  seed = 0,
  xlab = "Time",
  xlim = NULL,
  ylim = NULL,
  legend = c("Treated", "Control"),
  cex = 0.9,
  ...
)
```

Arguments

x	A fitted object from surv.ICH or scr.ICH.
type	Which plot to create: ate indicates to plot the estimated treatment effect; inc indicates to plot the estimated cumulative incidence function.
decrease	A logical variable indicating whether displaying the cumulative incidence function (decrease = FALSE) or survival function (decrease = TRUE).
conf.int	Level of the confidence interval. If conf.int = NULL, then the condifence interval will not be provided.
nboot	Number of resamplings in bootstrapping. Default nboot = 0, using the explicit formula of the standard error.
seed	Seed for bootstrapping.
xlab	Label for x-axis.
xlim	Limit for x-axis.
ylim	Limit for y-axis.
legend	Change the legend of the estimated cumulative incidence function plot. Only valid when type=inc.
cex	Size of legend.
...	Other augments in function plot.default or function curve

See Also

plot_ate, plot_inc

Examples

```
## load data
data(bmt)
bmt = transform(bmt, d4=d2+d3)
A = as.numeric(bmt$group>1)
## plot treatment effects with p-values
for (st in c('composite','natural','removed','whileon','principal')){
fit = surv.ICH(A, bmt$t2, bmt$d4, st)
plot(fit, type="inc", ylim=c(0,1))
p = fit$p.val
if (!is.null(p)) text(200, 0.8, paste0('P = ', round(p,3)))
}
## plot counterfactual cumulative incidence functions
for (st in c('composite','natural','removed','whileon','principal')){
fit = surv.ICH(A, bmt$t2, bmt$d4, st)
plot(fit, type="ate", ylim=c(0,1))
}
```

`plot_ate` *Plotting the estimated treatment effect*

Description

This function plots the estimated treatment effect (difference in potential cumulative incidences under treated and control) with pointwise confidence intervals.

Usage

```
plot_ate(
  fit,
  decrease = FALSE,
  conf.int = 0.95,
  nboot = 0,
  seed = 0,
  xlab = "Time",
  xlim = NULL,
  ylim = c(-1, 1),
  ...
)
```

Arguments

`fit`	A fitted object from `surv.ICH`.
`decrease`	A logical variable indicating whether to display the difference in cumulative incidence functions (`decrease = FALSE`) or survival functions (`decrease = TRUE`).
`conf.int`	Level of the confidence interval. If `conf.int = NULL`, then the condifence interval will not be provided.
`nboot`	Number of resamplings in bootstrapping. Default `nboot = 0`, using the explicit formula of the standard error.
`seed`	Seed for bootstrapping.

xlab	Label for x-axis.
xlim	Limit for x-axis.
ylim	Limit for y-axis.
...	Other augments in function plot.default or function curve

See Also

plot.default, points, curve, plot.ICH

Examples

```
## load data and fit the model
data(bmt)
bmt = transform(bmt, d4=d2+d3)
A = as.numeric(bmt$group>1)
fit = surv.ICH(A, bmt$t2, bmt$d4, 'composite')
## plot asymptotic confidence intervals based on explicit formulas
plot_ate(fit, legend=c('AML','ALL'), ylim=c(-0.4,0.4))
## plot bootstrap confidence intervals
plot_ate(fit, nboot=200, legend=c('AML','ALL'), ylim=c(-0.4,0.4))
```

---

plot_inc *Plotting the estimated cumulative incidence function*

Description

This function plots the estimated potential cumulative incidence function with pointwise confidence intervals.

Usage

```
plot_inc(
  fit,
  decrease = FALSE,
  conf.int = 0.95,
  nboot = 0,
  seed = 0,
  xlab = "Time",
  xlim = NULL,
  ylim = c(0, 1),
  legend = c("Treated", "Control"),
  cex = 0.9,
  ...
)
```

Arguments

fit	A fitted object from surv.ICH.
decrease	A logical variable indicating whether to display the cumulative incidence function (decrease = FALSE) or survival function (decrease = TRUE).

conf.int	Level of the confidence interval. If conf.int = NULL, then the condifence interval will not be provided.
nboot	Number of resamplings in bootstrapping. Default nboot = 0, using the explicit formula of the standard error.
seed	Seed for bootstrapping.
xlab	Label for x-axis.
xlim	Limit for x-axis.
ylim	Limit for y-axis.
legend	Legend.
cex	Size of legend.
...	Other augments in function plot.default or function curve

See Also

plot.default, points, curve, plot.ICH

Examples

```
## load data and fit the model
data(bmt)
bmt = transform(bmt, d4=d2+d3)
A = as.numeric(bmt$group>1)
fit = surv.ICH(A, bmt$t2, bmt$d4, 'composite')
## plot asymptotic confidence intervals based on explicit formulas
plot_inc(fit, legend=c('AML','ALL'), ylim=c(0,1))
## plot bootstrap confidence intervals
plot_inc(fit, nboot=200, legend=c('AML','ALL'), ylim=c(0,1))
```

---

scr.composite *Fitting the cumulative incidence function using composite variable strategy*

Description

This function nonparametrically estimates the potential cumulative incidence function using composite variable strategy (semicompeting risks data structure). This strategy adopts the first occurrence of either the intermediate or primary event as the event of interest.

Usage

```
scr.composite(
  A,
  Time,
  status,
  Time_int,
  status_int,
  weights = rep(1, length(A)),
  subset = NULL
)
```

Arguments

A	Treatment indicator, 1 for treatment and 0 for control.
Time	Time to the primary (terminal) event.
status	Indicator of the primary (terminal) event, 1 for event and 0 for censoring.
Time_int	Time to the intercurrent event.
status_int	Indicator of the intercurrent event, 1 for event and 0 for censoring.
weights	Weight for each subject.
subset	Subset, either numerical or logical.

Details

The composite variable strategy addresses the problem of intercurrent events by expanding the outcome variables. It aggregates the intercurrent event and the primary outcome event into a single composite outcome variable. The idea is not new in the context of progression-free survival, where the composite outcome variable is defined as the occurrence of either a non-terminal event (e.g., cancer progression) or a terminal event (e.g., death). One widely used composite outcome variable has the form $Q(w) = \min\{T(w), R(w)\}$ for $w = 1, 0$. When this simple form is adopted, the difference in counterfactual cumulative incidences is $\tau(t) = P(Q(1) < t) - P(Q(0) < t)$, representing the difference in probabilities of experiencing either intercurrent events or primary outcome events during $(0, t)$ under active treatment and placebo.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect based on logrank test.

See Also

scr.composite.eff, scr.ICH

`scr.composite.eff` *Fitting the cumulative incidence function using composite variable strategy*

Description

This function estimates the potential cumulative incidence function based on efficient influence functions using composite variable strategy (semicompeting risks data structure). Cox models are employed for survival models. This strategy adopts the first occurrence of either the intermediate or primary event as the event of interest.

Usage

```
scr.composite.eff(
  A,
  Time,
  status,
  Time_int,
  status_int,
  X = NULL,
  subset = NULL
)
```

Arguments

`A`	Treatment indicator, 1 for treatment and 0 for control.
`Time`	Time to the primary (terminal) event.
`status`	Indicator of the primary (terminal) event, 1 for event and 0 for censoring.
`Time_int`	Time to the intercurrent event.
`status_int`	Indicator of the intercurrent event, 1 for event and 0 for censoring.
`X`	Baseline covariates.
`subset`	Subset, either numerical or logical.

Details

The composite variable strategy addresses the problem of intercurrent events by expanding the outcome variables. It aggregates the intercurrent event and the primary outcome event into a single composite outcome variable. The idea is not new in the context of progression-free survival, where the composite outcome variable is defined as the occurrence of either a non-terminal event (e.g., cancer progression) or a terminal event (e.g., death). One widely used composite outcome variable has the form $Q(w) = \min\{T(w), R(w)\}$ for $w = 1, 0$. When this simple form is adopted, the difference in counterfactual cumulative incidences is $\tau(t) = P(Q(1) < t) - P(Q(0) < t)$, representing the difference in probabilities of experiencing either intercurrent events or primary outcome events during $(0, t)$ under active treatment and placebo.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect based on the efficient influence function of the restricted mean survival time lost by the end of study.

See Also

`scr.composite`, `scr.ICH`

---

scr.ICH *Fitting the cumulative incidence function for time-to-event data under ICH E9 (R1)*

Description

This function estimates the potential cumulative incidence function for time-to event data under ICH E9 (R1) to address intercurrent events. The input data should be of a semicompeting risks structure.

Usage

```
scr.ICH(
  A,
  Time,
  status,
  Time_int,
  status_int,
  strategy = "composite",
  cov1 = NULL,
  method = "np",
  weights = NULL,
  subset = NULL
)
```

Arguments

A	Treatment indicator, 1 for treatment and 0 for control.
Time	Time to the primary (terminal) event.
status	Indicator of the primary (terminal) event, 1 for event and 0 for censoring.
Time_int	Time to the intercurrent event.
status_int	Indicator of the intercurrent event, 1 for event and 0 for censoring.
strategy	Stragety to address intercurrent events, "treatment" indicating treatment policy strategy, "composite" indicating composite variable strategy, "natural" indicating hypothetical strategy (Scenario I, controlling the hazard of intercurrent events), "removed" indicating hypothetical strategy (Scenario II, removing intercurrent events), "whileon" indicating while on treatment strategy, and "principal" indicating principal stratum strategy.
cov1	Baseline covariates.
method	Estimation method, "np" indicating nonparametric estimation, "eff" indicating semiparametrically efficient estimation based on efficient influence functions.
weights	Weight for each subject.
subset	Subset, either numerical or logical.

Details

Background Intercurrent events refer to the events occurring after treatment initiation of clinical trials that affect either the interpretation of or the existence of the measurements associated with the clinical question of interest. The International Conference on Harmonization (ICH) E9 (R1) addendum proposed five strategies to address intercurrent events, namely, treatment policy strategy, composite variable strategy, while on treatment strategy, hypothetical strategy, and principal stratum strategy. To answer a specific scientific question, a strategy with a particular estimand is chosen before the study design.

Model We adopt the potential outcomes framework that defines a causal estimand as the contrast between functionals of potential outcomes. Consider a randomized controlled trial with n individuals randomly assigned to one of two treatment conditions, denoted by w, where $w = 1$ represents the active treatment (a test drug) and $w = 0$ represents the control (placebo). Assume that all patients adhere to their treatment assignments and do not discontinue treatment. Associated with individual $i = 1, ..., n$ are two potential time-to-event primary outcomes $T_i(1)$ and $T_i(0)$, if any, which represent the time durations from treatment initiation to the primary outcome event under two treatment assignments respectively. Let $R_i(1)$ and $R_i(0)$ denote the occurrence time of potential intercurrent events, if any, under the two treatment assignments, respectively. Intercurrent events are considered as absent if no post-treatment intercurrent events occur until the end of study.

Estimand We adopt the potential cumulative incidences under both treatment assignments as the target estimands. Potential cumulative incidences describe the probability of time-to-event outcomes occurring at each time point. We define the treatment effect as the contrast of two potential cumulative incidences. Cumulative incidences are model-free and collapsible, enjoying causal interpretations.

Value

A list including the fitted object and input variables.

See Also

surv.boot

Examples

```
## load data
data(bmt)
bmt = transform(bmt, d4=d2+d3)
A = as.numeric(bmt$group>1)
X = as.matrix(bmt[,c('z1','z3','z5')])
## Composite variable strategy,
## nonparametric estimation without covariates
fit1 = scr.ICH(A, bmt$t1, bmt$d1, bmt$t2, bmt$d2, "composite")
## Hypothetical strategy (natural effects),
## nonparametric estimation with inverse probability weighting
ps = predict(glm(A ~ X, family='binomial'), type='response')
w = A/ps + (1-A)/(1-ps)
fit2 = scr.ICH(A, bmt$t1, bmt$d1, bmt$t2, bmt$d2, "natural", X, weights=w)
## Hypothetical strategy (natural effects),
## semiparametrically efficient estimation with covariates
fit3 = scr.ICH(A, bmt$t1, bmt$d1, bmt$t2, bmt$d2, "natural", X, method='eff')
```

---

scr.natural *Fitting the cumulative incidence function using hypothetical strategy (I)*

Description

This function nonparametrically estimates the potential cumulative incidence function using hypothetical strategy (semicompeting risks data structure). The intercurrent event is only permitted under treated if it would occur under control.

Usage

```
scr.natural(
  A,
  Time,
  status,
  Time_int,
  status_int,
  weights = rep(1, length(A)),
  subset = NULL
)
```

Arguments

A	Treatment indicator, 1 for treatment and 0 for control.
Time	Time to the primary (terminal) event.
status	Indicator of the primary (terminal) event, 1 for event and 0 for censoring.
Time_int	Time to the intercurrent event.

status_int	Indicator of the intercurrent event, 1 for event and 0 for censoring.
weights	Weight for each subject.
subset	Subset, either numerical or logical.

Details

The hypothetical strategy envisions a hypothetical clinical trial condition where the occurrence of intercurrent events is restricted in certain ways. By doing so, the distribution of potential outcomes under the hypothetical scenario can capture the impact of intercurrent events explicitly through a pre-specified criterion. We use $T'(w), w = 1, 0$ to denote the time to the primary outcome event in the hypothetical scenario. The time-dependent treatment effect specific to this hypothetical scenario is written as $\tau(t) = P(T'(1) < t) - P(T'(0) < t)$, representing the difference in probabilities of experiencing primary outcome events during $(0, t)$ in the pre-specified hypothetical scenario under active treatment and placebo.
The key question is how to envision $T'(w)$. We manipulate the hazard specific to intercurrent event $\lambda_2(t; w)$ while assuming the hazard specific to the primary outcome event $\lambda_1(t; w)$ remains unchanged. Specifically, we envision that the intercurrent events that occurred when individuals were assigned to test drugs were only permitted if these intercurrent events would have also occurred if these individuals had been assigned to the placebo. In this hypothetical scenario, when assigned to placebo, individuals would be equally likely to experience intercurrent events as they are assigned to placebo in the real-world trial in terms of the hazards; when assigned to test drug, the hazard of intercurrent events would be identical to that if assigned to placebo in the real-world trial. That is, $\lambda_2'(t; 0) = \lambda_2'(t; 1) = \lambda_2(t; 0)$. The treatment effect corresponds to the natural direct effect, with the hazard of intercurrent events set at the level under control. Markovness is assumed in estimation.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect based on logrank test.

See Also

scr.natural.eff, scr.ICH

`scr.natural.eff` *Fitting the cumulative incidence function using hypothetical strategy (I)*

Description

This function estimates the potential cumulative incidence function based on efficient influence functions using hypothetical strategy (semicompeting risks data structure). Cox models are employed for survival models. The intercurrent event is only permitted under treated if it would occur under control.

Usage

```
scr.natural.eff(A, Time, status, Time_int, status_int, X = NULL, subset = NULL)
```

Arguments

`A`	Treatment indicator, 1 for treatment and 0 for control.
`Time`	Time to the primary (terminal) event.
`status`	Indicator of the primary (terminal) event, 1 for event and 0 for censoring.
`Time_int`	Time to the intercurrent event.
`status_int`	Indicator of the intercurrent event, 1 for event and 0 for censoring.
`X`	Baseline covariates.
`subset`	Subset, either numerical or logical.

Details

The hypothetical strategy envisions a hypothetical clinical trial condition where the occurrence of intercurrent events is restricted in certain ways. By doing so, the distribution of potential outcomes under the hypothetical scenario can capture the impact of intercurrent events explicitly through a pre-specified criterion. We use $T'(w)$, $w = 1, 0$ to denote the time to the primary outcome event in the hypothetical scenario. The time-dependent treatment effect specific to this hypothetical scenario is written as $\tau(t) = P(T'(1) < t) - P(T'(0) < t)$, representing the difference in probabilities of experiencing primary outcome events during $(0, t)$ in the pre-specified hypothetical scenario under active treatment and placebo.

The key question is how to envision $T'(w)$. We manipulate the hazard specific to intercurrent event $\lambda_2(t; w)$ while assuming the hazard specific to the primary outcome event $\lambda_1(t; w)$ remains unchanged. Specifically, we envision that the intercurrent events that occurred when individuals were assigned to test drugs were only permitted if these intercurrent events would have also occurred if these individuals had been assigned to the placebo. In this hypothetical scenario, when assigned to placebo, individuals would be equally likely to experience intercurrent events as they are assigned to placebo in the real-world trial in terms of the hazards; when assigned to test drug, the hazard of intercurrent events would be identical to that if assigned to placebo in the real-world trial. That is, $\lambda_2'(t; 0) = \lambda_2'(t; 1) = \lambda_2(t; 0)$. The treatment effect corresponds to the natural direct effect, with the hazard of intercurrent events set at the level under control. Markovness is assumed in estimation.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect based on the efficient influence function of the restricted mean survival time lost by the end of study.

See Also

`scr.natural`, `scr.ICH`

---

scr.principal *Fitting the cumulative incidence function using principal stratum strategy*

Description

This function nonparametrically estimates the potential cumulative incidence function using principal stratum strategy (semicompeting risks data structure). The estimand is defined in a subpopulation where intercurrent events would never occur regardless of treatment conditions.

Usage

```
scr.principal(
  A,
  Time,
  status,
  Time_int,
  status_int,
  weights = rep(1, length(A)),
  subset = NULL
)
```

Arguments

`A`	Treatment indicator, 1 for treatment and 0 for control.
`Time`	Time to the primary (terminal) event.
`status`	Indicator of the primary (terminal) event, 1 for event and 0 for censoring.
`Time_int`	Time to the intercurrent event.
`status_int`	Indicator of the intercurrent event, 1 for event and 0 for censoring.
`weights`	Weight for each subject.
`subset`	Subset, either numerical or logical.

Details

The principal stratum strategy aims to stratify the population into subpopulations based on the joint potential occurrences of intercurrent events under the two treatment assignments $(R(1), R(0))$. Suppose we are interested in a principal stratum comprised of individuals who would never experience intercurrent events, regardless of which treatment they receive. This principal stratum can be indicated by $\{R(1) = R(0) = \infty\}$. The treatment effect is now defined within this subpopulation, $\tau(t) = P(T(1) < t \mid R(1) = R(0) = \infty) - P(T(0) < t \mid R(1) = R(0) = \infty)$, representing the difference in probabilities of experiencing primary outcome events during $(0, t)$ under active treatment and placebo in the subpopulation that will not experience intercurrent events regardless of treatment during $(0, t)$. A principal ignorability assumption is made for identification.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect, which is not available under this strategy.

See Also

`scr.principal.eff`, `scr.ICH`

---

scr.principal.eff *Fitting the cumulative incidence function using principal stratum strategy*

Description

This function estimates the potential cumulative incidence function based on efficient influence functions using principal stratum strategy (semicompeting risks data structure). Cox models are employed for survival models. The estimand is defined in a subpopulation where intercurrent events would never occur regardless of treatment conditions.

Usage

```
scr.principal.eff(
  A,
  Time,
  status,
  Time_int,
  status_int,
  X = NULL,
  subset = NULL
)
```

Arguments

A	Treatment indicator, 1 for treatment and 0 for control.
Time	Time to the primary (terminal) event.
status	Indicator of the primary (terminal) event, 1 for event and 0 for censoring.
Time_int	Time to the intercurrent event.
status_int	Indicator of the intercurrent event, 1 for event and 0 for censoring.
X	Baseline covariates.
subset	Subset, either numerical or logical.

Details

The principal stratum strategy aims to stratify the population into subpopulations based on the joint potential occurrences of intercurrent events under the two treatment assignments $(R(1), R(0))$. Suppose we are interested in a principal stratum comprised of individuals who would never experience intercurrent events, regardless of which treatment they receive. This principal stratum can be indicated by $\{R(1) = R(0) = \infty\}$. The treatment effect is now defined within this subpopulation, $\tau(t) = P(T(1) < t \mid R(1) = R(0) = \infty) - P(T(0) < t \mid R(1) = R(0) = \infty)$, representing the difference in probabilities of experiencing primary outcome events during $(0, t)$ under active treatment and placebo in the subpopulation that will not experience intercurrent events regardless of treatment during $(0, t)$. A principal ignorability assumption is made for identification.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect based on the efficient influence function of the restricted mean survival time lost by the end of study.

See Also

scr.principal, scr.ICH

---

scr.removed *Fitting the cumulative incidence function using hypothetical strategy (II)*

Description

This function nonparametrically estimates the potential cumulative incidence function using hypothetical strategy (semicompeting risks data structure). The intercurrent event is assumed to be absent in the hypothetical scenario.

Usage

```
scr.removed(
  A,
  Time,
  status,
  Time_int,
  status_int,
  weights = rep(1, length(A)),
  subset = NULL
)
```

Arguments

A	Treatment indicator, 1 for treatment and 0 for control.
Time	Time to the primary (terminal) event.
status	Indicator of the primary (terminal) event, 1 for event and 0 for censoring.
Time_int	Time to the intercurrent event.
status_int	Indicator of the intercurrent event, 1 for event and 0 for censoring.
weights	Weight for each subject.
subset	Subset, either numerical or logical.

Details

The hypothetical strategy envisions a hypothetical clinical trial condition where the occurrence of intercurrent events is restricted in certain ways. By doing so, the distribution of potential outcomes under the hypothetical scenario can capture the impact of intercurrent events explicitly through a pre-specified criterion. We use $T'(w), w = 1, 0$ to denote the time to the primary outcome event in the hypothetical scenario. The time-dependent treatment effect specific to this hypothetical scenario is written as $\tau(t) = P(T'(1) < t) - P(T'(0) < t)$, representing the difference in probabilities of experiencing primary outcome events during $(0, t)$ in the pre-specified hypothetical scenario under active treatment and placebo.

The key question is how to envision $T'(w)$. We manipulate the hazard specific to intercurrent event $\lambda_2(t; w)$ while assuming the hazard specific to the primary outcome event $\lambda_1(t; w)$ remains unchanged. Specifically, we envision that intercurrent events are absent in the hypothetical scenario for all individuals, so $\lambda_2'(t; 0) = \Lambda_2'(t; 1) = 0$. This hypothetical scenario leads to an estimand called the marginal cumulative incidence. The treatment effect corresponds to the controlled direct effect with the intercurrent events removed.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect based on logrank test.

See Also

`scr.removed.eff`, `scr.ICH`

---

scr.removed.eff *Fitting the cumulative incidence function using hypothetical strategy (II)*

Description

This function estimates the potential cumulative incidence function based on efficient influence functions using hypothetical strategy (semicompeting risks data structure). Cox models are employedfor survival models. The intercurrent event is assumed to be absent in the hypothetical scenario.

Usage

```
scr.removed.eff(A, Time, status, Time_int, status_int, X = NULL, subset = NULL)
```

Arguments

`A`	Treatment indicator, 1 for treatment and 0 for control.
`Time`	Time to the primary (terminal) event.
`status`	Indicator of the primary (terminal) event, 1 for event and 0 for censoring.
`Time_int`	Time to the intercurrent event.
`status_int`	Indicator of the intercurrent event, 1 for event and 0 for censoring.
`X`	Baseline covariates.
`subset`	Subset, either numerical or logical.

Details

The hypothetical strategy envisions a hypothetical clinical trial condition where the occurrence of intercurrent events is restricted in certain ways. By doing so, the distribution of potential outcomes under the hypothetical scenario can capture the impact of intercurrent events explicitly through a pre-specified criterion. We use $T'(w)$, $w = 1, 0$ to denote the time to the primary outcome event in the hypothetical scenario. The time-dependent treatment effect specific to this hypothetical scenario is written as $\tau(t) = P(T'(1) < t) - P(T'(0) < t)$, representing the difference in probabilities of experiencing primary outcome events during $(0, t)$ in the pre-specified hypothetical scenario under active treatment and placebo.
The key question is how to envision $T'(w)$. We manipulate the hazard specific to intercurrent event $\lambda_2(t; w)$ while assuming the cause-specific hazard specific to the primary outcome event under no intercurrent events $\lambda_1(t; w)$ remains unchanged. Specifically, we envision that intercurrent events are absent in the hypothetical scenario for all individuals, so $\lambda_2'(t; 0) = \Lambda_2'(t; 1) = 0$. This hypothetical scenario leads to an estimand called the marginal cumulative incidence. The treatment effect corresponds to the controlled direct effect with the intercurrent events removed.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect based on the efficient influence function of the restricted mean survival time lost by the end of study.

See Also

`scr.removed`, `scr.ICH`

`scr.treatment` *Fitting the cumulative incidence function using treatment policy strategy*

Description

This function nonparametrically estimates the potential cumulative incidence function using treatment policy strategy (semicompeting risks data structure). This strategy ignores the intercurrent event and uses the time to the primary event as it was recorded.

Usage

```
scr.treatment(
  A,
  Time,
  status,
  Time_int,
  status_int,
  weights = rep(1, length(A)),
  subset = NULL
)
```

Arguments

A	Treatment indicator, 1 for treatment and 0 for control.
Time	Time to the primary (terminal) event.
status	Indicator of the primary (terminal) event, 1 for event and 0 for censoring.
Time_int	Time to the intercurrent event.
status_int	Indicator of the intercurrent event, 1 for event and 0 for censoring.
weights	Weight for each subject.
subset	Subset, either numerical or logical.

Details

The treatment policy strategy addresses the problem of intercurrent events by expanding the initial treatment conditions to a treatment policy. This strategy is applicable only if intercurrent events do not hinder primary outcome events. The treatments under comparison are now two treatment policies: $(w, R(w))$, where $w = 1, 0$. One policy $(1, R(1))$ involves administering the test drug, along with any naturally occurring intercurrents, whereas the other policy $(0, R(0))$ involves administering a placebo, along with any naturally occurring intercurrents. Thus, the potential outcomes are $T(1, R(1))$ and $T(0, R(0))$. Instead of comparing the test drug and placebo themselves, the contrast of interest is made between the two treatment policies. The difference in cumulative incidences under the two treatment policies is then $\tau(t) = P(T(1, R(1)) < t) - P(T(0, R(0)) < t)$, representing the difference in probabilities of experiencing primary outcome events during $(0, t)$ under active treatment and placebo.
The average treatment effect $\tau^{\text{tp}}(t)$ has a meaningful causal interpretation only when $T(1, R(1))$ and $T(0, R(0))$ are well defined. Because the treatment policy includes the occurrence of the intercurrent event as natural, the entire treatment policy is determined by manipulating the initial treatment condition w only. Therefore, we can simplify the notations $T(w, R(w)) = T(w)$ in defining estimands. As such, $\tau(t) = P(T(1)) < t) - P(T(0) < t)$ as the intention-to-treat analysis.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect based on logrank test.

See Also

`scr.treatment.eff`, `scr.ICH`

`scr.treatment.eff` *Fitting the cumulative incidence function using treatment policy strategy*

Description

This function estimates the potential cumulative incidence function based on efficient influence functions using treatment policy strategy (semicompeting risks data structure). Cox models are employed for the survival model. This strategy ignores the intercurrent event and uses the time to the primary event as it was recorded.

Usage

```
scr.treatment.eff(
  A,
  Time,
  status,
  Time_int,
  status_int,
  X = NULL,
  subset = NULL
)
```

Arguments

`A`	Treatment indicator, 1 for treatment and 0 for control.
`Time`	Time to the primary (terminal) event.
`status`	Indicator of the primary (terminal) event, 1 for event and 0 for censoring.
`Time_int`	Time to the intercurrent event.
`status_int`	Indicator of the intercurrent event, 1 for event and 0 for censoring.
`X`	Baseline covariates.
`subset`	Subset, either numerical or logical.

Details

The treatment policy strategy addresses the problem of intercurrent events by expanding the initial treatment conditions to a treatment policy. This strategy is applicable only if intercurrent events do not hinder primary outcome events. The treatments under comparison are now two treatment policies: $(w, R(w))$, where $w = 1, 0$. One policy $(1, R(1))$ involves administering the test drug, along with any naturally occurring intercurrents, whereas the other policy $(0, R(0))$ involves administering a placebo, along with any naturally occurring intercurrents. Thus, the potential outcomes are $T(1, R(1))$ and $T(0, R(0))$. Instead of comparing the test drug and placebo themselves, the contrast of interest is made between the two treatment policies. The difference in cumulative incidences under the two treatment policies is then $\tau(t) = P(T(1, R(1)) < t) - P(T(0, R(0)) < t)$, representing the difference in probabilities of experiencing primary outcome events during $(0, t)$ under active treatment and placebo.
The average treatment effect $\tau^{\text{tp}}(t)$ has a meaningful causal interpretation only when $T(1, R(1))$ and $T(0, R(0))$ are well defined. Because the treatment policy includes the occurrence of the intercurrent event as natural, the entire treatment policy is determined by manipulating the initial treatment condition w only. Therefore, we can simplify the notations $T(w, R(w)) = T(w)$ in defining estimands. As such, $\tau(t) = P(T(1)) < t) - P(T(0) < t)$ as the intention-to-treat analysis.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect based on the efficient influence function of the restricted mean survival time lost by the end of study.

See Also

`scr.treatment`, `scr.ICH`

---

scr.whileon *Fitting the cumulative incidence function using while on treatment strategy*

Description

This function nonparametrically estimates the potential cumulative incidence function using while on treatment strategy (semicompeting risks data structure). This strategy can be understood as the competing risks model, which gives the subdistribution of the primary event.

Usage

```
scr.whileon(
  A,
  Time,
  status,
  Time_int,
  status_int,
  weights = rep(1, length(A)),
  subset = NULL
)
```

Arguments

A	Treatment indicator, 1 for treatment and 0 for control.
Time	Time to the primary (terminal) event.
status	Indicator of the primary (terminal) event, 1 for event and 0 for censoring.
Time_int	Time to the intercurrent event.
status_int	Indicator of the intercurrent event, 1 for event and 0 for censoring.
weights	Weight for each subject.
subset	Subset, either numerical or logical.

Details

The while on treatment strategy considers the measure of outcome variables taken only up to the occurrence of intercurrent events. The failures of primary outcome events should not be counted in the cumulative incidences if intercurrent events occurred. The difference in counterfactual cumulative incidences under this strategy is $\tau(t) = P(T(1) < t, R(1) \geq t) - P(T(0) < t, R(0) \geq t)$, representing the difference in probabilities of experiencing primary outcome events without intercurrent events during $(0, t)$ under active treatment and placebo. The cumulative incidence function is also known as the cause-specific cumulative incidence or subdistribution function.

The while on treatment strategy is closely related to the competing risks model. However, for causal interpretations, it is worth emphasizing that the hazard of $R(1)$ may differ from that of $R(0)$, leading to vast difference in the underlying features of individuals who have not experienced the primary outcome event between treatment conditions until any time $t \in (0, t^*)$, where t^* is the end of study. When the scientific question of interest is the impact of treatment on the primary outcome event, the estimand $\tau(t)$ is hard to interpret if systematic difference in the risks of intercurrent events between two treatment conditions under comparison is anticipated.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect based on Gray test.

See Also

scr.whileon.eff, scr.ICH

`scr.whileon.eff` *Fitting the cumulative incidence function using while on treatment strategy*

Description

This function estimates the potential cumulative incidence function based on efficient influence functions using while on treatment strategy (semicompeting risks data structure). Cox models are employed for survival models. This strategy can be understood as the competing risks model, which gives the subdistribution of the primary event.

Usage

```
scr.whileon.eff(A, Time, status, Time_int, status_int, X = NULL, subset = NULL)
```

Arguments

`A`	Treatment indicator, 1 for treatment and 0 for control.
`Time`	Time to the primary (terminal) event.
`status`	Indicator of the primary (terminal) event, 1 for event and 0 for censoring.
`Time_int`	Time to the intercurrent event.
`status_int`	Indicator of the intercurrent event, 1 for event and 0 for censoring.
`X`	Baseline covariates.
`subset`	Subset, either numerical or logical.

Details

The while on treatment strategy considers the measure of outcome variables taken only up to the occurrence of intercurrent events. The failures of primary outcome events should not be counted in the cumulative incidences if intercurrent events occurred. The difference in counterfactual cumulative incidences under this strategy is $\tau(t) = P(T(1) < t, R(1) \geq t) - P(T(0) < t, R(0) \geq t)$, representing the difference in probabilities of experiencing primary outcome events without intercurrent events during $(0, t)$ under active treatment and placebo. The cumulative incidence function is also known as the cause-specific cumulative incidence or subdistribution function.

The while on treatment strategy is closely related to the competing risks model. However, for causal interpretations, it is worth emphasizing that the hazard of $R(1)$ may differ from that of $R(0)$, leading to vast difference in the underlying features of individuals who have not experienced the primary outcome event between treatment conditions until any time $t \in (0, t^*)$, where t^* is the end of study. When the scientific question of interest is the impact of treatment on the primary outcome event, the estimand $\tau(t)$ is hard to interpret if systematic difference in the risks of intercurrent events between two treatment conditions under comparison is anticipated.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect based on the efficient influence function of the restricted mean survival time lost by the end of study.

See Also

`scr.whileon`, `scr.ICH`

`surv.boot` *Calculating the standard error for the estimated cumulative incidence function and treatment effect*

Description

This function calculates the standard error for the estimated potential cumulative incidence function and treatment effect. Two methods to calculate the standard error are considered: asymptotic standard error based on the explicit formula and bootstrapping.

Usage

```
surv.boot(fit, nboot = 0, seed = 0)
```

Arguments

`fit`	A fitted object from `surv.ICH`.
`nboot`	Number of resamplings in the boostrapping method. If `nboot` is smaller than 1, then asymptotic standard error based on the explicit form is calculated instead of bootstrapping.
`seed`	Seed for bootstrapping.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

time Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

strategy Strategy used.

method Estimation method used.

See Also

`surv.ICH`, `scr.ICH`

---

surv.composite *Fitting the cumulative incidence function using composite variable strategy*

Description

This function nonparametrically estimates the potential cumulative incidence function using composite variable strategy (competing risks data structure). This strategy adopts the first occurrence of either the intermediate or primary event as the event of interest.

Usage

```
surv.composite(A, Time, cstatus, weights = rep(1, length(A)), subset = NULL)
```

Arguments

`A`	Treatment indicator, 1 for treatment and 0 for control.
`Time`	Time to event.
`cstatus`	Indicator of event, 1 for the primary event, 2 for the intercurrent event, 0 for censoring.
`weights`	Weight for each subject.
`subset`	Subset, either numerical or logical.

Details

The composite variable strategy addresses the problem of intercurrent events by expanding the outcome variables. It aggregates the intercurrent event and the primary outcome event into a single composite outcome variable. The idea is not new in the context of progression-free survival, where the composite outcome variable is defined as the occurrence of either a non-terminal event (e.g., cancer progression) or a terminal event (e.g., death). One widely used composite outcome variable has the form $Q(w) = \min\{T(w), R(w)\}$ for $w = 1, 0$. When this simple form is adopted, the difference in counterfactual cumulative incidences is $\tau(t) = P(Q(1) < t) - P(Q(0) < t)$, representing the difference in probabilities of experiencing either intercurrent events or primary outcome events during $(0, t)$ under active treatment and placebo.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect based on logrank test.

See Also

`surv.composite.eff`, `surv.ICH`

---

surv.composite.eff *Fitting the cumulative incidence function using composite variable strategy*

Description

This function estimates the potential cumulative incidence function based on efficient influence functions using composite variable strategy (competing risks data structure). Cox models are employed for survival models. This strategy adopts the first occurrence of either the intermediate or primary event as the event of interest.

Usage

```
surv.composite.eff(A, Time, cstatus, X = NULL, subset = NULL)
```

Arguments

A	Treatment indicator, 1 for treatment and 0 for control.
Time	Time to event.
cstatus	Indicator of event, 1 for the primary event, 2 for the intercurrent event, 0 for censoring.
X	Baseline covariates.
subset	Subset, either numerical or logical.

Details

The composite variable strategy addresses the problem of intercurrent events by expanding the outcome variables. It aggregates the intercurrent event and the primary outcome event into a single composite outcome variable. The idea is not new in the context of progression-free survival, where the composite outcome variable is defined as the occurrence of either a non-terminal event (e.g., cancer progression) or a terminal event (e.g., death). One widely used composite outcome variable has the form $Q(w) = \min\{T(w), R(w)\}$ for $w = 1, 0$. When this simple form is adopted, the difference in counterfactual cumulative incidences is $\tau(t) = P(Q(1) < t) - P(Q(0) < t)$, representing the difference in probabilities of experiencing either intercurrent events or primary outcome events during $(0, t)$ under active treatment and placebo.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect based on the efficient influence function of the restricted mean survival time lost by the end of study.

See Also

surv.composite, surv.ICH

surv.HR *Estimating the hazard ratio under ICH E9 (R1)*

Description

This function estimates the hazard ratio for time-to event data under ICH E9 (R1) to address intercurrent events. Multiple strategies except the principal stratum strategy are allowed.

Usage

```
surv.HR(
  A,
  Time,
  cstatus,
  strategy = "composite",
  cov1 = NULL,
  conf.int = 0.95,
  weights = NULL,
  subset = NULL
)
```

Arguments

A	Treatment indicator, 1 for treatment and 0 for control.
Time	Time to event.
cstatus	Indicator of event, 1 for the primary event, 2 for the intercurrent event, 0 for censoring.
strategy	Strategy to address intercurrent events, "treatment" indicating treatment policy strategy, "composite" indicating composite variable strategy, "natural" indicating hypothetical strategy (Scenario I, controlling the hazard of intercurrent events), "removed" indicating hypothetical strategy (Scenario II, removing intercurrent events), and "whileon" indicating while on treatment strategy.
cov1	Baseline covariates.
conf.int	Level of the confidence interval.
weights	Weight for each subject (not applied to the while on treatment strategy).
subset	Subset, either numerical or logical.

Details

For the treatment policy and hypothetical strategies, the hazard ratio (HR) is given by the Cox regression regarding intercurrent events as censoring. For the composite variable strategy, the hazard ratio is given by the Cox regression regarding the first occurrence of either intercurrent event or primary event as the event of interest. For the while on treatment strategy, the hazard ratio is given by the Fine-Gray subdistribution model. There is no existing method to estimate the hazard ratio using principal stratum strategy.

The weakness of using hazard ratio to infer treatment effects is critical. First, the hazard ratio relies on model specification. Second, the hazard ratio is not collapsible. Therefore, the hazard ratio should only be treated as a descriptive or exploratory measure of the treatment effect.

Value

A list including

logHR Estimated log hazard ratio (logHR) of the treatment effect on the primary event.

se Standard error of the estimated log hazard ratio (logHR).

CI Confidence interval of the hazard ratio (HR).

p.val P value of the hazard ratio.

See Also

surv.ICH

Examples

```
data(bmt)
bmt = transform(bmt, d4=d2+d3)
A = as.numeric(bmt$group>1)
## composite variable strategy
fit = surv.HR(A, bmt$t2, bmt$d4, "composite")
## while on treatment strategy
X = bmt[,c('z1','z3','z5')]
fit = surv.HR(A, bmt$t2, bmt$d4, "whileon", cov1=X)
```

---

surv.ICH *Fitting the cumulative incidence function for time-to-event data under ICH E9 (R1)*

Description

This function estimates the potential cumulative incidence function for time-to event data under ICH E9 (R1) to address intercurrent events. The input data should be of a competing risks structure.

Usage

```
surv.ICH(
  A,
  Time,
  cstatus,
  strategy = "composite",
  cov1 = NULL,
  method = "np",
  weights = NULL,
  subset = NULL
)
```

Arguments

A	Treatment indicator, 1 for treatment and 0 for control.
Time	Time to event.
cstatus	Indicator of event, 1 for the primary event, 2 for the intercurrent event, 0 for censoring.
strategy	Stragety to address intercurrent events, "treatment" indicating treatment policy strategy, "composite" indicating composite variable strategy, "natural" indicating hypothetical strategy (Scenario I, controlling the hazard of intercurrent events), "removed" indicating hypothetical strategy (Scenario II, removing intercurrent events), "whileon" indicating while on treatment strategy, and "principal" indicating principal stratum strategy.
cov1	Baseline covariates.
method	Estimation method, "np" indicating nonparametric estimation, "eff" indicating semiparametrically efficient estimation based on efficient influence functions.
weights	Weight for each subject.
subset	Subset, either numerical or logical.

Details

Background Intercurrent events refer to the events occurring after treatment initiation of clinical trials that affect either the interpretation of or the existence of the measurements associated with the clinical question of interest. The International Conference on Harmonization (ICH) E9 (R1) addendum proposed five strategies to address intercurrent events, namely, treatment policy strategy, composite variable strategy, while on treatment strategy, hypothetical strategy, and principal stratum strategy. To answer a specific scientific question, a strategy with a particular estimand is chosen before the study design.

Model We adopt the potential outcomes framework that defines a causal estimand as the contrast between functionals of potential outcomes. Consider a randomized controlled trial with n individuals randomly assigned to one of two treatment conditions, denoted by w, where $w = 1$ represents the active treatment (a test drug) and $w = 0$ represents the control (placebo). Assume that all patients adhere to their treatment assignments and do not discontinue treatment. Associated with individual $i = 1, ..., n$ are two potential time-to-event primary outcomes $T_i(1)$ and $T_i(0)$, if any, which represent the time durations from treatment initiation to the primary outcome event under two treatment assignments respectively. Let $R_i(1)$ and $R_i(0)$ denote the occurrence time of potential intercurrent events, if any, under the two treatment assignments, respectively. Intercurrent events are considered as absent if no post-treatment intercurrent events occur until the end of study.

Estimand We adopt the potential cumulative incidences under both treatment assignments as the target estimands. Potential cumulative incidences describe the probability of time-to-event outcomes occurring at each time point. We define the treatment effect as the contrast of two potential cumulative incidences. Cumulative incidences are model-free and collapsible, enjoying causal interpretations.

Value

A list including the fitted object and input variables.

See Also

surv.boot

Examples

```
## load data
data(bmt)
bmt = transform(bmt, d4=d2+d3)
A = as.numeric(bmt$group>1)
X = as.matrix(bmt[,c('z1','z3','z5')])
## Composite variable strategy,
## nonparametric estimation without covariates
fit1 = surv.ICH(A, bmt$t2, bmt$d4, "composite")
## Hypothetical strategy (natural effects),
## nonparametric estimation with inverse probability weighting
ps = predict(glm(A ~ X, family='binomial'), type='response')
w = A/ps + (1-A)/(1-ps)
fit2 = surv.ICH(A, bmt$t2, bmt$d4, "natural", X, weights=w)
## Hypothetical strategy (natural effects),
## semiparametrically efficient estimation with covariates
fit3 = surv.ICH(A, bmt$t2, bmt$d4, "natural", X, method='eff')
```

`surv.natural` *Fitting the cumulative incidence function using hypothetical strategy (I)*

Description

This function nonparametrically estimates the potential cumulative incidence function using hypothetical strategy (competing risks data structure). The intercurrent event is only permitted under treated if it would occur under control.

Usage

```
surv.natural(A, Time, cstatus, weights = rep(1, length(A)), subset = NULL)
```

Arguments

`A`	Treatment indicator, 1 for treatment and 0 for control.
`Time`	Time to event.
`cstatus`	Indicator of event, 1 for the primary event, 2 for the intercurrent event, 0 for censoring.
`weights`	Weight for each subject.
`subset`	Subset, either numerical or logical.

Details

The hypothetical strategy envisions a hypothetical clinical trial condition where the occurrence of intercurrent events is restricted in certain ways. By doing so, the distribution of potential outcomes under the hypothetical scenario can capture the impact of intercurrent events explicitly through a pre-specified criterion. We use $T'(w), w = 1, 0$ to denote the time to the primary outcome event in the hypothetical scenario. The time-dependent treatment effect specific to this hypothetical scenario is written as $\tau(t) = P(T'(1) < t) - P(T'(0) < t)$, representing

the difference in probabilities of experiencing primary outcome events during $(0, t)$ in the pre-specified hypothetical scenario under active treatment and placebo.
The key question is how to envision $T'(w)$. We manipulate the hazard specific to intercurrent event $\lambda_2(t; w)$ while assuming the hazard specific to the primary outcome event $\lambda_1(t; w)$ remains unchanged. Specifically, we envision that the intercurrent events that occurred when individuals were assigned to test drugs were only permitted if these intercurrent events would have also occurred if these individuals had been assigned to the placebo. In this hypothetical scenario, when assigned to placebo, individuals would be equally likely to experience intercurrent events as they are assigned to placebo in the real-world trial in terms of the hazards; when assigned to test drug, the hazard of intercurrent events would be identical to that if assigned to placebo in the real-world trial. That is, $\lambda_2'(t; 0) = \lambda_2'(t; 1) = \lambda_2(t; 0)$. The treatment effect corresponds to the natural direct effect with the hazard of intercurrent events set at the level under control.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect based on logrank test.

See Also

`surv.natural.eff`, `surv.ICH`

---

surv.natural.eff *Fitting the cumulative incidence function using hypothetical strategy (I)*

Description

This function estimates the potential cumulative incidence function based on efficient influence functions using hypothetical strategy (competing risks data structure). Cox models are employed for survival models. The intercurrent event is only permitted under treated if it would occur under control.

Usage

```
surv.natural.eff(A, Time, cstatus, X = NULL, subset = NULL)
```

Arguments

A	Treatment indicator, 1 for treatment and 0 for control.
Time	Time to event.
cstatus	Indicator of event, 1 for the primary event, 2 for the intercurrent event, 0 for censoring.
X	Baseline covariates.
subset	Subset, either numerical or logical.

Details

The hypothetical strategy envisions a hypothetical clinical trial condition where the occurrence of intercurrent events is restricted in certain ways. By doing so, the distribution of potential outcomes under the hypothetical scenario can capture the impact of intercurrent events explicitly through a pre-specified criterion. We use $T'(w), w = 1, 0$ to denote the time to the primary outcome event in the hypothetical scenario. The time-dependent treatment effect specific to this hypothetical scenario is written as $\tau(t) = P(T'(1) < t) - P(T'(0) < t)$, representing the difference in probabilities of experiencing primary outcome events during $(0, t)$ in the pre-specified hypothetical scenario under active treatment and placebo.

The key question is how to envision $T'(w)$. We manipulate the hazard specific to intercurrent event $\lambda_2(t; w)$ while assuming the hazard specific to the primary outcome event $\lambda_1(t; w)$ remains unchanged. Specifically, we envision that the intercurrent events that occurred when individuals were assigned to test drugs were only permitted if these intercurrent events would have also occurred if these individuals had been assigned to the placebo. In this hypothetical scenario, when assigned to placebo, individuals would be equally likely to experience intercurrent events as they are assigned to placebo in the real-world trial in terms of the hazards; when assigned to test drug, the hazard of intercurrent events would be identical to that if assigned to placebo in the real-world trial. That is, $\lambda_2'(t; 0) = \lambda_2'(t; 1) = \lambda_2(t; 0)$. The treatment effect corresponds to the natural direct effect with the hazard of intercurrent events set at the level under control.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect based on the efficient influence function of the restricted mean survival time lost by the end of study.

See Also

surv.natural, surv.ICH

`surv.principal` *Fitting the cumulative incidence function using principal stratum strategy*

Description

This function nonparametrically estimates the potential cumulative incidence function using principal stratum strategy (competing risks data structure). The estimand is defined in a subpopulation where intercurrent events would never occur regardless of treatment conditions.

Usage

```
surv.principal(A, Time, cstatus, weights = rep(1, length(A)), subset = NULL)
```

Arguments

`A`	Treatment indicator, 1 for treatment and 0 for control.
`Time`	Time to event.
`cstatus`	Indicator of event, 1 for the primary event, 2 for the intercurrent event, 0 for censoring.
`weights`	Weight for each subject.
`subset`	Subset, either numerical or logical.

Details

The principal stratum strategy aims to stratify the population into subpopulations based on the joint potential occurrences of intercurrent events under the two treatment assignments $(R(1), R(0))$. Suppose we are interested in a principal stratum comprised of individuals who would never experience intercurrent events, regardless of which treatment they receive. This principal stratum can be indicated by $\{R(1) = R(0) = \infty\}$. The treatment effect is now defined within this subpopulation, $\tau(t) = P(T(1) < t \mid R(1) = R(0) = \infty) - P(T(0) < t \mid R(1) = R(0) = \infty)$, representing the difference in probabilities of experiencing primary outcome events during $(0, t)$ under active treatment and placebo in the subpopulation that will not experience intercurrent events regardless of treatment during $(0, t)$. A principal ignorability assumption is made for identification.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect, which is not available under this strategy.

See Also

surv.principal.eff, surv.ICH

---

surv.principal.eff *Fitting the cumulative incidence function using principal stratum strategy*

Description

This function estimates the potential cumulative incidence function based on efficient influence functions using principal stratum strategy (competing risks data structure). Cox models are employed for survival models. The estimand is defined in a subpopulation where intercurrent events would never occur regardless of treatment conditions.

Usage

```
surv.principal.eff(A, Time, cstatus, X = NULL, subset = NULL)
```

Arguments

A	Treatment indicator, 1 for treatment and 0 for control.
Time	Time to event.
cstatus	Indicator of event, 1 for the primary event, 2 for the intercurrent event, 0 for censoring.
X	Baseline covariates.
subset	Subset, either numerical or logical.

Details

The principal stratum strategy aims to stratify the population into subpopulations based on the joint potential occurrences of intercurrent events under the two treatment assignments $(R(1), R(0))$. Suppose we are interested in a principal stratum comprised of individuals who would never experience intercurrent events, regardless of which treatment they receive. This principal stratum can be indicated by $\{R(1) = R(0) = \infty\}$. The treatment effect is now defined within this subpopulation, $\tau(t) = P(T(1) < t \mid R(1) = R(0) = \infty) - P(T(0) < t \mid R(1) = R(0) = \infty)$, representing the difference in probabilities of experiencing primary outcome events during $(0, t)$ under active treatment and placebo in the subpopulation that will not experience intercurrent events regardless of treatment during $(0, t)$. A principal ignorability assumption is made for identification.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect based on the efficient influence function of the restricted mean survival time lost by the end of study.

See Also

surv.principal, surv.ICH

`surv.removed` *Fitting the cumulative incidence function using hypothetical strategy (II)*

Description

This function nonparametrically estimates the potential cumulative incidence function using hypothetical strategy (competing risks data structure). The intercurrent event is assumed to be absent in the hypothetical scenario.

Usage

```
surv.removed(A, Time, cstatus, weights = rep(1, length(A)), subset = NULL)
```

Arguments

`A`	Treatment indicator, 1 for treatment and 0 for control.
`Time`	Time to event.
`cstatus`	Indicator of event, 1 for the primary event, 2 for the intercurrent event, 0 for censoring.
`weights`	Weight for each subject.
`subset`	Subset, either numerical or logical.

Details

The hypothetical strategy envisions a hypothetical clinical trial condition where the occurrence of intercurrent events is restricted in certain ways. By doing so, the distribution of potential outcomes under the hypothetical scenario can capture the impact of intercurrent events explicitly through a pre-specified criterion. We use $T'(w), w = 1, 0$ to denote the time to the primary outcome event in the hypothetical scenario. The time-dependent treatment effect specific to this hypothetical scenario is written as $\tau(t) = P(T'(1) < t) - P(T'(0) < t)$, representing the difference in probabilities of experiencing primary outcome events during $(0, t)$ in the pre-specified hypothetical scenario under active treatment and placebo.

The key question is how to envision $T'(w)$. We manipulate the hazard specific to intercurrent event $\lambda_2(t; w)$ while assuming the hazard specific to the primary outcome event $\lambda_1(t; w)$ remains unchanged. Specifically, we envision that intercurrent events are absent in the hypothetical scenario for all individuals, so $\lambda_2'(t; 0) = \Lambda_2'(t; 1) = 0$. This hypothetical scenario leads to an estimand called the marginal cumulative incidence. The treatment effect corresponds to the controlled direct effect with the intercurrent events removed.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect based on logrank test.

See Also

`surv.removed.eff`, `surv.ICH`

`surv.removed.eff` *Fitting the cumulative incidence function using hypothetical strategy (II)*

Description

This function estimates the potential cumulative incidence function based on efficient influence functions using hypothetical strategy (competing risks data structure). Cox models are employedfor survival models. The intercurrent event is assumed to be absent in the hypothetical scenario.

Usage

```
surv.removed.eff(A, Time, cstatus, X = NULL, subset = NULL)
```

Arguments

`A`	Treatment indicator, 1 for treatment and 0 for control.
`Time`	Time to event.
`cstatus`	Indicator of event, 1 for the primary event, 2 for the intercurrent event, 0 for censoring.
`X`	Baseline covariates.
`subset`	Subset, either numerical or logical.

Details

The hypothetical strategy envisions a hypothetical clinical trial condition where the occurrence of intercurrent events is restricted in certain ways. By doing so, the distribution of potential outcomes under the hypothetical scenario can capture the impact of intercurrent events explicitly through a pre-specified criterion. We use $T'(w)$, $w = 1, 0$ to denote the time to the primary outcome event in the hypothetical scenario. The time-dependent treatment effect specific to this hypothetical scenario is written as $\tau(t) = P(T'(1) < t) - P(T'(0) < t)$, representing the difference in probabilities of experiencing primary outcome events during $(0, t)$ in the pre-specified hypothetical scenario under active treatment and placebo.
The key question is how to envision $T'(w)$. We manipulate the hazard specific to intercurrent event $\lambda_2(t; w)$ while assuming the hazard specific to the primary outcome event $\lambda_1(t; w)$ remains unchanged. Specifically, we envision that intercurrent events are absent in the hypothetical scenario for all individuals, so $\lambda_2'(t; 0) = \Lambda_2'(t; 1) = 0$. This hypothetical scenario leads to an estimand called the marginal cumulative incidence. The treatment effect corresponds to the controlled direct effect with the intercurrent events removed.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect based on the efficient influence function of the restricted mean survival time lost by the end of study.

See Also

surv.removed, surv.ICH

---

surv.treatment *Fitting the cumulative incidence function using treatment policy strategy*

Description

This function nonparametrically estimates the potential cumulative incidence function using treatment policy strategy (competing risks data structure). This strategy ignores the intercurrent event and uses the time to the primary event as it was recorded.

Usage

```
surv.treatment(A, Time, cstatus, weights = rep(1, length(A)), subset = NULL)
```

Arguments

A	Treatment indicator, 1 for treatment and 0 for control.
Time	Time to event.
cstatus	Indicator of event, 1 for the primary event, 2 for the intercurrent event, 0 for censoring.
weights	Weight for each subject.
subset	Subset, either numerical or logical.

Details

The treatment policy strategy addresses the problem of intercurrent events by expanding the initial treatment conditions to a treatment policy. This strategy is applicable only if intercurrent events do not hinder primary outcome events. The treatments under comparison are now two treatment policies: $(w, R(w))$, where $w = 1, 0$. One policy $(1, R(1))$ involves administering the test drug, along with any naturally occurring intercurrents, whereas the other policy $(0, R(0))$ involves administering a placebo, along with any naturally occurring intercurrents. Thus, the potential outcomes are $T(1, R(1))$ and $T(0, R(0))$. Instead of comparing the test drug and placebo themselves, the contrast of interest is made between the two treatment policies. The difference in cumulative incidences under the two treatment policies is then $\tau(t) = P(T(1, R(1)) < t) - P(T(0, R(0)) < t)$, representing the difference in probabilities of experiencing primary outcome events during $(0, t)$ under active treatment and placebo.
The average treatment effect $\tau^{\text{tp}}(t)$ has a meaningful causal interpretation only when $T(1, R(1))$ and $T(0, R(0))$ are well defined. Because the treatment policy includes the occurrence of the intercurrent event as natural, the entire treatment policy is determined by manipulating the initial treatment condition w only. Therefore, we can simplify the notations $T(w, R(w)) = T(w)$ in defining estimands. As such, $\tau(t) = P(T(1)) < t) - P(T(0) < t)$ as the intention-to-treat analysis.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect based on logrank test.

See Also

surv.treatment.eff, surv.ICH

`surv.treatment.eff` *Fitting the cumulative incidence function using treatment policy strategy*

Description

This function estimates the potential cumulative incidence function based on efficient influence functions using treatment policy strategy (competing risks data structure). Cox models are employed for the survival model. This strategy ignores the intercurrent event and uses the time to the primary event as it was recorded.

Usage

```
surv.treatment.eff(A, Time, cstatus, X = NULL, subset = NULL)
```

Arguments

`A`	Treatment indicator, 1 for treatment and 0 for control.
`Time`	Time to event.
`cstatus`	Indicator of event, 1 for the primary event, 2 for the intercurrent event, 0 for censoring.
`X`	Baseline covariates.
`subset`	Subset, either numerical or logical.

Details

The treatment policy strategy addresses the problem of intercurrent events by expanding the initial treatment conditions to a treatment policy. This strategy is applicable only if intercurrent events do not hinder primary outcome events. The treatments under comparison are now two treatment policies: $(w, R(w))$, where $w = 1, 0$. One policy $(1, R(1))$ involves administering the test drug, along with any naturally occurring intercurrents, whereas the other policy $(0, R(0))$ involves administering a placebo, along with any naturally occurring intercurrents. Thus, the potential outcomes are $T(1, R(1))$ and $T(0, R(0))$. Instead of comparing the test drug and placebo themselves, the contrast of interest is made between the two treatment policies. The difference in cumulative incidences under the two treatment policies is then $\tau(t) = P(T(1, R(1)) < t) - P(T(0, R(0)) < t)$, representing the difference in probabilities of experiencing primary outcome events during $(0, t)$ under active treatment and placebo.
The average treatment effect $\tau^{\text{tp}}(t)$ has a meaningful causal interpretation only when $T(1, R(1))$ and $T(0, R(0))$ are well defined. Because the treatment policy includes the occurrence of the intercurrent event as natural, the entire treatment policy is determined by manipulating the initial treatment condition \$w\$ only. Therefore, we can simplify the notations $T(w, R(w)) = T(w)$ in defining estimands. As such, $\tau(t) = P(T(1)) < t) - P(T(0) < t)$ as the intention-to-treat analysis.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect based on the efficient influence function of the restricted mean survival time lost by the end of study.

See Also

surv.treatment, surv.ICH

`surv.whileon` *Fitting the cumulative incidence function using while on treatment strategy*

Description

This function nonparametrically estimates the potential cumulative incidence function using while on treatment strategy (competing risks data structure). This strategy can be understood as the competing risks model, which gives the subdistribution of the primary event.

Usage

```
surv.whileon(A, Time, cstatus, weights = rep(1, length(A)), subset = NULL)
```

Arguments

`A`	Treatment indicator, 1 for treatment and 0 for control.
`Time`	Time to event.
`cstatus`	Indicator of event, 1 for the primary event, 2 for the intercurrent event, 0 for censoring.
`weights`	Weight for each subject.
`subset`	Subset, either numerical or logical.

Details

The while on treatment strategy considers the measure of outcome variables taken only up to the occurrence of intercurrent events. The failures of primary outcome events should not be counted in the cumulative incidences if intercurrent events occurred. The difference in counterfactual cumulative incidences under this strategy is $\tau(t) = P(T(1) < t, R(1) \geq t) - P(T(0) < t, R(0) \geq t)$, representing the difference in probabilities of experiencing primary outcome events without intercurrent events during $(0, t)$ under active treatment and placebo. The cumulative incidence function is also known as the cause-specific cumulative incidence or subdistribution function.

The while on treatment strategy is closely related to the competing risks model. However, for

causal interpretations, it is worth emphasizing that the hazard of $R(1)$ may differ from that of $R(0)$, leading to vast difference in the underlying features of individuals who have not experienced the primary outcome event between treatment conditions until any time $t \in (0, t^*)$, where t^* is the end of study. When the scientific question of interest is the impact of treatment on the primary outcome event, the estimand $\tau(t)$ is hard to interpret if systematic difference in the risks of intercurrent events between two treatment conditions under comparison is anticipated.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect based on Gray test.

See Also

surv.whileon.eff, surv.ICH

---

surv.whileon.eff *Fitting the cumulative incidence function using while on treatment strategy*

Description

This function estimates the potential cumulative incidence function based on efficient influence functions using while on treatment strategy (competing risks data structure). Cox models are employed for survival models. This strategy can be understood as the competing risks model, which gives the subdistribution of the primary event.

Usage

```
surv.whileon.eff(A, Time, cstatus, X = NULL, subset = NULL)
```

Arguments

A	Treatment indicator, 1 for treatment and 0 for control.
Time	Time to event.
cstatus	Indicator of event, 1 for the primary event, 2 for the intercurrent event, 0 for censoring.
X	Baseline covariates.
subset	Subset, either numerical or logical.

Details

The while on treatment strategy considers the measure of outcome variables taken only up to the occurrence of intercurrent events. The failures of primary outcome events should not be counted in the cumulative incidences if intercurrent events occurred. The difference in counterfactual cumulative incidences under this strategy is $\tau(t) = P(T(1) < t, R(1) \geq t) - P(T(0) < t, R(0) \geq t)$, representing the difference in probabilities of experiencing primary outcome events without intercurrent events during $(0, t)$ under active treatment and placebo. The cumulative incidence function is also known as the cause-specific cumulative incidence or subdistribution function.

The while on treatment strategy is closely related to the competing risks model. However, for causal interpretations, it is worth emphasizing that the hazard of $R(1)$ may differ from that of $R(0)$, leading to vast difference in the underlying features of individuals who have not experienced the primary outcome event between treatment conditions until any time $t \in (0, t^*)$, where t^* is the end of study. When the scientific question of interest is the impact of treatment on the primary outcome event, the estimand $\tau(t)$ is hard to interpret if systematic difference in the risks of intercurrent events between two treatment conditions under comparison is anticipated.

Value

A list including

time1 Time points in the treated group.

time0 Time points in the control group.

cif1 Estimated cumulative incidence function in the treated group.

cif0 Estimated cumulative incidence function in the control group.

se1 Standard error of the estimated cumulative incidence function in the treated group.

se0 Standard error of the estimated cumulative incidence function in the control group.

tt Time points in both groups.

ate Estimated treatment effect (difference in cumulative incidence functions).

se Standard error of the estimated treatment effect.

p.val P value of testing the treatment effect based on the efficient influence function of the restricted mean survival time lost by the end of study.

See Also

`surv.whileon`, `surv.ICH`

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