

Package ‘ipw’

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Title Estimate inverse probability weights.

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Description Estimate inverse probability weights. These are typically used to perform inverse probability weighting (IPW) to fit a marginal structural model (MSM), to estimate causal effects from observational data. Both data from point treatment situations and longitudinal studies can be used.

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basdat

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)

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References

Van der Wal W.M. & Geskus R.B. (2011). ipw: An R Package for Inverse Probability Weighting. *Journal of Statistical Software*, **43**(13), 1-23. <http://www.jstatsoft.org/v43/i13/>.

Van der Wal W.M., Prins M., Lumbreras B. & Geskus R.B. (2009). A simple G-computation algorithm to quantify the causal effect of a secondary illness on the progression of a chronic disease. *Statistics in Medicine*, **28**(18), 2325-2337.

See Also

[basdat](#), [haartdat](#), [ipwplot](#), [ipwpoint](#), [ipwtm](#), [timedat](#), [tstartfun](#).

Examples

```
#see ?ipwtm for example
```

`haartdat`*HAART and Survival in HIV Patients*

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

```
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

Van der Wal W.M. & Geskus R.B. (2011). ipw: An R Package for Inverse Probability Weighting. *Journal of Statistical Software*, **43**(13), 1-23. <http://www.jstatsoft.org/v43/i13/>.

See Also

[basdat](#), [haartdat](#), [ipwplot](#), [ipwpoint](#), [ipwtm](#), [timedat](#), [tstartfun](#).

Examples

```
#see ?ipwtm for example
```

healthdat	<i>IQ, Income and Health</i>
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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

Van der Wal W.M. & Geskus R.B. (2011). ipw: An R Package for Inverse Probability Weighting. *Journal of Statistical Software*, **43**(13), 1-23. <http://www.jstatsoft.org/v43/i13/>.

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

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

Value

A plot is displayed.

Author(s)

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

References

Van der Wal W.M. & Geskus R.B. (2011). ipw: An R Package for Inverse Probability Weighting. *Journal of Statistical Software*, **43**(13), 1-23. <http://www.jstatsoft.org/v43/i13/>.

See Also

[basdat](#), [haartdat](#), [ipwplot](#), [ipwpoint](#), [ipwtm](#), [timedat](#), [tstartfun](#).

Examples

#see ?ipwpoint and ?ipwtm for examples

ipwpoint	<i>Estimate Inverse Probability Weights (Point Treatment)</i>
----------	---

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

```
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 <code>glm</code> , <code>multinom</code> , <code>polr</code> or <code>glm</code> , respectively.
link	specifies the link function between the variables in numerator or denominator and exposure, respectively. For family = "binomial" (fitted using <code>glm</code>) 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 <code>multinom</code>). For family = "ordinal" (fitted using <code>polr</code>) 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 <code>glm</code>).
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.

<code>trunc</code>	optional truncation percentile (0-0.5). E.g. when <code>trunc = 0.01</code> , 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.
<code>...</code>	are further arguments passed to the function that is used to estimate the numerator and denominator models (the function is chosen using <code>family</code>).

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 weights 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:

<code>ipw.weights</code>	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 <code>data</code> , to facilitate merging.
<code>weights.trunc</code>	is a vector containing truncated inverse probability weights for each unit under observation. This vector is only returned when <code>trunc</code> is specified.
<code>call</code>	is the original function call to <code>ipwpoint</code> .
<code>num.mod</code>	is the numerator model, only returned when <code>numerator</code> is specified.
<code>den.mod</code>	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

Cole, S.R. & Hernán, M.A. (2008). Constructing inverse probability weights for marginal structural models. *American Journal of Epidemiology*, **168**(6), 656-664.

Robins, J.M., Hernán, M.A. & Brumback, B.A. (2000). Marginal structural models and causal inference in epidemiology. *Epidemiology*, **11**, 550-560.

Van der Wal W.M. & Geskus R.B. (2011). ipw: An R Package for Inverse Probability Weighting. *Journal of Statistical Software*, **43**(13), 1-23. <http://www.jstatsoft.org/v43/i13/>.

See Also

[basdat](#), [haartdat](#), [ipwplot](#), [ipwpoint](#), [ipwtm](#), [timedat](#), [tstartfun](#).

Examples

```
#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 = ~ 1,
  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
```

```

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

#Compute basic bootstrap confidence interval .
#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")

```

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

```

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 <code>glm</code> , <code>coxph</code> , <code>multinom</code> , <code>polr</code> or <code>geeglm</code> , 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).
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.
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:

<code>ipw.weights</code>	vector containing inverse probability weights for each observation. Returned in the same order as the observations in <code>data</code> , to facilitate merging.
<code>weights.trunc</code>	vector containing truncated inverse probability weights, only returned when <code>trunc</code> is specified.
<code>call</code>	the original function call.
<code>selvar</code>	selection variable. With <code>type = "first"</code> , <code>selvar = 1</code> 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 <code>selvar = 0</code> after the first switch. For <code>type = "all"</code> , <code>selvar = 1</code> for all measurements. The numerator and denominator models are fitted only on observations with <code>selvar = 1</code> . Returned in the same order as observations in <code>data</code> , to facilitate merging.
<code>num.mod</code>	the numerator model, only returned when <code>numerator</code> is specified.
<code>den.mod</code>	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

Cole, S.R. & Hernán, M.A. (2008). Constructing inverse probability weights for marginal structural models. *American Journal of Epidemiology*, **168**(6), 656-664.

Robins, J.M., Hernán, M.A. & Brumback, B.A. (2000). Marginal structural models and causal inference in epidemiology. *Epidemiology*, **11**, 550-560.

Van der Wal W.M. & Geskus R.B. (2011). ipw: An R Package for Inverse Probability Weighting. *Journal of Statistical Software*, **43**(13), 1-23. <http://www.jstatsoft.org/v43/i13/>.

See Also

[basdat](#), [haartdat](#), [ipwplot](#), [ipwpoint](#), [ipwtm](#), [timedat](#), [tstartfun](#).

Examples

```
#####
#EXAMPLE 1

#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.
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()
ipwplot(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
graphics.off()
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 = temp$ipw.weights*temp2$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
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$id, each = length(times)),
  fuptime = rep(times, nrow(basdat)))
#add baseline data to dataframe
startstop <- merge(startstop, basdat, by = "id", all.x = TRUE)
#limit individual follow-up using Tend
startstop <- startstop[with(startstop, fuptime <= Tend),]
startstop$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
  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))

#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
# 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$id == dat
#   cd4.lme <- lme(cd4.sqrt ~ fuptime + tb.lag, random = ~ fuptime | id.samp, data = data.tm.samp)
#   times <- sort(unique(c(data.samp$Ttb, data.samp$Tend)))
#   startstop.samp <- data.frame(id.samp = rep(data.samp$id.samp, each = length(times)), fuptime = rep(times, nro
#   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 =
#   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")
```

timedat

HIV: TB and Survival (Longitudinal Measurements)

Description

Simulated dataset. Time varying CD4 measurements of 386 HIV positive individuals. Time of first active tuberculosis, time of death and individual end time of the patients are included in dataset [basdat](#).

Usage

```
data(timedat)
```

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)

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References

Cole, S.R. & Hernán, M.A. (2008). Constructing inverse probability weights for marginal structural models. *American Journal of Epidemiology*, **168**(6), 656-664.

Robins, J.M., Hernán, M.A. & Brumback, B.A. (2000). Marginal structural models and causal inference in epidemiology. *Epidemiology*, **11**, 550-560.

Van der Wal W.M. & Geskus R.B. (2011). ipw: An R Package for Inverse Probability Weighting. *Journal of Statistical Software*, **43**(13), 1-23. <http://www.jstatsoft.org/v43/i13/>.

Van der Wal W.M., Prins M., Lumbreras B. & Geskus R.B. (2009). A simple G-computation algorithm to quantify the causal effect of a secondary illness on the progression of a chronic disease. *Statistics in Medicine*, **28**(18), 2325-2337.

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.

Usage

```
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

Van der Wal W.M. & Geskus R.B. (2011). `ipw`: An R Package for Inverse Probability Weighting. *Journal of Statistical Software*, **43**(13), 1-23. <http://www.jstatsoft.org/v43/i13/>.

See Also

[basdat](#), [haartdat](#), [ipwplot](#), [ipwpoint](#), [ipwtm](#), [timedat](#), [tstartfun](#).

Examples

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

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

#result
mydata1

#see also ?ipwtm for example
```

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