Package ‘ipw’

August 18, 2015

Version 1.0-11
Date 2015-08-18
Title Estimate Inverse Probability Weights
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Depends R (>= 3.0.0)
Imports MASS, nnet, survival, geepack, graphics, methods, stats
Suggests nlme, survey, boot
Description Functions to estimate the probability to receive the observed treatment, based on
individual characteristics. The inverse of these probabilities can be used as weights when
estimating causal effects from observational data via marginal structural models. Both point
treatment situations and longitudinal studies can be analysed. The same functions can be used to
correct for informative censoring.
Encoding latin1
License GPL (>= 2)
LazyData true
NeedsCompilation no
Repository CRAN
Date/Publication 2015-08-18 16:58:46

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HIV: TB and Survival (Baseline Data)

Description
Simulated dataset. Baseline data of 386 HIV positive individuals, including time of first active tuberculosis, time of death, individual end time. Time varying CD4 measurements of these patients are included in dataset timedat.

Usage
data(basdat)

Format
A data frame with 386 observations on the following 4 variables.

id patient ID.
ttb time of first active tuberculosis, measured in days since HIV seroconversion.
tdeath time of death, measured in days since HIV seroconversion.
tend individual end time (either death or censoring), measured in days since HIV seroconversion.

Details
These simulated data are used together with data in timedat in a detailed causal modelling example using inverse probability weighting (IPW). See ipwtm for the example. Data were simulated using the algorithm described in Van der Wal e.a. (2009).

Author(s)
Willem M. van der Wal <w.m.vanderwal@amc.uva.nl>

References

See Also
basdat, haartdat, ipwplot, ipwpoint, ipwtm, timedat, tstartfun.

Examples
#see ?ipwtm for example
**Description**

Survival data measured in 1200 HIV positive patients. Start of follow-up is HIV seroconversion. Each row corresponds to a 100 day interval of follow-up time, using the counting process notation. Patients can initiate HAART therapy. CD4 count is a confounder for the effect of HAART on mortality.

**Usage**

```r
data(haartdat)
```

**Format**

- **patient**: patient ID
- **tstart**: starting time for each interval of follow-up, measured in days since HIV seroconversion
- **fuptime**: end time for each interval of follow-up, measured in days since HIV seroconversion
- **haartind**: indicator for the initiation of HAART therapy at the end of the interval (0=HAART not initiated/1=HAART initiated).
- **event**: indicator for death at the end of the interval (0=alive/1=died)
- **sex**: sex (0=male/1=female)
- **age**: age at the start of follow-up (years)
- **cd4.sqrt**: square root of CD4 count, measured at fuptime, before haartind

**Details**

These data were simulated. Patients can initiate HAART at fuptime=0. Therefore, to allow the fitting of a model predicting initiation of HAART, starting time for the first interval within each patient is negative (-100).

**Author(s)**

Willem M. van der Wal <w.m.vanderwal@amc.uva.nl>

**References**


**See Also**

basdat, haartdat, ipwplot, ipwpoint, ipwtm, timedat, tstartfun.
Examples

#see ?ipwtm for example


healthdat  

IQ, Income and Health

Description

A simulated dataset containing IQ, income and health score measurements in 1000 individuals.

Usage

data(healthdat)

Format

A data frame with 1000 rows, with each row corresponding to a separate individual. The following variables are included:

- id  individual ID.
- iq  IQ score.
- income gross monthly income (EUR).
- health health score (0-100).

Details

In these simulated data, IQ is a confounder for the effect of income on health.

Author(s)

Willem M. van der Wal <w.m.vanderwal@amc.uva.nl>

References


See Also

basdat, haartdat, healthdat, ipwplot, ipwpoint, ipwtm, timedat, tstartfun.

Examples

#see ?ipwpoint for example
ipwplot

Plot Inverse Probability Weights

Description
For time varying weights: display boxplots within strata of follow-up time. For point treatment weights: display density plot.

Usage

ipwplot(weights, timevar = NULL, binwidth = NULL, logscale = TRUE,
         xlab = NULL, ylab = NULL, main = "", ref = TRUE, ...)

Arguments
weights numerical vector of inverse probability weights to plot.
timevar numerical vector representing follow-up time. When specified, boxplots within strata of follow-up time are displayed. When left unspecified, a density plot is displayed.
binwidth numerical value indicating the width of the intervals of follow-up time; for each interval a boxplot is made. Ignored when timevar is not specified.
logscale logical value. If TRUE, weights are plotted on a logarithmic scale.
xlab label for the horizontal axis.
ylab label for the vertical axis.
main main title for the plot.
ref logical value. If TRUE, a reference line is plotted at y=1.
... additional arguments passed to boxplot (when timevar is specified) or plot (when timevar is not specified).

Value
A plot is displayed.

Author(s)
Willem M. van der Wal <w.m.vanderwal@amc.uva.nl>

References

See Also
basdat, haartdat, ipwplot, ipwpoint, ipwtm, timedat, tstartfun.
Examples

# see ?ipwpoint and ?ipwtm for examples

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**ipwpoint**  
*Estimate Inverse Probability Weights (Point Treatment)*

**Description**

Estimate inverse probability weights to fit marginal structural models in a point treatment situation. The exposure for which we want to estimate the causal effect can be binomial, multinomial, ordinal or continuous. Both stabilized and unstabilized weights can be estimated.

**Usage**

```r
ipwpoint(exposure, family, link, numerator = NULL, denominator, data, trunc = NULL, ...)
```

**Arguments**

- **exposure**: a vector, representing the exposure variable of interest. Both numerical and categorical variables can be used. A binomial exposure variable should be coded using values 0/1.
- **family**: is used to specify a family of link functions, used to model the relationship between the variables in numerator or denominator and exposure, respectively. Alternatives are "binomial", "multinomial", "ordinal" and "gaussian". A specific link function is then chosen using the argument `link`, as explained below. Regression models are fitted using `glm`, `multinom`, `polr` or `glm`, respectively.
- **link**: specifies the link function between the variables in numerator or denominator and exposure, respectively. For family = "binomial" (fitted using `glm`) alternatives are "logit", "probit", "cauchit", "log" and "cloglog". For family = "multinomial" this argument is ignored, and multinomial logistic regression models are always used (fitted using `multinom`). For family = "ordinal" (fitted using `polr`) alternatives are "logit", "probit", "cauchit", and "cloglog". For family = "gaussian" this argument is ignored, and a linear regression model with identity link is always used (fitted using `glm`).
- **numerator**: is a formula, specifying the right-hand side of the model used to estimate the elements in the numerator of the inverse probability weights. When left unspecified, unstabilized weights with a numerator of 1 are estimated.
- **denominator**: is a formula, specifying the right-hand side of the model used to estimate the elements in the denominator of the inverse probability weights. This typically includes the variables specified in the numerator model, as well as confounders for which to correct.
- **data**: is a dataframe containing exposure and the variables used in numerator and denominator.
ipwpoint

trunc optimal truncation percentile (0-0.5). E.g. when trunc = 0.01, the left tail is truncated to the 1st percentile, and the right tail is truncated to the 99th percentile. When specified, both un-truncated and truncated weights are returned.

... are further arguments passed to the function that is used to estimate the numerator and denominator models (the function is chosen using family).

Details

For each unit under observation, this function computes an inverse probability weight, which is the ratio of two probabilities:

- the numerator contains the probability of the observed exposure level given observed values of stabilization factors (usually a set of baseline covariates). These probabilities are estimated using the model regressing exposure on the terms in numerator, using the link function indicated by family and link.
- the denominator contains the probability of the observed exposure level given the observed values of a set of confounders, as well as the stabilization factors in the numerator. These probabilities are estimated using the model regressing exposure on the terms in denominator, using the link function indicated by family and link.

When the models from which the elements in the numerator and denominator are predicted are correctly specified, and there is no unmeasured confounding, weighting the observations by the inverse probability weights adjusts for confounding of the effect of the exposure of interest. On the weighted dataset a marginal structural model can then be fitted, quantifying the causal effect of the exposure on the outcome of interest.

With numerator specified, stabilized weights are computed, otherwise unstabilized weighs with a numerator of 1 are computed. With a continuous exposure, using family = "gaussian", weights are computed using the ratio of predicted densities. Therefore, for family = "gaussian" only stabilized weights can be used, since unstabilized weights would have infinity variance.

Value

A list containing the following elements:

- ipw.weights is a vector containing inverse probability weights for each unit under observation. This vector is returned in the same order as the measurements contained in data, to facilitate merging.
- weights.trunc is a vector containing truncated inverse probability weights for each unit under observation. This vector is only returned when trunc is specified.
- call is the original function call to ipwpoint.
- num.mod is the numerator model, only returned when numerator is specified.
- den.mod is the denominator model.

Missing values

Currently, the exposure variable and the variables used in numerator and denominator should not contain missing values.
Author(s)
Willem M. van der Wal <w.m.vanderwal@amc.uva.nl>

References


See Also
basdat, haartdat, ipwplot, ipwpoint, ipwtm, timedat, tstartfun.

Examples

```r
#Simulate data with continuous confounder and outcome, binomial exposure.
#Marginal causal effect of exposure on outcome: 10.
n <- 1000
simdat <- data.frame(l = rnorm(n, 10, 5))
a.lin <- simdat$l - 10
pa <- exp(a.lin)/(1 + exp(a.lin))
simdat$a <- rbinom(n, 1, prob = pa)
simdat$y <- 10*simdat$a + 0.5*simdat$l + rnorm(n, -10, 5)
simdat[1:5,]

#Estimate ipw weights.
temp <- ipwpoint(
exposure = a,
family = "binomial",
link = "logit",
numerator = ~ 1,
denominator = ~ l,
data = simdat)
summary(temp$ipw.weights)

#Plot inverse probability weights
graphics.off()
ipwplot(weights = temp$ipw.weights, logscale = FALSE,
main = "Stabilized weights", xlim = c(0, 8))

#Examine numerator and denominator models.
summary(temp$num.mod)
summary(temp$den.mod)

#Paste inverse probability weights
simdat$sw <- temp$ipw.weights

#Marginal structural model for the causal effect of a on y
```
ipwtm

```r
#corrected for confounding by l using inverse probability weighting
#with robust standard error from the survey package.
require("survey")
msm <- (svyglm(y ~ a, design = svydesign(~ 1, weights = ~ sw,
data = simdat)))
coef(msm)
confint(msm)

## Not run:
#Compute basic bootstrap confidence interval .
require(boot)
boot.fun <- function(dat, index){
  coef(glm(
    formula = y ~ a,
data = dat[index,],
weights = ipwpoint(
  exposure = a,
family = "gaussian",
numerator = ~ 1,
denominator = ~ 1,
data = dat[index,]$ipw.weights)))[2]
}
bootres <- boot(simdat, boot.fun, 499);bootres
boot.ci(bootres, type = "basic")
## End(Not run)
```

---

**ipwtm**  
**Estimate Inverse Probability Weights (Time Varying)**

**Description**

Estimate inverse probability weights to fit marginal structural models, with a time-varying exposure and time-varying confounders. Within each unit under observation this function computes inverse probability weights at each time point during follow-up. The exposure can be binomial, multinomial, ordinal or continuous. Both stabilized and unstabilized weights can be estimated.

**Usage**

```r
ipwtm(exposure, family, link, numerator = NULL, denominator, id,
tstart, timevar, type, data, corstr = "ar1", trunc = NULL, ...
```

**Arguments**

- **exposure** vector, representing the exposure of interest. Both numerical and categorical variables can be used. A binomial exposure variable should be coded using values 0/1.
family specifies a family of link functions, used to model the relationship between the variables in numerator or denominator and exposure, respectively. Alternatives are "binomial", "survival", "multinomial", "ordinal" and "gaussian". A specific link function is then chosen using the argument link, as explained below. Regression models are fitted using glm, coxph, multinom, polr or geeglm, respectively.

link specifies the specific link function between the variables in numerator or denominator and exposure, respectively. For family= "binomial" (fitted using glm) alternatives are "logit", "probit", "cauchit", "log" and "cloglog". For family= "survival" this argument is ignored, and Cox proportional hazards models are always used (fitted using coxph). For family= "multinomial" this argument is ignored, and multinomial logistic regression models are always used (fitted using multinom). For family= "ordinal" (fitted using polr) alternatives are "logit", "probit", "cauchit", and "cloglog". For family= "gaussian" this argument is ignored, and GEE models with an identity link are always used (fitted using geeglm).

denominator is a formula, specifying the right-hand side of the model used to estimate the elements in the denominator of the inverse probability weights. When left unspecified, unstabilized weights with a numerator of 1 are estimated.

id vector, uniquely identifying the units under observation (typically patients) within which the longitudinal measurements are taken.

tstart numerical vector, representing the starting time of follow-up intervals, using the counting process notation. This argument is only needed when family= "survival", otherwise it is ignored. The Cox proportional hazards models are fitted using counting process data. Since a switch in exposure level can occur at the start of follow-up, tstart should be negative for the first interval (with timevar=0) within each patient.

timevar numerical vector, representing follow-up time, starting at 0. This variable is used as the end time of follow-up intervals, using the counting process notation, when family= "survival".

type specifies the type of exposure. Alternatives are "first" and "all". With type= "first", weights are estimated up to the first switch from the lowest exposure value (typically 0 or the first factor level) to any other value. After this switch, weights will then be constant. Such a weight is e.g. used when estimating the effect of "initiation of HAART" on mortality (see example below). With type= "all", all time points are used to estimate weights. Currently, only "first" is implemented for "survival", "multinomial" and "ordinal" families. Only value "all" is implemented for the "gaussian" family. Both type= "first" and type= "all" are implemented for the "binomial" family.

data dataframe containing exposure, variables in numerator and denominator, id, tstart and timevar.

corstr correlation structure, only needed when using family = "gaussian". Defaults to "ar1". See geeglm for details.

trunc optional truncation percentile (0-0.5). E.g. when trunc = 0.01, the left tail is truncated to the 1st percentile, and the right tail is truncated to the 99th percentile. When specified, both un-truncated and truncated weights are returned.
are further arguments passed to the function that is used to estimate the numerator and denominator models (the function is chosen using family).

Details

Within each unit under observation i (usually patients), this function computes inverse probability weights at each time point j during follow-up. These weights are the cumulative product over all previous time points up to j of the ratio of two probabilities:

- the numerator contains at each time point the probability of the observed exposure level given observed values of stabilization factors and the observed exposure history up to the time point before j. These probabilities are estimated using the model regressing exposure on the terms in numerator, using the link function indicated by family and link.

- the denominator contains at each time point the probability of the observed exposure level given the observed history of time varying confounders up to j, as well as the stabilization factors in the numerator and the observed exposure history up to the time point before j. These probabilities are estimated using the model regressing exposure on the terms in denominator, using the link function indicated by family and link.

When the models from which the elements in the numerator and denominator are predicted are correctly specified, and there is no unmeasured confounding, weighting observations ij by the inverse probability weights adjusts for confounding of the effect of the exposure of interest. On the weighted dataset a marginal structural model can then be fitted, quantifying the causal effect of the exposure on the outcome of interest.

With numerator specified, stabilized weights are computed, otherwise unstabilized weights with a numerator of 1 are computed. With a continuous exposure, using family = "gaussian", weights are computed using the ratio of predicted densities at each time point. Therefore, for family = "gaussian" only stabilized weights can be used, since unstabilized weights would have infinity variance.

Value

A list containing the following elements:

- ipw.weights: vector containing inverse probability weights for each observation. Returned in the same order as the observations in data, to facilitate merging.

- weights.trunc: vector containing truncated inverse probability weights, only returned when trunc is specified.

- call: the original function call.

- selvar: selection variable. With type = "first", selvar = 1 within each unit under observation, up to and including the first time point at which a switch from the lowest value of exposure to any other value is made, and selvar = 0 after the first switch. For type = "all", selvar = 1 for all measurements. The numerator and denominator models are fitted only on observations with selvar = 1. Returned in the same order as observations in data, to facilitate merging.

- num.mod: the numerator model, only returned when numerator is specified.

- den.mod: the denominator model.
Missing values

Currently, the exposure variable and the variables used in numerator and denominator, id, tstart and timevar should not contain missing values.

Author(s)

Willem M. van der Wal <w.m.vanderwal@amc.uva.nl>

References


See Also

basdat, haartdat, ipwpplot, ipwpoint, ipwtm, timedat, tstartfun.

Examples

# Load longitudinal data from HIV positive individuals.
data(haartdat)

# CD4 is confounder for the effect of initiation of HAART therapy on mortality.
# Estimate inverse probability weights to correct for confounding.
# Exposure allocation model is Cox proportional hazards model.
require(survival)
temp <- ipwtm(
  exposure = haartind,
  family = "survival",
  numerator = ~ sex + age,
  denominator = ~ sex + age + cd4.sqrt,
  id = patient,
  tstart = tstart,
  timevar = fuptime,
  type = "first",
  data = haartdat)

# Plot inverse probability weights
graphics.off()
ipwpplot(weights = temp$ipw.weights, timevar = haartdat$fuptime,
  binwidth = 100, ylim = c(-1.5, 1.5), main = "Stabilized inverse probability weights")

# CD4 count has an effect both on dropout and mortality, which causes informative censoring.
# Use inverse probability of censoring weighting to correct for effect of CD4 on dropout.
# Use Cox proportional hazards model for dropout.

```
temp2 <- ipwtm(
  exposure = dropout,
  family = "survival",
  numerator = ~ sex + age,
  denominator = ~ sex + age + cd4.sqrt,
  id = patient,
  tstart = tstart,
  timevar = fuptime,
  type = "first",
  data = haartdat)
```

# Plot inverse probability of censoring weights
```
ipwplot(weights = temp2$ipw.weights, timevar = haartdat$fuptime,
        binwidth = 100, ylim = c(-1.5, 1.5), main = "Stabilized inverse probability of censoring weights")
```

# MSM for the causal effect of initiation of HAART on mortality.
# Corrected both for confounding and informative censoring.
# With robust standard error obtained using cluster().
```
summary(coxph(Surv(tstart, fuptime, event) ~ haartind + cluster(patient),
             data = haartdat, weights = temp2$ipw.weights*temp2$ipw.weights))
```

# Uncorrected model
```
summary(coxph(Surv(tstart, fuptime, event) ~ haartind, data = haartdat))
```

# Example 2
```
data(basdat)
data(timedat)
```

# Aim: to model the causal effect of active tuberculosis (TB) on mortality.
# Longitudinal CD4 is a confounder as well as intermediate for the effect of TB.

# Process original measurements
# Check for ties (not allowed)
```
table(duplicated(timedat[,c("id", "fuptime")]))
```
# Take square root of CD4 because of skewness
```
timedat$cd4.sqrt <- sqrt(timedat$cd4count)
```
# Add TB time to dataframe
```
timedat <- merge(timedat, basdat[,c("id", "Ttb")], by = "id", all.x = TRUE)
```
# Compute TB status
```
timedat$tb.lag <- ifelse(with(timedat, !is.na(Ttb) & fuptime > Ttb), 1, 0)
```
# Longitudinal CD4-model
```
require nlme

cd4.lme <- lme(cd4.sqrt ~ fuptime + tb.lag, random = ~ fuptime | id, data = timedat)
```

# Build new dataset:
# Rows corresponding to TB-status switches, and individual end times
```
times <- sort(unique(c(basdat$Ttb, basdat$Tend)))
startstop <- data.frame(
  id = rep(basdat$id, each = length(times)),
  fuptime = rep(times, nrow(basdat)))
#add baseline data to dataframe
startstop <- merge(startstop, basdat, by = "id", all.x = TRUE)
#limit individual follow-up using Tend
startstop$tstart <- tstartfun(id, fuptime, startstop) #compute tstart (?tstartfun)
#indicate TB status
startstop$tb <- ifelse(with(startstop, !is.na(Ttb) & fuptime >= Ttb), 1, 0)
#indicate TB status at previous time point
startstop$tb.lag <- ifelse(with(startstop, !is.na(Ttb) & fuptime > Ttb), 1, 0)
#indicate death
startstop$event <- ifelse(with(startstop, !is.na(Tdeath) & fuptime >= Tdeath),
  1, 0)
#impute CD4, based on TB status at previous time point.
startstop$cd4.sqrt <- predict(cd4.lme, newdata = data.frame(id = startstop$id,
  fuptime = startstop$fuptime, tb.lag = startstop$tb.lag))

#compute inverse probability weights
require(survival)
temp <- ipwtm(
  exposure = tb,
  family = "survival",
  numerator = ~ 1,
  denominator = ~ cd4.sqrt,
  id = id,
  tstart = tstart,
  timevar = fuptime,
  type = "first",
  data = startstop)
summary(temp$ipw.weights)
ipwplot(weights = temp$ipw.weights, timevar = startstop$fuptime, binwidth = 100)

#models
#IPW-fitted MSM, using cluster() to obtain robust standard error estimate
summary(coxph(Surv(tstart, fuptime, event) ~ tb + cluster(id),
  data = startstop, weights = temp$ipw.weights))
#unadjusted
summary(coxph(Surv(tstart, fuptime, event) ~ tb, data = startstop))
#adjusted using conditioning: part of the effect of TB is adjusted away
summary(coxph(Surv(tstart, fuptime, event) ~ tb + cd4.sqrt, data = startstop))

## Not run:
#compute bootstrap CI for TB parameter (takes a few hours)
#taking into account the uncertainty introduced by modelling longitudinal CD4
#taking into account the uncertainty introduced by estimating the inverse probability weights
#robust with regard to weights unequal to 1
require(boot)
boot.fun <- function(data, index, data.tm){
  data.samp <- data[index,]
  data.samp$id.samp <- 1:nrow(data.samp)
  data.tm.samp <- do.call("rbind", lapply(data.samp$id.samp, function(id.samp) {
cbind(data.tm$data.tm$id == data.samp$id[data.samp$id.samp == id.samp],
   id.samp = id.samp)
}
)
cd4.lme <- lme(cbindHdataNsampDid{dataNsampDidNsamp 
                   idNsamp}L\L
                     idNsamp 
                      idNsampI
                      cdTNlme <M lmeHcdTNsqrt ~ fuptime + tbNlagL random = ~ fuptime | idNsamp, data = data.tm.samp)
times <- sort(unique(c(data.samp$Ttb, data.samp$Tend)))
startstop.samp <- data.frame(id.samp = rep(data.samp$id.samp, each = length(times)),
                             fuptime = rep(times, nrow(data.samp)))
startstop.samp <- merge(startstop.samp, data.samp, by = "id.samp", all.x = TRUE)
startstop.samp <- startstop.samp[with(startstop.samp, fuptime <= Tend),]
startstop.samp$tstart <- tstartfun(id.samp, fuptime, startstop.samp)
startstop.samp$tb <- ifelse(with(startstop.samp, is.na(Ttb) & fuptime > Ttb), 1, 0)
startstop.samp$tb.lag <- ifelse(with(startstop.samp, is.na(Ttb) & fuptime > Ttb), 1, 0)
startstop.samp$event <- ifelse(with(startstop.samp, is.na(Tdeath) & fuptime > Tdeath), 1, 0)
startstop.samp$cd4.sqrt <- predict(cd4.lme, newdata = data.frame(id.samp =
                                           startstop.samp$id.samp, fuptime = startstop.samp$fuptime, tb.lag = startstop.samp$tb.lag))

return(coef(coxph(Surv(tstart, fuptime, event) ~ tb, data = startstop.samp,
               weights = ipwtm(
                   exposure = tb,
                   family = "survival",
                   numerator = ~ 1,
                   denominator = ~ cd4.sqrt,
                   id = id.samp,
                   tstart = tstart,
                   timevar = fuptime,
                   type = "first",
                   data = startstop.samp$ipw.weights))[1]))
)
bootres <- boot(data = basdat, statistic = boot.fun, R = 999, data.tm = timedat)
bootres
boot.ci(bootres, type = "basic")

## End(Not run)
Format

A data frame with 6291 observations on the following 3 variables.

- id  patient ID.
- fuptime  follow-up time (days since HIV seroconversion).
- cd4count  CD4 count measured at fuptime.

Details

These simulated data are used together with data in basdat in a detailed causal modelling example using inverse probability weighting (IPW). See ipwtm for the example. Data were simulated using the algorithm described in Van der Wal e.a. (2009).

Author(s)

Willem M. van der Wal <w.m.vanderwal@amc.uva.nl>

References


See Also

basdat, haartdat, ipwplot, ipwpoint, ipwtm, timedat, tstartfun.

Examples

#See ?ipwtm for example

---

tstartfun  Compute Starting Time For Counting Process Notation

Description

Function to compute starting time for intervals of follow-up, when using the counting process notation. Within each unit under observation (usually individuals), computes starting time equal to:

- time of previous record when there is a previous record.
- -1 for first record.
tstartfun

Usage

```r
tstartfun(id, timevar, data)
```

Arguments

- **id**: numerical vector, uniquely identifying the units under observation, within which the longitudinal measurements are taken.
- **timevar**: numerical vector, representing follow-up time, starting at 0.
- **data**: dataframe containing `id` and `timevar`.

Value

Numerical vector containing starting time for each record. In the same order as the records in `data`, to facilitate merging.

Missing values

Currently, `id` and `timevar` should not contain missing values.

Author(s)

Willem M. van der Wal <w.m.vanderwal@amc.uva.nl>

References


See Also

`basdat`, `haartdat`, `ipwplot`, `ipwpoint`, `ipwtm`, `timedat`, `tstartfun`.

Examples

```r
#data
mydata1 <- data.frame(
  patient = c(1, 1, 1, 1, 1, 1, 2, 2, 2),
  time.days = c(14, 34, 41, 56, 72, 98, 0, 11, 28, 35))

#compute starting time for each interval
mydata1$tstart <- tstartfun(patient, time.days, mydata1)

#result
mydata1

#see also ?ipwtm for example
```
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