Package: SurrogateTest (via r-universe)

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Type Package

Title Early Testing for a Treatment Effect using Surrogate Marker Information

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Description Provides functions to test for a treatment effect in terms of the difference in survival between a treatment group and a control group using surrogate marker information obtained at some early time point in a time-to-event outcome setting. Nonparametric kernel estimation is used to estimate the test statistic and perturbation resampling is used for variance estimation. More details will be available in the future in: Parast L, Cai T, Tian L (2019) ``Using a Surrogate Marker for Early Testing of a Treatment Effect" Biometrics, 75(4):1253-1263. [<doi:10.1111/biom.13067>](https://doi.org/10.1111/biom.13067).

License GPL

Imports stats, survival

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Contents

dataA *Hypothetical Study A data*

Description

Hypothetical Study A data to be used in examples; $t=1$ and the landmark time = 0.50.

Usage

data(dataA)

Format

A list with 6 elements representing 1000 observations from a control group and 1000 observations from a treatment group:

- s1 Surrogate marker measurement for treated observations; this marker is measured at time = 0.5. For observations that experience the primary outcome or are censored before 0.5, this value is NA.
- x1 The observed event or censoring time for treated observations; $X = min(T, C)$ where T is the time of the primary outcome and C is the censoring time.
- delta1 The indicator identifying whether the treated observation was observed to have the event or was censored; $D =1*(T\le C)$ where T is the time of the primary outcome and C is the censoring time.
- s θ Surrogate marker measurement for control observations; this marker is measured at time = 0.5. For observations that experience the primary outcome or are censored before 0.5, this value is NA.
- $x \in \mathbb{R}^n$ The observed event or censoring time for control observations; $X = \min(T, C)$ where T is the time of the primary outcome and C is the censoring time.
- delta0 The indicator identifying whether the control observation was observed to have the event or was censored; $D = 1*(T < C)$ where T is the time of the primary outcome and C is the censoring time.

Details

Note that if the observation is censored or experienced the primary outcome before the landmark time of 0.50, the surrogate marker measurement is not observed and coded NA.

Examples

data(dataA) names(dataA)

Description

Hypothetical Study B data to be used in examples; landmark time $= 0.50$.

Usage

data(dataB)

Format

A list with 6 elements representing 800 observations from a control group and 800 observations from a treatment group:

- s1 Surrogate marker measurement for treated observations; this marker is measured at time $= 0.5$. For observations that experience the primary outcome or are censored before 0.5, this value is NA.
- x1 The observed event or censoring time for treated observations; $X = min(T, C)$ where T is the time of the primary outcome and C is the censoring time. This time is administratively censored at 0.55 (see details).
- delta1 The indicator identifying whether the treated observation was observed to have the event or was censored; $D =1*(T\le C)$ where T is the time of the primary outcome and C is the censoring time.
- s θ Surrogate marker measurement for control observations; this marker is measured at time = 0.5. For observations that experience the primary outcome or are censored before 0.5, this value is NA.
- $x\theta$ The observed event or censoring time for control observations; $X = min(T, C)$ where T is the time of the primary outcome and C is the censoring time. This time is administratively censored at 0.55 (see details).
- delta0 The indicator identifying whether the control observation was observed to have the event or was censored; $D =1*(T\le C)$ where T is the time of the primary outcome and C is the censoring time.

Details

Note that if the observation is censored or experienced the primary outcome before the landmark time of 0.50, the surrogate marker measurement is not observed and coded NA. In addition, Study B data is only observed up to the landmark time plus some epsilon, here epsilon=0.05 such that all observations are essentially adminstratively censored at time=0.55.

Examples

data(dataB) names(dataB)

Description

This function calculates the treatment effect in the survival setting i.e. the difference in survival at time t between the treatment group and the control group. The inverse probability of censoring weighted estimate of survival within each treatment group is used; there is an option to use the Kaplan-Meier estimate instead. This function is generally not expected to be used directly by the user, it is called by the recover.B function.

Usage

delta.estimate(xone, xzero, deltaone, deltazero, t, weight = NULL, KM = FALSE)

Arguments

Value

the difference in survival at time t (treatment group minus control group)

Author(s)

Layla Parast

design.study 5

Examples

```
data(dataA)
delta.estimate(xone = dataA$x1, xzero = dataA$x0, deltaone = dataA$delta1, deltazero =
dataA$delta0, t=1)
delta.estimate(xone = dataA$x1, xzero = dataA$x0, deltaone = dataA$delta1, deltazero =
dataA$delta0, t=0.5)
```
design.study *Power and sample size calculation for designing a future study*

Description

Power and sample size calculation for designing a future study

Usage

```
design.study(Axzero, Adeltazero, Aszero, Axone = NULL, Adeltaone = NULL, Asone =
NULL, delta.ea = NULL, psi = NULL, R.A.given = NULL, t, landmark, extrapolate = T,
adjustment = F, n = NULL, power = NULL, pi.1 = 0.5, pi.0 = 0.5, cens.rate, transform = F)
```
Arguments

Details

Assume information is available on a prior study, Study A, examining the effectiveness of a treatment up to some time of interest, t. The aim is to plan a future study, Study B, that would be conducted only up to time $t_0 < t$ and a test for a treatment effect would occur at t_0 . In both studies, we assume a surrogate marker is/will be measured at time t_0 for individuals still observable at t_0 . Let G be the binary treatment indicator with $G = 1$ for treatment and $G = 0$ for control and we assume throughout that subjects are randomly assigned to a treatment group at baseline. Let $T_K^{(1)}$ and $T_K^{(0)}$ denote the time of the primary outcome of interest, death for example, under the treatment and

design.study 7

under the control, respectively, in Study K. Let $S_K^{(1)}$ and $S_K^{(0)}$ denote the surrogate marker measured at time t_0 under the treatment and the control, respectively, in Study K.

The null and alternative hypotheses of interest are:

$$
H_0: \Delta_B(t) \equiv P(T_B^{(1)} > t) - P(T_B^{(0)} > t) = 0
$$

$$
H_1: \Delta_B(t) = \psi > 0
$$

Here, we plan to test H_0 in Study B using the test statistic

$$
Z_{EB}(t, t_0) = \sqrt{n_B} \frac{\hat{\Delta}_{EB}(t, t_0)}{\hat{\sigma}_{EB}(t, t_0)}
$$

(see early.delta.test documentation). The estimated power at a type I error rate of 0.05 is thus

$$
1-\Phi\left\{1.96-\frac{\sqrt{n_B}\hat{R}_{SA}(t,t_0)\psi}{\hat{\sigma}_{EB0}(t,t_0\mid\hat{r}_A^{(0)},W_B^C)}\right\}
$$

where $\hat{R}_{SA}(t,t_0) = \hat{\Delta}_{EA}(t,t_0)/\hat{\Delta}_{A}(t)$, and

$$
\hat{\Delta}_A(t) = n_{A1}^{-1} \sum_{i=1}^{n_{A1}} \frac{I(X_{Ai}^{(1)} > t)}{\hat{W}_{A1}^C(t)} - n_{A0}^{-1} \sum_{i=1}^{n_{A0}} \frac{I(X_{Ai}^{(0)} > t)}{\hat{W}_{A0}^C(t)},
$$

and $\hat{\Delta}_{EA}(t,t_0)$ is parallel to $\hat{\Delta}_{EB}(t,t_0)$ except replacing $n_{A0}^{-1} \sum_{i=1}^{n_{A0}} \hat{r}_A^{(0)}(t|S_{Ai}^{(0)}, t_0) \frac{I(X_{Ai}^{(0)} > t_0)}{\hat{W}_{A}^{C}(t_0)}$ $\frac{(\Lambda_{Ai} > t_0)}{\hat{W}_{A0}^C(t_0)}$ by $n_{A0}^{-1} \sum_{i=1}^{n_{A0}} \hat{W}_{A0}^{C}(t)^{-1} I(X_{Ai}^{(0)} > t)$, and $\hat{W}_{Ag}^{C}(t)$ is the Kaplan-Meier estimator of the survival function for $C_A^{(g)}$ for $g = 0, 1$. In addition, $\hat{\sigma}_{EBO}(t, t_0 | \hat{r}_A^{(0)}, W_B^C)^2 =$

$$
\frac{1}{\pi_{B0}\pi_{B1}} \left[\frac{\hat{\mu}_{AB2}^{(0)}(t, t_0, \mid \hat{r}_A^{(0)})}{W_B^C(t_0)} - \hat{\mu}_{AB1}^{(0)}(t, t_0, \mid \hat{r}_A^{(0)})^2 \left\{ 1 + \int_0^{t_0} \frac{\lambda_B^C(u) du}{\hat{W}_{A0}^T(u) W_B^C(u)} \right\} \right]
$$

assuming that the survival function of the censoring distribution is $W_B^C(t)$ in both arms, where $\pi_{Bg} = n_{Bg}/n_B$ and $\hat{W}_{AQ}^T(\cdot)$ is the Kaplan-Meier estimator of the survival function of $T_A^{(0)}$ based on the observations from Study A, and

$$
\hat{\mu}_{ABm}^{(0)}(t, t_0, |\hat{r}_A^{(0)}\rangle) = n_{A0}^{-1} \sum_{i=1}^{n_{A0}} \frac{\hat{r}_A^{(0)}(t | S_{Ai}^{(0)}, t_0)^m I(X_{Ai}^{(0)} > t_0)}{\hat{W}_{A0}^C(t_0)}
$$

where $\hat{r}_A^{(0)}(t|s,t_0)$ is provided in the early.delta.test documentation.

This can be re-arranged to calculate the sample size needed in Study B to achieve a power of $100(1 - \beta)\%$:

$$
n_B = \left\{\hat{\sigma}_{EBO}(t, t_0 \mid \hat{r}_A^{(0)}, W_B^C) \left(\frac{1.96 - \Phi^{-1}(\beta)}{\hat{R}_{SA}(t, t_0)\psi}\right)\right\}^2.
$$

When the outcome rate is low (i.e., survival rate at t is high), an adjustment to the variance calculation is needed. This is automatically implemented if the survival rate at t in either arm is 0.90 or higher.

Value

Author(s)

Layla Parast

References

Parast L, Cai T, Tian L (2019). Using a Surrogate Marker for Early Testing of a Treatment Effect. Biometrics, 75(4):1253-1263.

Examples

```
data(dataA)
design.study(Axzero = dataA$x0, Adeltazero = dataA$delta0, Aszero = dataA$s0,
Axone = dataA$x1, Adeltaone = dataA$delta1, Asone = dataA$s1, t=1, landmark=0.5,
power = 0.80, cens.rate=0.5)
design.study(Axzero = dataA$x0, Adeltazero = dataA$delta0, Aszero = dataA$s0,
Axone = dataA$x1, Adeltaone = dataA$delta1, Asone = dataA$s1, t=1, landmark=0.5,
n=2500, cens.rate=0.5)
design.study(Axzero = dataA$x0, Adeltazero = dataA$delta0, Aszero = dataA$s0,
Axone = dataA$x1, Adeltaone = dataA$delta1, Asone = dataA$s1, t=1, landmark=0.5,
power = 0.80, cens.rate=0.5, psi = 0.05)
```
early.delta.test *Estimate and test the early treatment effect*

Description

Estimates the early treatment effect estimate and provides two versions of the standard error; tests the null hypothesis that this treatment effect is equal to 0

Usage

```
early.delta.test(Axzero, Adeltazero, Aszero, Bxzero, Bdeltazero, Bszero, Bxone,
Bdeltaone, Bsone, t, landmark, perturb = T, extrapolate = T, transform = F)
```
early.delta.test 9

Arguments

Details

Assume there are two randomized studies of a treatment effect, a prior study (Study A) and a current study (Study B). Study A was completed up to some time t, while Study B was stopped at time $t_0 < t$. In both studies, a surrogate marker was measured at time t_0 for individuals still observable at t_0 . Let G be the binary treatment indicator with $G = 1$ for treatment and $G = 0$ for control and we assume throughout that subjects are randomly assigned to a treatment group at baseline. Let $T_K^{(1)}$ and $T_K^{(0)}$ denote the time of the primary outcome of interest, death for example, under the treatment and under the control, respectively, in Study K. Let $S_K^{(1)}$ and $S_K^{(0)}$ denote the surrogate marker measured at time t_0 under the treatment and the control, respectively, in Study K.

The treatment effect quantity of interest, $\Delta_K(t)$, is the difference in survival rates by time t under treatment versus control,

$$
\Delta_K(t) = E\{I(T_K^{(1)} > t)\} - E\{I(T_K^{(0)} > t)\} = P(T_K^{(1)} > t) - P(T_K^{(0)} > t)
$$

where $t > t_0$. Here, we estimate an early treatment effect quantity using surrogate marker information defined as,

$$
\Delta_{EB}(t, t_0) = P(T_B^{(1)} > t_0) \int r(t|s, t_0) dF_B^{(1)}(s|t_0) - P(T_B^{(0)} > t_0) \int r(t|s, t_0) dF_B^{(0)}(s|t_0)
$$

where $r(t|s, t_0) = P(T_A^{(0)} > t|T_A^{(0)} > t_0, S_A^{(0)} = s)$ and $F_B^{(g)}(s|t_0) = P(S_B^{(g)} \le s | T_B^{(g)} > t_0)$.

To test the null hypothesis that $\Delta_B(t) = 0$, we test the null hypothesis $\Delta_{EB}(t, t_0) = 0$ using the test statistic

$$
Z_{EB}(t, t_0) = \sqrt{n_B} \frac{\hat{\Delta}_{EB}(t, t_0)}{\hat{\sigma}_{EB}(t, t_0)}
$$

where $\Delta_{EB}(t, t_0)$ is a consistent estimate of $\Delta_{EB}(t, t_0)$ and $\hat{\sigma}_{EB}(t, t_0)$ is the estimated standard error of $\sqrt{n_B} \{\hat{\Delta}_{EB}(t,t_0) - \Delta_{EB}(t,t_0)\}$. We reject the null hypothesis when $|Z_{EB}(t,t_0)| >$ $\Phi^{-1}(1-\alpha/2)$ where α is the Type 1 error rate.

To obtain $\hat{\Delta}_{EB}(t, t_0)$, we use

$$
\hat{\Delta}_{EB}(t,t_0) = n_{B1}^{-1} \sum_{i=1}^{n_{B1}} \hat{r}_A^{(0)}(t|S_{Bi}^{(1)}, t_0) \frac{I(X_{Bi}^{(1)} > t_0)}{\hat{W}_{B1}^C(t_0)} - n_{B0}^{-1} \sum_{i=1}^{n_{B0}} \hat{r}_A^{(0)}(t|S_{Bi}^{(0)}, t_0) \frac{I(X_{Bi}^{(0)} > t_0)}{\hat{W}_{B0}^C(t_0)}
$$

where $\hat{W}_{kg}^C(u)$ is the Kaplan-Meier estimator of $W_{kg}^C(u) = P(C_k^{(g)} > u)$ and $\hat{r}_A^{(0)}(t|s,t_0) =$ $\exp{\{-\hat{\Lambda}_A^{(0)}(t\mid s,t_0)\}}$, where

$$
\hat{\Lambda}_A^{(0)}(t \mid t_0, s) = \int_{t_0}^t \frac{\sum_{i=1}^{n_{A0}} I(X_{Ai}^{(0)} > t_0) K_h\{\gamma(S_{Ai}^{(0)}) - \gamma(s)\} dN_{Ai}^{(0)}(z)}{\sum_{i=1}^{n_{A0}} K_h\{\gamma(S_{Ai}^{(0)}) - \gamma(s)\} Y_{Ai}^{(0)}(z)}
$$

is a consistent estimate of $\Lambda_A^{(0)}(t \mid t_0, s) = -\log[r_A^{(0)}(t \mid t_0, s)], Y_{Ai}^{(0)}(t) = I(X_{Ai}^{(0)} \ge t),$ $N_{Ai}^{(0)}(t) = I(X_{Ai}^{(0)} \le t)\delta_{Ai}^{(0)}, K(\cdot)$ is a smooth symmetric density function, $K_h(x) = K(x/h)/h$ and $\gamma(\cdot)$ is a given monotone transformation function. For the bandwidth h, we require the standard undersmoothing assumption of $h = O(n_q^{-\gamma})$ with $\gamma \in (1/4, 1/2)$ in order to eliminate the impact of the bias of the conditional survival function on the resulting estimator.

The quantity $\hat{\sigma}_{EB}(t, t_0)$ is obtained using either a closed form expression under the null or a perturbation resampling approach. If a confidence interval is desired, perturbation resampling is required.

Value

recover. B 11

Author(s)

Layla Parast

References

Parast L, Cai T, Tian L (2019). Using a Surrogate Marker for Early Testing of a Treatment Effect. Biometrics, 75(4):1253-1263.

Examples

```
data(dataA)
data(dataB)
early.delta.test(Axzero = dataA$x0, Adeltazero = dataA$delta0, Aszero = dataA$s0,
Bxzero = dataB$x0, Bdeltazero = dataB$delta0, Bszero = dataB$s0, Bxone = dataB$x1,
Bdeltaone = dataB$delta1, Bsone = dataB$s1, t=1, landmark=0.5, perturb = FALSE,
extrapolate = TRUE)
```
early.delta.test(Axzero = dataA\$x0, Adeltazero = dataA\$delta0, Aszero = dataA\$s0, Bxzero = dataB\$x0, Bdeltazero = dataB\$delta0, Bszero = dataB\$s0, Bxone = dataB\$x1, Bdeltaone = dataB\$delta1, Bsone = dataB\$s1, t=0.75, landmark=0.5, perturb = FALSE, extrapolate = TRUE)

```
early.delta.test(Axzero = dataA$x0, Adeltazero = dataA$delta0, Aszero = dataA$s0,
Bxzero = dataB$x0, Bdeltazero = dataB$delta0, Bszero = dataB$s0, Bxone = dataB$x1,
Bdeltaone = dataB$delta1, Bsone = dataB$s1, t=1, landmark=0.5, perturb = TRUE,
extrapolate = TRUE)
```
recover.B *Recover an estimate of the treatment effect at time t in Study B*

Description

Recover an estimate of the treatment effect at time t in Study B

Usage

```
recover.B(Axzero, Adeltazero, Aszero, Axone, Adeltaone, Asone, Bxzero, Bdeltazero,
Bszero, Bxone, Bdeltaone, Bsone, t, landmark, extrapolate = T, transform = F)
```
Arguments

Details

Assume there are two randomized studies of a treatment effect, a prior study (Study A) and a current study (Study B). Study A was completed up to some time t, while Study B was stopped at time $t_0 < t$. In both studies, a surrogate marker was measured at time t_0 for individuals still observable at t_0 . Let G be the binary treatment indicator with $G = 1$ for treatment and $G = 0$ for control and we assume throughout that subjects are randomly assigned to a treatment group at baseline. Let $T_K^{(1)}$ and $T_K^{(0)}$ denote the time of the primary outcome of interest, death for example, under the treatment and under the control, respectively, in Study K. Let $S_K^{(1)}$ and $S_K^{(0)}$ denote the surrogate marker measured at time t_0 under the treatment and the control, respectively, in Study K. The treatment effect quantity of interest, $\Delta_K(t)$, is the difference in survival rates by time t under treatment versus control,

$$
\Delta_K(t) = E\{I(T_K^{(1)} > t)\} - E\{I(T_K^{(0)} > t)\} = P(T_K^{(1)} > t) - P(T_K^{(0)} > t)
$$

where $t > t_0$. Here, we recover an estimate of $\Delta_B(t)$ using Study B information (which stopped follow-up at time $t_0 < t$) and Study A information (which has follow-up information through time t). The estimate is obtained as

$$
\hat{\Delta}_{EB}(t,t_0)/\hat{R}_{SA}(t,t_0)
$$

where $\Delta_{EB}(t, t_0)$ is the early treatment effect estimate in Study B, described in the early.delta.test documention, and $\hat{R}_{SA}(t,t_0)$ is the proportion of treatment effect explained by the surrogate marker information at t_0 in Study A. This proportion is calculated as $\hat{R}_{SA}(t,t_0) = \hat{\Delta}_{EA}(t,t_0)/\hat{\Delta}_{A}(t)$ where

$$
\hat{\Delta}_A(t) = n_{A1}^{-1} \sum_{i=1}^{n_{A1}} \frac{I(X_{Ai}^{(1)} > t)}{\hat{W}_{A1}^C(t)} - n_{A0}^{-1} \sum_{i=1}^{n_{A0}} \frac{I(X_{Ai}^{(0)} > t)}{\hat{W}_{A0}^C(t)},
$$

and $\hat{\Delta}_{EA}(t,t_0)$ is parallel to $\hat{\Delta}_{EB}(t,t_0)$ except replacing $n_{A0}^{-1} \sum_{i=1}^{n_{A0}} \hat{r}_A^{(0)}(t|S_{Ai}^{(0)}, t_0) \frac{I(X_{Ai}^{(0)} > t_0)}{\hat{W}_{A}^{C}(t_0)}$ $\frac{N_{Ai} > t_0}{W_{A_0}^C(t_0)}$ by $n_{A0}^{-1} \sum_{i=1}^{n_{A0}} \hat{W}_{A0}^C(t)^{-1} I(X_{Ai}^{(0)} > t)$, and $\hat{W}_{Ag}^C(\cdot)$ is the Kaplan-Meier estimator of the survival function for $C_A^{(g)}$ for $g = 0, 1$.

Perturbation resampling is used to provide a standard error estimate for the estimate of $\Delta_B(t)$ and a confidence interval.

Value

recovered.deltaB

The recovered estimate of $\Delta_B(t)$.

sd.recovered.deltaB

The standard error estimate of the recovered estimate of $\Delta_B(t)$.

conf.quantile.recovered.deltaB

A confidence interval for the recovered estimate of $\Delta_B(t)$.

Author(s)

Layla Parast

References

Parast L, Cai T, Tian L (2019). Using a Surrogate Marker for Early Testing of a Treatment Effect. Biometrics, In press.

Parast L, Cai T and Tian L (2017). Evaluating Surrogate Marker Information using Censored Data. Statistics in Medicine, 36(11): 1767-1782.

Examples

```
data(dataA)
data(dataB)
recover.B(Axzero = dataA$x0, Adeltazero = dataA$delta0, Aszero = dataA$s0, Axone
= dataA$x1, Adeltaone = dataA$delta1, Asone = dataA$s1, Bxzero = dataB$x0, Bdeltazero
= dataB$delta0, Bszero = dataB$s0, Bxone = dataB$x1, Bdeltaone = dataB$delta1, Bsone
= dataB$s1, t=1, landmark=0.5, extrapolate = TRUE)
recover.B(Axzero = dataA$x0, Adeltazero = dataA$delta0, Aszero = dataA$s0, Axone
= dataA$x1, Adeltaone = dataA$delta1, Asone = dataA$s1, Bxzero = dataB$x0, Bdeltazero
```

```
= dataB$delta0, Bszero = dataB$s0, Bxone = dataB$x1, Bdeltaone = dataB$delta1, Bsone
= dataB$s1, t=0.75, landmark=0.5, extrapolate = TRUE)
```
Index

∗ datasets dataA, [2](#page-1-0) dataB, [3](#page-2-0) ∗ htest design.study, [5](#page-4-0) early.delta.test, [8](#page-7-0) ∗ nonparametric delta.estimate, [4](#page-3-0) design.study, [5](#page-4-0) early.delta.test, [8](#page-7-0) recover.B, [11](#page-10-0) ∗ survival delta.estimate, [4](#page-3-0) design.study, [5](#page-4-0) early.delta.test, [8](#page-7-0) recover.B, [11](#page-10-0) ∗ univar delta.estimate, [4](#page-3-0) dataA, [2](#page-1-0) dataB, [3](#page-2-0) delta.estimate, [4](#page-3-0) design.study, [5](#page-4-0) early.delta.test, [8](#page-7-0) recover.B, [11](#page-10-0)