Package 'mets'

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Type Package

Title Analysis of Multivariate Event Times

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Description Implementation of various statistical models for multivariate event history data <doi:10.1007/s10985-013-9244-x>. Including multivariate cumulative incidence models <doi:10.1002/sim.6016>, and bivariate random effects probit models (Liability models) <doi:10.1016/j.csda.2015.01.014>. Modern methods for survival analysis, including regression modelling (Cox, Fine-Gray, Ghosh-Lin, Binomial regression) with fast computation of influence functions.

License GPL (>= 2)

LazyLoad yes

URL https://kkholst.github.io/mets/

BugReports https://github.com/kkholst/mets/issues

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mets-package *Analysis of Multivariate Events*

Description

Implementation of various statistical models for multivariate event history data. Including multivariate cumulative incidence models, and bivariate random effects probit models (Liability models)

Author(s)

Klaus K. Holst and Thomas Scheike

Examples

```
## To appear
```

aalenfrailty *Aalen frailty model*

Description

Additive hazards model with (gamma) frailty

Usage

```
aalenfrailty(time, status, X, id, theta, B = NULL, ...)
```

Arguments

time	Time variable
status	Status variable (0,1)
X	Covariate design matrix
id	cluster variable
theta	list of thetas (returns score evaluated here), or starting point for optimization (defaults to magic number 0.1)
B	(optional) Cumulative coefficients (update theta by fixing B)
...	Additional arguments to lower level functions

Details

Aalen frailty model

Value

Parameter estimates

Author(s)

Klaus K. Holst

Examples

```
library("timereg")
dd <- simAalenFrailty(5000)
f <- ~1##+x
X <- model.matrix(f,dd) ## design matrix for non-parametric terms
system.time(out<-timereg::aalen(update(f,Surv(time,status)~.),dd,n.sim=0,robust=0))
dix <- which(dd$status==1)
t1 <- system.time(bb <- .Call("Bhat",as.integer(dd$status),
                              X,0.2,as.integer(dd$id),NULL,NULL,
                              PACKAGE="mets"))
spec <- 1
##plot(out,spec=spec)
## plot(dd$time[dix],bb$B2[,spec],col="red",type="s",
##      ylim=c(0,max(dd$time)*c(beta0,beta)[spec]))
## abline(a=0,b=c(beta0,beta)[spec])
##'

## Not run:
thetas <- seq(0.1,2,length.out=10)
Us <- unlist(aalenfrailty(dd$time,dd$status,X,dd$id,as.list(thetas)))
##plot(thetas,Us,type="l",ylim=c(-.5,1)); abline(h=0,lty=2); abline(v=theta,lty=2)
op <- aalenfrailty(dd$time,dd$status,X,dd$id)
op

## End(Not run)
```

`aalenMets` *Fast additive hazards model with robust standard errors*

Description

Fast Lin-Ying additive hazards model with a possibly stratified baseline. Robust variance is default variance with the summary.

Usage

```
aalenMets(formula, data = data, ...)
```

Arguments

formula	formula with 'Surv' outcome (see coxph)
data	data frame
...	Additional arguments to phreg

Details

influence functions (iid) will follow numerical order of given cluster variable so ordering after $id will give iid in order of data-set.

Author(s)

Thomas Scheike

Examples

```
data(bmt); bmt$time <- bmt$time+runif(408)*0.001
out <- aalenMets(Surv(time,cause==1)~tcell+platelet+age,data=bmt)
summary(out)

## out2 <- timereg::aalen(Surv(time,cause==1)~const(tcell)+const(platelet)+const(age),data=bmt)
## summary(out2)
```

---

back2timereg *Convert to timereg object*

Description

convert to timereg object

Usage

```
back2timereg(obj)
```

Arguments

obj	no use

Author(s)

Thomas Scheike

base1cumhaz *rate of CRBSI for HPN patients of Copenhagen*

Description

rate of CRBSI for HPN patients of Copenhagen

Source

Estimated data

base44cumhaz *rate of Occlusion/Thrombosis complication for catheter of HPN patients of Copenhagen*

Description

rate of Occlusion/Thrombosis complication for catheter of HPN patients of Copenhagen

Source

Estimated data

base4cumhaz *rate of Mechanical (hole/defect) complication for catheter of HPN patients of Copenhagen*

Description

rate of Mechanical (hole/defect) complication for catheter of HPN patients of Copenhagen

Source

Estimated data

basehazplot.phreg *Plotting the baslines of stratified Cox*

Description

Plotting the baselines of stratified Cox

Usage

```
basehazplot.phreg(
  x,
  se = FALSE,
  time = NULL,
  add = FALSE,
  ylim = NULL,
  xlim = NULL,
  lty = NULL,
  col = NULL,
  lwd = NULL,
  legend = TRUE,
  ylab = NULL,
  xlab = NULL,
  polygon = TRUE,
  level = 0.95,
  stratas = NULL,
  robust = FALSE,
  conf.type = c("plain", "log"),
  ...
)
```

Arguments

x	phreg object
se	to include standard errors
time	to plot for specific time variables
add	to add to previous plot
ylim	to give ylim
xlim	to give xlim
lty	to specify lty of components
col	to specify col of components
lwd	to specify lwd of components
legend	to specify col of components
ylab	to specify ylab
xlab	to specify xlab

polygon	to get standard error in shaded form
level	of standard errors
stratas	wich strata to plot
robust	to use robust standard errors if possible
conf.type	"plain" or "log" transformed
...	Additional arguments to lower level funtions

Author(s)

Klaus K. Holst, Thomas Scheike

Examples

```
data(TRACE)
dcut(TRACE) <- ~.
out1 <- phreg(Surv(time,status==9)~vf+chf+strata(wmicat.4),data=TRACE)

par(mfrow=c(2,2))
bplot(out1)
bplot(out1,stratas=c(0,3))
bplot(out1,stratas=c(0,3),col=2:3,lty=1:2,se=TRUE)
bplot(out1,stratas=c(0),col=2,lty=2,se=TRUE,polygon=FALSE)
bplot(out1,stratas=c(0),col=matrix(c(2,1,3),1,3),lty=matrix(c(1,2,3),1,3),se=TRUE,polygon=FALSE)
```

---

bicomprisk *Estimation of concordance in bivariate competing risks data*

Description

Estimation of concordance in bivariate competing risks data

Usage

```
bicomprisk(
  formula,
  data,
  cause = c(1, 1),
  cens = 0,
  causes,
  indiv,
  strata = NULL,
  id,
  num,
  max.clust = 1000,
  marg = NULL,
  se.clusters = NULL,
  wname = NULL,
```

```
  prodlim = FALSE,
  messages = TRUE,
  model,
  return.data = 0,
  uniform = 0,
  conservative = 1,
  resample.iid = 1,
  ...
)
```

Arguments

formula	Formula with left-hand-side being a Event object (see example below) and the left-hand-side specying the covariate structure
data	Data frame
cause	Causes (default (1,1)) for which to estimate the bivariate cumulative incidence
cens	The censoring code
causes	causes
indiv	indiv
strata	Strata
id	Clustering variable
num	num
max.clust	max number of clusters in timereg::comp.risk call for iid decompostion, max.clust=NULL uses all clusters otherwise rougher grouping.
marg	marginal cumulative incidence to make stanard errors for same clusters for subsequent use in casewise.test()
se.clusters	to specify clusters for standard errors. Either a vector of cluster indices or a column name in data. Defaults to the id variable.
wname	name of additonal weight used for paired competing risks data.
prodlim	prodlim to use prodlim estimator (Aalen-Johansen) rather than IPCW weighted estimator based on comp.risk function.These are equivalent in the case of no covariates. These esimators are the same in the case of stratified fitting.
messages	Control amount of output
model	Type of competing risk model (default is Fine-Gray model "fg", see comp.risk).
return.data	Should data be returned (skipping modeling)
uniform	to compute uniform standard errors for concordance estimates based on resampling.
conservative	for conservative standard errors, recommended for larger data-sets.
resample.iid	to return iid residual processes for further computations such as tests.
...	Additional arguments to timereg::comp.risk function

Author(s)

Thomas Scheike, Klaus K. Holst

References

Scheike, T. H.; Holst, K. K. & Hjelmborg, J. B. Estimating twin concordance for bivariate competing risks twin data Statistics in Medicine, Wiley Online Library, 2014 , 33 , 1193-204

Examples

```
library("timereg")

## Simulated data example
prt <- simnordic.random(2000,delayed=TRUE,ptrunc=0.7,
      cordz=0.5,cormz=2,lam0=0.3)
## Bivariate competing risk, concordance estimates
p11 <- bicomprisk(Event(time,cause)~strata(zyg)+id(id),data=prt,cause=c(1,1))

p11mz <- p11$model$"MZ"
p11dz <- p11$model$"DZ"
par(mfrow=c(1,2))
## Concordance
plot(p11mz,ylim=c(0,0.1));
plot(p11dz,ylim=c(0,0.1));

## entry time, truncation weighting
### other weighting procedure
prtl <-  prt[!prt$truncated,]
prt2 <- ipw2(prtl,cluster="id",same.cens=TRUE,
     time="time",cause="cause",entrytime="entry",
     pairs=TRUE,strata="zyg",obs.only=TRUE)

prt22 <- fast.reshape(prt2,id="id")

prt22$event <- (prt22$cause1==1)*(prt22$cause2==1)*1
prt22$timel <- pmax(prt22$time1,prt22$time2)
ipwc <- timereg::comp.risk(Event(timel,event)~-1+factor(zyg1),
  data=prt22,cause=1,n.sim=0,model="rcif2",times=50:90,
  weights=prt22$weights1,cens.weights=rep(1,nrow(prt22)))

p11wmz <- ipwc$cum[,2]
p11wdz <- ipwc$cum[,3]
lines(ipwc$cum[,1],p11wmz,col=3)
lines(ipwc$cum[,1],p11wdz,col=3)
```

`BinAugmentCifstrata` *Augmentation for Binomial regression based on stratified NPMLE Cif (Aalen-Johansen)*

Description

Computes the augmentation term for each individual as well as the sum

$$A = \int_0^t H(u, X) \frac{1}{S^*(u, s)} \frac{1}{G_c(u)} dM_c(u)$$

with

$$H(u, X) = F_1^*(t, s) - F_1^*(u, s)$$

using a KM for

$$G_c(t)$$

and a working model for cumulative baseline related to

$$F_1^*(t, s)$$

and

$$s$$

is strata,

$$S^*(t, s) = 1 - F_1^*(t, s) - F_2^*(t, s)$$

.

Usage

```
BinAugmentCifstrata(
  formula,
  data = data,
  cause = 1,
  cens.code = 0,
  km = TRUE,
  time = NULL,
  weights = NULL,
  offset = NULL,
  ...
)
```

Arguments

formula	formula with 'Event', strata model for CIF given by strata, and strataC specifies censoring strata
data	data frame
cause	of interest
cens.code	code of censoring
km	to use Kaplan-Meier
time	of interest
weights	weights for estimating equations
offset	offsets for logistic regression
...	Additional arguments to binreg function.

Details

Standard errors computed under assumption of correct

$$G_c(s)$$

model.

Author(s)

Thomas Scheike

Examples

```
data(bmt)
dcut(bmt,breaks=2) <- ~age
out1<-BinAugmentCifstrata(Event(time,cause)~platelet+agecat.2+
  strata(platelet,agecat.2),data=bmt,cause=1,time=40)
summary(out1)

out2<-BinAugmentCifstrata(Event(time,cause)~platelet+agecat.2+
    strata(platelet,agecat.2)+strataC(platelet),data=bmt,cause=1,time=40)
summary(out2)
```

`binomial.twostage` *Fits Clayton-Oakes or bivariate Plackett (OR) models for binary data using marginals that are on logistic form. If clusters contain more than two times, the algoritm uses a compososite likelihood based on all pairwise bivariate models.*

Description

The pairwise pairwise odds ratio model provides an alternative to the alternating logistic regression (ALR).

Usage

```
binomial.twostage(
  margbin,
  data = parent.frame(),
  method = "nr",
  detail = 0,
  clusters = NULL,
  silent = 1,
  weights = NULL,
  theta = NULL,
  theta.des = NULL,
  var.link = 0,
  var.par = 1,
```

```
  var.func = NULL,
  iid = 1,
  notaylor = 1,
  model = "plackett",
  marginal.p = NULL,
  beta.iid = NULL,
  Dbeta.iid = NULL,
  strata = NULL,
  max.clust = NULL,
  se.clusters = NULL,
  numDeriv = 0,
  random.design = NULL,
  pairs = NULL,
  dim.theta = NULL,
  additive.gamma.sum = NULL,
  pair.ascertained = 0,
  case.control = 0,
  no.opt = FALSE,
  twostage = 1,
  beta = NULL,
  ...
)
```

Arguments

margbin	Marginal binomial model
data	data frame
method	Scoring method "nr", for lava NR optimizer
detail	Detail
clusters	Cluster variable
silent	Debug information
weights	Weights for log-likelihood, can be used for each type of outcome in 2x2 tables.
theta	Starting values for variance components
theta.des	design for dependence parameters, when pairs are given the indeces of the theta-design for this pair, is given in pairs as column 5
var.link	Link function for variance
var.par	parametrization
var.func	when alternative parametrizations are used this function can specify how the paramters are related to the λ_j's.
iid	Calculate i.i.d. decomposition when iid>=1, when iid=2 then avoids adding the uncertainty for marginal paramters for additive gamma model (default).
notaylor	Taylor expansion
model	model
marginal.p	vector of marginal probabilities

beta.iid	iid decomposition of marginal probability estimates for each subject, if based on GLM model this is computed.
Dbeta.iid	derivatives of marginal model wrt marginal parameters, if based on GLM model this is computed.
strata	strata for fitting: considers only pairs where both are from same strata
max.clust	max clusters
se.clusters	clusters for iid decomposition for roubst standard errors
numDeriv	uses Fisher scoring aprox of second derivative if 0, otherwise numerical derivatives
random.design	random effect design for additive gamma model, when pairs are given the indeces of the pairs random.design rows are given as columns 3:4
pairs	matrix with rows of indeces (two-columns) for the pairs considered in the pairwise composite score, useful for case-control sampling when marginal is known.
dim.theta	dimension of theta when pairs and pairs specific design is given. That is when pairs has 6 columns.
additive.gamma.sum	this is specification of the lamtot in the models via a matrix that is multiplied onto the parameters theta (dimensions=(number random effects x number of theta parameters), when null then sums all parameters. Default is a matrix of 1's
pair.ascertained	if pairs are sampled only when there are events in the pair i.e. Y1+Y2>=1.
case.control	if data is case control data for pair call, and here 2nd column of pairs are probands (cases or controls)
no.opt	for not optimizing
twostage	default twostage=1, to fit MLE use twostage=0
beta	is starting value for beta for MLE version
...	for NR of lava

Details

The reported standard errors are based on a cluster corrected score equations from the pairwise likelihoods assuming that the marginals are known. This gives correct standard errors in the case of the Odds-Ratio model (Plackett distribution) for dependence, but incorrect standard errors for the Clayton-Oakes types model (that is also called "gamma"-frailty). For the additive gamma version of the standard errors are adjusted for the uncertainty in the marginal models via an iid deomposition using the iid() function of lava. For the clayton oakes model that is not speicifed via the random effects these can be fixed subsequently using the iid influence functions for the marginal model, but typically this does not change much.

For the Clayton-Oakes version of the model, given the gamma distributed random effects it is assumed that the probabilities are indpendent, and that the marginal survival functions are on logistic form

$$logit(P(Y=1|X)) = \alpha + x^T\beta$$

therefore conditional on the random effect the probability of the event is

$$logit(P(Y=1|X,Z)) = exp(-Z \cdot Laplace^{-1}(lamtot, lamtot, P(Y=1|x)))$$

Can also fit a structured additive gamma random effects model, such the ACE, ADE model for survival data:

Now random.design specificies the random effects for each subject within a cluster. This is a matrix of 1's and 0's with dimension n x d. With d random effects. For a cluster with two subjects, we let the random.design rows be v_1 and v_2. Such that the random effects for subject 1 is

$$v_1^T(Z_1, ..., Z_d)$$

, for d random effects. Each random effect has an associated parameter $(\lambda_1, ..., \lambda_d)$. By construction subjects 1's random effect are Gamma distributed with mean $\lambda_j / v_1^T \lambda$ and variance $\lambda_j / (v_1^T \lambda)^2$. Note that the random effect $v_1^T(Z_1, ..., Z_d)$ has mean 1 and variance $1/(v_1^T \lambda)$. It is here asssumed that $lamtot = v_1^T \lambda$ is fixed over all clusters as it would be for the ACE model below.

The DEFAULT parametrization uses the variances of the random effecs (var.par=1)

$$\theta_j = \lambda_j / (v_1^T \lambda)^2$$

For alternative parametrizations (var.par=0) one can specify how the parameters relate to λ_j with the function

Based on these parameters the relative contribution (the heritability, h) is equivalent to the expected values of the random effects $\lambda_j / v_1^T \lambda$

Given the random effects the probabilities are independent and on the form

$$logit(P(Y = 1|X)) = exp(-Laplace^{-1}(lamtot, lamtot, P(Y = 1|x)))$$

with the inverse laplace of the gamma distribution with mean 1 and variance lamtot.

The parameters $(\lambda_1, ..., \lambda_d)$ are related to the parameters of the model by a regression construction $pard$ (d x k), that links the d λ parameters with the (k) underlying θ parameters

$$\lambda = theta.des\theta$$

here using theta.des to specify these low-dimension association. Default is a diagonal matrix.

Author(s)

Thomas Scheike

References

Two-stage binomial modelling

Examples

```
data(twinstut)
twinstut0 <- subset(twinstut, tvparnr<4000)
twinstut <- twinstut0
twinstut$binstut <- (twinstut$stutter=="yes")*1
theta.des <- model.matrix( ~-1+factor(zyg),data=twinstut)
margbin <- glm(binstut~factor(sex)+age,data=twinstut,family=binomial())
bin <- binomial.twostage(margbin,data=twinstut,var.link=1,
         clusters=twinstut$tvparnr,theta.des=theta.des,detail=0)
```

```
summary(bin)

twinstut$cage <- scale(twinstut$age)
theta.des <- model.matrix( ~-1+factor(zyg)+cage,data=twinstut)
bina <- binomial.twostage(margbin,data=twinstut,var.link=1,
         clusters=twinstut$tvparnr,theta.des=theta.des)
summary(bina)

theta.des <- model.matrix( ~-1+factor(zyg)+factor(zyg)*cage,data=twinstut)
bina <- binomial.twostage(margbin,data=twinstut,var.link=1,
         clusters=twinstut$tvparnr,theta.des=theta.des)
summary(bina)

 ## Reduce Ex.Timings
## refers to zygosity of first subject in eash pair : zyg1
## could also use zyg2 (since zyg2=zyg1 within twinpair's))
out <- easy.binomial.twostage(stutter~factor(sex)+age,data=twinstut,
                          response="binstut",id="tvparnr",var.link=1,
                     theta.formula=~-1+factor(zyg1))
summary(out)

## refers to zygosity of first subject in eash pair : zyg1
## could also use zyg2 (since zyg2=zyg1 within twinpair's))
desfs<-function(x,num1="zyg1",num2="zyg2")
    c(x[num1]=="dz",x[num1]=="mz",x[num1]=="os")*1

out3 <- easy.binomial.twostage(binstut~factor(sex)+age,
      data=twinstut,response="binstut",id="tvparnr",var.link=1,
      theta.formula=desfs,desnames=c("mz","dz","os"))
summary(out3)


### use of clayton oakes binomial additive gamma model
############################################################
 ## Reduce Ex.Timings
data <- simbinClaytonOakes.family.ace(10000,2,1,beta=NULL,alpha=NULL)
margbin <- glm(ybin~x,data=data,family=binomial())
margbin

head(data)
data$number <- c(1,2,3,4)
data$child <- 1*(data$number==3)

### make ace random effects design
out <- ace.family.design(data,member="type",id="cluster")
out$pardes
head(out$des.rv)

bints <- binomial.twostage(margbin,data=data,
     clusters=data$cluster,detail=0,var.par=1,
     theta=c(2,1),var.link=0,
     random.design=out$des.rv,theta.des=out$pardes)
summary(bints)
```

```
data <- simbinClaytonOakes.twin.ace(10000,2,1,beta=NULL,alpha=NULL)
out  <- twin.polygen.design(data,id="cluster",zygname="zygosity")
out$pardes
head(out$des.rv)
margbin <- glm(ybin~x,data=data,family=binomial())

bintwin <- binomial.twostage(margbin,data=data,
     clusters=data$cluster,var.par=1,
     theta=c(2,1),random.design=out$des.rv,theta.des=out$pardes)
summary(bintwin)
concordanceTwinACE(bintwin)
```

---

binreg *Binomial Regression for censored competing risks data*

Description

Simple version of comp.risk function of timereg for just one time-point thus fitting the model

$$P(T \leq t, \epsilon = 1|X) = expit(X^T beta)$$

Usage

```
binreg(
  formula,
  data,
  cause = 1,
  time = NULL,
  beta = NULL,
  offset = NULL,
  weights = NULL,
  cens.weights = NULL,
  cens.model = ~+1,
  se = TRUE,
  kaplan.meier = TRUE,
  cens.code = 0,
  no.opt = FALSE,
  method = "nr",
  augmentation = NULL,
  ...
)
```

Arguments

formula	formula with outcome (see coxph)

data	data frame
cause	cause of interest (numeric variable)
time	time of interest
beta	starting values
offset	offsets for partial likelihood
weights	for score equations
cens.weights	censoring weights
cens.model	only stratified cox model without covariates
se	to compute se's based on IPCW
kaplan.meier	uses Kaplan-Meier for IPCW in contrast to exp(-Baseline)
cens.code	gives censoring code
no.opt	to not optimize
method	for optimization
augmentation	to augment binomial regression
...	Additional arguments to lower level funtions

Details

Based on binomial regresion IPCW response estimating equation:

$$X(\Delta I(T \leq t, \epsilon = 1)/G_c(T_i-) - expit(X^T beta)) = 0$$

for IPCW adjusted responses.

logitIPCW instead considers

$$XI(min(T_i, t) < G_i)/G_c(min(T_i, t))(I(T \leq t, \epsilon = 1) - expit(X^T beta)) = 0$$

a standard logistic regression with weights that adjust for IPCW.

variance is based on

$$\sum w_i^2$$

also with IPCW adjustment, and naive.var is variance under known censoring model.

Censoring model may depend on strata.

Author(s)

Thomas Scheike

Examples

```
data(bmt)
# logistic regresion with IPCW binomial regression
out <- binreg(Event(time,cause)~tcell+platelet,bmt,time=50)
summary(out)
predict(out,data.frame(tcell=c(0,1),platelet=c(1,1)),se=TRUE)
```

```
outs <- binreg(Event(time,cause)~tcell+platelet,bmt,time=50,cens.model=~strata(tcell,platelet))
summary(outs)

## glm with IPCW weights
outl <- logitIPCW(Event(time,cause)~tcell+platelet,bmt,time=50)
summary(outl)

########################################
### risk-ratio of different causes #######
########################################
data(bmt)
bmt$id <- 1:nrow(bmt)
bmt$status <- bmt$cause
bmt$strata <- 1
bmtdob <- bmt
bmtdob$strata <-2
bmtdob <- dtransform(bmtdob,status=1,cause==2)
bmtdob <- dtransform(bmtdob,status=2,cause==1)
###
bmtdob <- rbind(bmt,bmtdob)
dtable(bmtdob,cause+status~strata)

cif1 <- cif(Event(time,cause)~+1,bmt,cause=1)
cif2 <- cif(Event(time,cause)~+1,bmt,cause=2)
bplot(cif1)
bplot(cif2,add=TRUE,col=2)

cifs1 <- binreg(Event(time,cause)~tcell+platelet+age,bmt,cause=1,time=50)
cifs2 <- binreg(Event(time,cause)~tcell+platelet+age,bmt,cause=2,time=50)
summary(cifs1)
summary(cifs2)

cifdob <- binreg(Event(time,status)~-1+factor(strata)+
 tcell*factor(strata)+platelet*factor(strata)+age*factor(strata)
 +cluster(id),bmtdob,cause=1,time=50,cens.model=~strata(strata)+cluster(id))
summary(cifdob)

riskratio <- function(p) {
  Z <- rbind(c(1,0,1,1,0,0,0,0), c(0,1,1,1,0,1,1,0))
  lp <- c(Z %*% p)
  p <- lava::expit(lp)
  return(p[1]/p[2])
}

lava::estimate(cifdob,f=riskratio)
```

---

binregATE *Average Treatment effect for censored competing risks data using Binomial Regression*

Description

Under the standard causal assumptions we can estimate the average treatment effect E(Y(1) - Y(0)). We need Consistency, ignorability (Y(1), Y(0) indep A given X), and positivity.

Usage

```
binregATE(
  formula,
  data,
  cause = 1,
  time = NULL,
  beta = NULL,
  treat.model = ~+1,
  cens.model = ~+1,
  offset = NULL,
  weights = NULL,
  cens.weights = NULL,
  se = TRUE,
  kaplan.meier = TRUE,
  cens.code = 0,
  no.opt = FALSE,
  method = "nr",
  augmentation = NULL,
  outcome = c("cif", "rmst", "rmst-cause"),
  model = "exp",
  Ydirect = NULL,
  ...
)
```

Arguments

formula	formula with outcome (see coxph)
data	data frame
cause	cause of interest
time	time of interest
beta	starting values
treat.model	logistic treatment model given covariates
cens.model	only stratified cox model without covariates
offset	offsets for partial likelihood
weights	for score equations
cens.weights	censoring weights
se	to compute se's with IPCW adjustment, otherwise assumes that IPCW weights are known
kaplan.meier	uses Kaplan-Meier for IPCW in contrast to exp(-Baseline)
cens.code	gives censoring code

no.opt	to not optimize
method	for optimization
augmentation	to augment binomial regression
outcome	can do CIF regression "cif"=F(t|X), "rmst"=E(min(T, t) | X) , or "rmst-cause"=E(I(epsilon==cause) (t - mint(T,t))) | X)
model	possible exp model for E(min(T, t) | X)=exp(X^t beta) , or E(I(epsilon==cause) (t - mint(T,t))) | X)=exp(X^t beta)
Ydirect	use this Y instead of outcome constructed inside the program (e.g. I(T< t, epsilon=1)), then uses IPCW vesion of the Y, set outcome to "rmst" to fit using the model specified by model
...	Additional arguments to lower level funtions

Details

The first covariate in the specification of the competing risks regression model must be the treatment effect that is a factor. If the factor has more than two levels then it uses the mlogit for propensity score modelling. If there are no censorings this is the same as ordinary logistic regression modelling.

Estimates the ATE using the the standard binary double robust estimating equations that are IPCW censoring adjusted. Rather than binomial regression we also consider a IPCW weighted version of standard logistic regression logitIPCWATE.

The original version of the program with only binary treatment binregATEbin take binary-numeric as input for the treatment, and also computes the ATT and ATC, average treatment effect on the treated (ATT), E(Y(1) - Y(0) | A=1), and non-treated, respectively. Experimental version.

Author(s)

Thomas Scheike

Examples

```
data(bmt)
dfactor(bmt)  <-  ~.

brs <- binregATE(Event(time,cause)~tcell.f+platelet+age,bmt,time=50,cause=1,
  treat.model=tcell.f~platelet+age)
summary(brs)

brsi <- binregATE(Event(time,cause)~tcell.f+tcell.f*platelet+tcell.f*age,bmt,time=50,cause=1,
  treat.model=tcell.f~platelet+age)
summary(brsi)
```

binregCasewise *Estimates the casewise concordance based on Concordance and marginal estimate using binreg*

Description

Estimates the casewise concordance based on Concordance and marginal estimate using binreg

Usage

```
binregCasewise(concbreg, margbreg, zygs = c("DZ", "MZ"), newdata = NULL, ...)
```

Arguments

concbreg	Concordance
margbreg	Marginal estimate
zygs	order of zygosity for estimation of concordance and casewise.
newdata	to give instead of zygs.
...	to pass to estimate function

Details

Uses cluster iid for the two binomial-regression estimates standard errors better than those of casewise that are often conservative.

Author(s)

Thomas Scheike

Examples

```
data(prt)
prt <- force.same.cens(prt,cause="status")

dd <- bicompriskData(Event(time, status)~strata(zyg)+id(id), data=prt, cause=c(2, 2))
newdata <- data.frame(zyg=c("DZ","MZ"),id=1)

## concordance
bcif1 <- binreg(Event(time,status)~-1+factor(zyg)+cluster(id), data=dd,
                time=80, cause=1, cens.model=~strata(zyg))
pconc <- predict(bcif1,newdata)

## marginal estimates
mbcif1 <- binreg(Event(time,status)~cluster(id), data=prt, time=80, cause=2)
mc <- predict(mbcif1,newdata)
mc

cse <- binregCasewise(bcif1,mbcif1)
cse
```

binregG *G-estimator for binomial regression model (Standardized estimates)*

Description

Computes G-estimator

$$\hat{F}(t, A = a) = n^{-1} \sum_i \hat{F}(t, A = a, Z_i)$$

. Assumes that the first covariate is A. Gives influence functions of these risk estimates and SE's are based on these. If first covariate is a factor then all contrast are computed, and if continuous then considered covariate values are given by Avalues.

Usage

```
binregG(x, data, Avalues = c(0, 1), varname = NULL)
```

Arguments

x	phreg or cifreg object
data	data frame for risk averaging
Avalues	values to compare for first covariate A
varname	if given then averages for this variable, default is first variable

Author(s)

Thomas Scheike

Examples

```
data(bmt); bmt$time <- bmt$time+runif(408)*0.001
bmt$event <- (bmt$cause!=0)*1

b1 <- binreg(Event(time,cause)~age+tcell+platelet,bmt,cause=1,time=50)
sb1 <- binregG(b1,bmt,Avalues=c(0,1,2))
summary(sb1)
```

binregTSR *2 Stage Randomization for Survival Data or competing Risks Data*

Description

Under two-stage randomization we can estimate the average treatment effect E(Y(i,j)) of treatment regime (i,j). The estimator can be agumented in different ways: using the two randomizations and the dynamic censoring augmetatation. The treatment's must be given as factors.

Usage

```
binregTSR(
  formula,
  data,
  cause = 1,
  time = NULL,
  cens.code = 0,
  response.code = NULL,
  augmentR0 = NULL,
  treat.model0 = ~+1,
  augmentR1 = NULL,
  treat.model1 = ~+1,
  augmentC = NULL,
  cens.model = ~+1,
  estpr = c(1, 1),
  response.name = NULL,
  offset = NULL,
  weights = NULL,
  cens.weights = NULL,
  beta = NULL,
  kaplan.meier = TRUE,
  no.opt = FALSE,
  method = "nr",
  augmentation = NULL,
  outcome = c("cif", "rmst", "rmst-cause"),
  model = "exp",
  Ydirect = NULL,
  return.dataw = 0,
  pi0 = 0.5,
  pi1 = 0.5,
  cens.time.fixed = 1,
  outcome.iid = 1,
  ...
)
```

Arguments

formula	formula with outcome (see coxph)

data	data frame
cause	cause of interest
time	time of interest
cens.code	gives censoring code
response.code	code of status of survival data that indicates a response at which 2nd randomization is performed
augmentR0	augmentation model for 1st randomization
treat.model0	logistic treatment model for 1st randomization
augmentR1	augmentation model for 2nd randomization
treat.model1	logistic treatment model for 2ndrandomization
augmentC	augmentation model for censoring
cens.model	stratification for censoring model based on observed covariates
estpr	estimate randomization probabilities using model
response.name	can give name of response variable, otherwise reads this as first variable of treat.model1
offset	not implemented
weights	not implemented
cens.weights	can be given
beta	starting values
kaplan.meier	for censoring weights, rather than exp cumulative hazard
no.opt	not implemented
method	not implemented
augmentation	not implemented
outcome	can be c("cif","rmst","rmst-cause")
model	not implemented, uses linear regression for augmentation
Ydirect	use this Y instead of outcome constructed inside the program (e.g. I(T< t, epsilon=1)), see binreg for more on this
return.dataw	to return weighted data for all treatment regimes
pi0	set up known randomization probabilities
pi1	set up known randomization probabilities
cens.time.fixed	to use time-dependent weights for censoring estimation using weights
outcome.iid	to get iid contribution from outcome model (here linear regression working models).
...	Additional arguments to lower level funtions

Details

The solved estimating eqution is

$$(I(min(T_i,t) < G_i)/G_c(min(T_i,t))I(T \leq t, \epsilon = 1) - AUG_0 - AUG_1 + AUG_C - p(i,j)) = 0$$

where using the covariates from augmentR0

$$AUG_0 = \frac{A_0(i) - \pi_0(i)}{\pi_0(i)} X_0 \gamma_0$$

and using the covariates from augmentR1

$$AUG_1 = \frac{A_0(i)}{\pi_0(i)} \frac{A_1(j) - \pi_1(j)}{\pi_1(j)} X_1 \gamma_1$$

and the censoring augmentation is

$$AUG_C = \int_0^t \gamma_c(s)^T (e(s) - \bar{e}(s)) \frac{1}{G_c(s)} dM_c(s)$$

where

$$\gamma_c(s)$$

is chosen to minimize the variance given the dynamic covariates specified by augmentC.

In the observational case, we can use propensity score modelling and outcome modelling (using linear regression).

Standard errors are estimated using the influence function of all estimators and tests of differences can therefore be computed subsequently.

Author(s)

Thomas Scheike

Examples

```
ddf <- mets:::gsim(200,covs=1,null=0,cens=1,ce=2)

bb <- binregTSR(Event(entry,time,status)~+1+cluster(id),ddf$datat,time=2,cause=c(1),
        cens.code=0,treat.model0=A0.f~+1,treat.model1=A1.f~A0.f,
        augmentR1=~X11+X12+TR,augmentR0=~X01+X02,
        augmentC=~A01+A02+X01+X02+A11t+A12t+X11+X12+TR,
        response.code=2)
summary(bb)
```

biprobit *Bivariate Probit model*

Description

Bivariate Probit model

Usage

```
biprobit(
  x,
  data,
  id,
  rho = ~1,
  num = NULL,
  strata = NULL,
  eqmarg = TRUE,
  indep = FALSE,
  weights = NULL,
  weights.fun = function(x) ifelse(any(x <= 0), 0, max(x)),
  randomeffect = FALSE,
  vcov = "robust",
  pairs.only = FALSE,
  allmarg = !is.null(weights),
  control = list(trace = 0),
  messages = 1,
  constrain = NULL,
  table = pairs.only,
  p = NULL,
  ...
)
```

Arguments

x	formula (or vector)
data	data.frame
id	The name of the column in the dataset containing the cluster id-variable.
rho	Formula specifying the regression model for the dependence parameter
num	Optional name of order variable
strata	Strata
eqmarg	If TRUE same marginals are assumed (exchangeable)
indep	Independence
weights	Weights
weights.fun	Function defining the bivariate weight in each cluster

randomeffect	If TRUE a random effect model is used (otherwise correlation parameter is estimated allowing for both negative and positive dependence)
vcov	Type of standard errors to be calculated
pairs.only	Include complete pairs only?
allmarg	Should all marginal terms be included
control	Control argument parsed on to the optimization routine. Starting values may be parsed as 'start'.
messages	Control amount of messages shown
constrain	Vector of parameter constraints (NA where free). Use this to set an offset.
table	Type of estimation procedure
p	Parameter vector p in which to evaluate log-Likelihood and score function
...	Optional arguments

Examples

```
data(prt)
prt0 <- subset(prt,country=="Denmark")
a <- biprobit(cancer~1+zyg, ~1+zyg, data=prt0, id="id")
b <- biprobit(cancer~1+zyg, ~1+zyg, data=prt0, id="id",pairs.only=TRUE)
predict(b,newdata=lava::Expand(prt,zyg=c("MZ")))
predict(b,newdata=lava::Expand(prt,zyg=c("MZ","DZ")))

 ## Reduce Ex.Timings
n <- 2e3
x <- sort(runif(n, -1, 1))
y <- rmvn(n, c(0,0), rho=cbind(tanh(x)))>0
d <- data.frame(y1=y[,1], y2=y[,2], x=x)
dd <- fast.reshape(d)

a <- biprobit(y~1+x,rho=~1+x,data=dd,id="id")
summary(a, mean.contrast=c(1,.5), cor.contrast=c(1,.5))
with(predict(a,data.frame(x=seq(-1,1,by=.1))), plot(p00~x,type="l"))

pp <- predict(a,data.frame(x=seq(-1,1,by=.1)),which=c(1))
plot(pp[,1]~pp$x, type="l", xlab="x", ylab="Concordance", lwd=2, xaxs="i")
lava::confband(pp$x,pp[,2],pp[,3],polygon=TRUE,lty=0,col=lava::Col(1))

pp <- predict(a,data.frame(x=seq(-1,1,by=.1)),which=c(9)) ## rho
plot(pp[,1]~pp$x, type="l", xlab="x", ylab="Correlation", lwd=2, xaxs="i")
lava::confband(pp$x,pp[,2],pp[,3],polygon=TRUE,lty=0,col=lava::Col(1))
with(pp, lines(x,tanh(-x),lwd=2,lty=2))

xp <- seq(-1,1,length.out=6); delta <- mean(diff(xp))
a2 <- biprobit(y~1+x,rho=~1+I(cut(x,breaks=xp)),data=dd,id="id")
pp2 <- predict(a2,data.frame(x=xp[-1]-delta/2),which=c(9)) ## rho
lava::confband(pp2$x,pp2[,2],pp2[,3],center=pp2[,1])
```

```
## Time
## Not run:
    a <- biprobit.time(cancer~1, rho=~1+zyg, id="id", data=prt, eqmarg=TRUE,
                       cens.formula=Surv(time,status==0)~1,
                       breaks=seq(75,100,by=3),fix.censweights=TRUE)

    a <- biprobit.time2(cancer~1+zyg, rho=~1+zyg, id="id", data=prt0, eqmarg=TRUE,
                       cens.formula=Surv(time,status==0)~zyg,
                       breaks=100)

   #a1 <- biprobit.time2(cancer~1, rho=~1, id="id", data=subset(prt0,zyg=="MZ"), eqmarg=TRUE,
    #                    cens.formula=Surv(time,status==0)~1,
    #                    breaks=100,pairs.only=TRUE)

   #a2 <- biprobit.time2(cancer~1, rho=~1, id="id", data=subset(prt0,zyg=="DZ"), eqmarg=TRUE,
    #                     cens.formula=Surv(time,status==0)~1,
    #                     breaks=100,pairs.only=TRUE)

## End(Not run)
```

`blocksample` *Block sampling*

Description

Sample blockwise from clustered data

Usage

```
blocksample(data, size, idvar = NULL, replace = TRUE, ...)
```

Arguments

`data`	Data frame
`size`	Size of samples
`idvar`	Column defining the clusters
`replace`	Logical indicating wether to sample with replacement
`...`	additional arguments to lower level functions

Details

Original id is stored in the attribute 'id'

Value

`data.frame`

Author(s)

Klaus K. Holst

Examples

```
d <- data.frame(x=rnorm(5), z=rnorm(5), id=c(4,10,10,5,5), v=rnorm(5))
(dd <- blocksample(d,size=20,~id))
attributes(dd)$id

## Not run:
blocksample(data.table::data.table(d),1e6,~id)

## End(Not run)


d <- data.frame(x=c(1,rnorm(9)),
                z=rnorm(10),
                id=c(4,10,10,5,5,4,4,5,10,5),
                id2=c(1,1,2,1,2,1,1,1,1,2),
                v=rnorm(10))
dsample(d,~id, size=2)
dsample(d,.~id+id2)
dsample(d,x+z~id|x>0,size=5)
```

---

bmt *The Bone Marrow Transplant Data*

Description

Bone marrow transplant data with 408 rows and 5 columns.

Format

The data has 408 rows and 5 columns.

cause a numeric vector code. Survival status. 1: dead from treatment related causes, 2: relapse , 0: censored.

time a numeric vector. Survival time.

platelet a numeric vector code. Plalelet 1: more than 100 x 10^9 per L, 0: less.

tcell a numeric vector. T-cell depleted BMT 1:yes, 0:no.

age a numeric vector code. Age of patient, scaled and centered ((age-35)/15).

Source

Simulated data

References

NN

Examples

```
data(bmt)
names(bmt)
```

Bootphreg *Wild bootstrap for Cox PH regression*

Description

wild bootstrap for uniform bands for Cox models

Usage

```
Bootphreg(
  formula,
  data,
  offset = NULL,
  weights = NULL,
  B = 1000,
  type = c("exp", "poisson", "normal"),
  ...
)
```

Arguments

formula	formula with 'Surv' outcome (see coxph)
data	data frame
offset	offsets for cox model
weights	weights for Cox score equations
B	bootstraps
type	distribution for multiplier
...	Additional arguments to lower level funtions

Author(s)

Klaus K. Holst, Thomas Scheike

References

Wild bootstrap based confidence intervals for multiplicative hazards models, Dobler, Pauly, and Scheike (2018),

Examples

```
n <- 100
x <- 4*rnorm(n)
time1 <- 2*rexp(n)/exp(x*0.3)
time2 <- 2*rexp(n)/exp(x*(-0.3))
status <- ifelse(time1<time2,1,2)
time <- pmin(time1,time2)
rbin <- rbinom(n,1,0.5)
cc <-rexp(n)*(rbin==1)+(rbin==0)*rep(3,n)
status <- ifelse(time < cc,status,0)
time  <- ifelse(time < cc,time,cc)
data <- data.frame(time=time,status=status,x=x)

b1 <- Bootphreg(Surv(time,status==1)~x,data,B=1000)
b2 <- Bootphreg(Surv(time,status==2)~x,data,B=1000)
c1 <- phreg(Surv(time,status==1)~x,data)
c2 <- phreg(Surv(time,status==2)~x,data)

### exp to make all bootstraps positive
out <- pred.cif.boot(b1,b2,c1,c2,gplot=0)

cif.true <- (1-exp(-out$time))*.5
with(out,plot(time,cif,ylim=c(0,1),type="l"))
lines(out$time,cif.true,col=3)
with(out,plotConfRegion(time,band.EE,col=1))
with(out,plotConfRegion(time,band.EE.log,col=3))
with(out,plotConfRegion(time,band.EE.log.o,col=2))
```

---

bptwin *Liability model for twin data*

Description

Liability-threshold model for twin data

Usage

```
bptwin(
  x,
  data,
  id,
  zyg,
  DZ,
  group = NULL,
  num = NULL,
  weights = NULL,
  weights.fun = function(x) ifelse(any(x <= 0), 0, max(x)),
```

```
  strata = NULL,
  messages = 1,
  control = list(trace = 0),
  type = "ace",
  eqmean = TRUE,
  pairs.only = FALSE,
  samecens = TRUE,
  allmarg = samecens & !is.null(weights),
  stderr = TRUE,
  robustvar = TRUE,
  p,
  indiv = FALSE,
  constrain,
  varlink,
  ...
)
```

Arguments

x	Formula specifying effects of covariates on the response.
data	data.frame with one observation pr row. In addition a column with the zygosity (DZ or MZ given as a factor) of each individual much be specified as well as a twin id variable giving a unique pair of numbers/factors to each twin pair.
id	The name of the column in the dataset containing the twin-id variable.
zyg	The name of the column in the dataset containing the zygosity variable.
DZ	Character defining the level in the zyg variable corresponding to the dyzogitic twins.
group	Optional. Variable name defining group for interaction analysis (e.g., gender)
num	Optional twin number variable
weights	Weight matrix if needed by the chosen estimator (IPCW)
weights.fun	Function defining a single weight each individual/cluster
strata	Strata
messages	Control amount of messages shown
control	Control argument parsed on to the optimization routine. Starting values may be parsed as 'start'.
type	Character defining the type of analysis to be performed. Should be a subset of "acde" (additive genetic factors, common environmental factors, dominant genetic factors, unique environmental factors).
eqmean	Equal means (with type="cor")?
pairs.only	Include complete pairs only?
samecens	Same censoring
allmarg	Should all marginal terms be included
stderr	Should standard errors be calculated?

robustvar	If TRUE robust (sandwich) variance estimates of the variance are used
p	Parameter vector p in which to evaluate log-Likelihood and score function
indiv	If TRUE the score and log-Likelihood contribution of each twin-pair
constrain	Development argument
varlink	Link function for variance parameters
...	Additional arguments to lower level functions

Author(s)

Klaus K. Holst

See Also

twinlm, twinlm.time, twinlm.strata, twinsim

Examples

```
data(twinstut)
b0 <- bptwin(stutter~sex,
             data=droplevels(subset(twinstut,zyg%in%c("mz","dz"))),
             id="tvparnr",zyg="zyg",DZ="dz",type="ae")
summary(b0)
```

---

casewise *Estimates the casewise concordance based on Concordance and marginal estimate using prodlim but no testing*

Description

.. content for description (no empty lines) ..

Usage

```
casewise(conc, marg, cause.marg)
```

Arguments

conc	Concordance
marg	Marginal estimate
cause.marg	specifiifes which cause that should be used for marginal cif based on prodlim

Author(s)

Thomas Scheike

Examples

```
 ## Reduce Ex.Timings
library(prodlim)
data(prt);
prt <- force.same.cens(prt,cause="status")

### marginal cumulative incidence of prostate cancer##'
outm <- prodlim(Hist(time,status)~+1,data=prt)

times <- 60:100
cifmz <- predict(outm,cause=2,time=times,newdata=data.frame(zyg="MZ")) ## cause is 2 (second cause)
cifdz <- predict(outm,cause=2,time=times,newdata=data.frame(zyg="DZ"))

### concordance for MZ and DZ twins
cc <- bicomprisk(Event(time,status)~strata(zyg)+id(id),data=prt,cause=c(2,2),prodlim=TRUE)
cdz <- cc$model$"DZ"
cmz <- cc$model$"MZ"

cdz <- casewise(cdz,outm,cause.marg=2)
cmz <- casewise(cmz,outm,cause.marg=2)

plot(cmz,ci=NULL,ylim=c(0,0.5),xlim=c(60,100),legend=TRUE,col=c(3,2,1))
par(new=TRUE)
plot(cdz,ci=NULL,ylim=c(0,0.5),xlim=c(60,100),legend=TRUE)
summary(cdz)
summary(cmz)
```

`casewise.test` *Estimates the casewise concordance based on Concordance and marginal estimate using timereg and performs test for independence*

Description

Estimates the casewise concordance based on Concordance and marginal estimate using timereg and performs test for independence

Usage

```
casewise.test(conc, marg, test = "no-test", p = 0.01)
```

Arguments

`conc`	Concordance
`marg`	Marginal estimate
`test`	Type of test for independence assumption. "conc" makes test on concordance scale and "case" means a test on the casewise concordance
`p`	check that marginal probability is greater at some point than p

Details

Uses cluster based conservative standard errors for marginal and sometimes only the uncertainty of the concordance estimates. This works prettey well, alternatively one can use also the funcions Casewise for a specific time point

Author(s)

Thomas Scheike

Examples

```
 ## Reduce Ex.Timings
library("timereg")
data("prt",package="mets");
prt <- force.same.cens(prt,cause="status")

prt <- prt[which(prt$id %in% sample(unique(prt$id),7500)),]
### marginal cumulative incidence of prostate cancer
times <- seq(60,100,by=2)
outm <- timereg::comp.risk(Event(time,status)~+1,data=prt,cause=2,times=times)

cifmz <- predict(outm,X=1,uniform=0,resample.iid=1)
cifdz <- predict(outm,X=1,uniform=0,resample.iid=1)

### concordance for MZ and DZ twins
cc <- bicomprisk(Event(time,status)~strata(zyg)+id(id),
                 data=prt,cause=c(2,2))
cdz <- cc$model$"DZ"
cmz <- cc$model$"MZ"

### To compute casewise cluster argument must be passed on,
###  here with a max of 100 to limit comp-time
outm <- timereg::comp.risk(Event(time,status)~+1,data=prt,
                 cause=2,times=times,max.clust=100)
cifmz <- predict(outm,X=1,uniform=0,resample.iid=1)
cc <- bicomprisk(Event(time,status)~strata(zyg)+id(id),data=prt,
                cause=c(2,2),se.clusters=outm$clusters)
cdz <- cc$model$"DZ"
cmz <- cc$model$"MZ"

cdz <- casewise.test(cdz,cifmz,test="case") ## test based on casewise
cmz <- casewise.test(cmz,cifmz,test="conc") ## based on concordance

plot(cmz,ylim=c(0,0.7),xlim=c(60,100))
par(new=TRUE)
plot(cdz,ylim=c(0,0.7),xlim=c(60,100))

slope.process(cdz$casewise[,1],cdz$casewise[,2],iid=cdz$casewise.iid)

slope.process(cmz$casewise[,1],cmz$casewise[,2],iid=cmz$casewise.iid)
```

cif *Cumulative incidence with robust standard errors*

Description

Cumulative incidence with robust standard errors

Usage

```
cif(formula, data = data, cause = 1, cens.code = 0, ...)
```

Arguments

formula	formula with 'Surv' outcome (see coxph)
data	data frame
cause	NULL looks at all, otherwise specify which cause to consider
cens.code	censoring code "0" is default
...	Additional arguments to lower level funtions

Author(s)

Thomas Scheike

Examples

```
data(TRACE)
TRACE$cluster <- sample(1:100,1878,replace=TRUE)
out1 <- cif(Event(time,status)~+1,data=TRACE,cause=9)
out2 <- cif(Event(time,status)~+1+cluster(cluster),data=TRACE,cause=9)

out1 <- cif(Event(time,status)~strata(vf,chf),data=TRACE,cause=9)
out2 <- cif(Event(time,status)~strata(vf,chf)+cluster(cluster),data=TRACE,cause=9)

par(mfrow=c(1,2))
bplot(out1,se=TRUE)
bplot(out2,se=TRUE)
```

`cifreg` *CIF regression*

Description

CIF logistic for propodds=1 default CIF Fine-Gray (cloglog) regression for propodds=NULL

Usage

```
cifreg(
  formula,
  data = data,
  cause = 1,
  cens.code = 0,
  cens.model = ~1,
  weights = NULL,
  offset = NULL,
  Gc = NULL,
  propodds = 1,
  ...
)
```

Arguments

`formula`	formula with 'Event' outcome
`data`	data frame
`cause`	of interest
`cens.code`	code of censoring
`cens.model`	for stratified Cox model without covariates
`weights`	weights for FG score equations
`offset`	offsets for FG model
`Gc`	censoring weights for time argument, default is to calculate these with a Kaplan-Meier estimator, should then give G_c(T_i-)
`propodds`	1 is logistic model, NULL is fine-gray model
`...`	Additional arguments to lower level funtions

Details

For FG model:

$$\int (X - E) Y_1(t) w(t) dM_1$$

is computed and summed over clusters and returned multiplied with inverse of second derivative as iid.naive. Where

$$w(t) = G(t)(I(T_i \wedge t < C_i)/G_c(T_i \wedge t))$$

and

$$E(t) = S_1(t)/S_0(t)$$

and

$$S_j(t) = \sum X_i^j Y_{i1}(t) w_i(t) \exp(X_i^T \beta)$$

The iid decomposition of the beta's, however, also have a censoring term that is also is computed and added to UUiid (still scaled with inverse second derivative)

$$\int (X - E) Y_1(t) w(t) dM_1 + \int q(s)/p(s) dM_c$$

and returned as iid

For logistic link standard errors are slightly to small since uncertainty from recursive baseline is not considered, so for smaller data-sets it is recommended to use the prop.odds.subdist of timereg that is also more efficient due to use of different weights for the estimating equations. Alternatively, one can also bootstrap the standard errors.

Author(s)

Thomas Scheike

Examples

```
## data with no ties
data(bmt,package="timereg")
bmt$time <- bmt$time+runif(nrow(bmt))*0.01
bmt$id <- 1:nrow(bmt)

## logistic link  OR interpretation
ll=cifreg(Event(time,cause)~tcell+platelet+age,data=bmt,cause=1)
summary(ll)
plot(ll)
nd <- data.frame(tcell=c(1,0),platelet=0,age=0)
pll <- predict(ll,nd)
plot(pll)

## Fine-Gray model
fg=cifreg(Event(time,cause)~tcell+platelet+age,data=bmt,cause=1,propodds=NULL)
summary(fg)
plot(fg)
nd <- data.frame(tcell=c(1,0),platelet=0,age=0)
pfg <- predict(fg,nd)
plot(pfg)

sfg <- cifreg(Event(time,cause)~strata(tcell)+platelet+age,data=bmt,cause=1,propodds=NULL)
summary(sfg)
plot(sfg)

### predictions with CI based on iid decomposition of baseline and beta
fg <- cifreg(Event(time,cause)~tcell+platelet+age,data=bmt,cause=1,propodds=NULL,cox.prep=TRUE)
Biid <- IIDbaseline.cifreg(fg,time=20)
```

```
FGprediid(Biid,bmt[1:5,])
```

`ClaytonOakes` *Clayton-Oakes model with piece-wise constant hazards*

Description

Clayton-Oakes frailty model

Usage

```
ClaytonOakes(
  formula,
  data = parent.frame(),
  cluster,
  var.formula = ~1,
  cuts = NULL,
  type = "piecewise",
  start,
  control = list(),
  var.invlink = exp,
  ...
)
```

Arguments

`formula`	formula specifying the marginal proportional (piecewise constant) hazard structure with the right-hand-side being a survival object (Surv) specifying the entry time (optional), the follow-up time, and event/censoring status at follow-up. The clustering can be specified using the special function `cluster` (see example below).
`data`	Data frame
`cluster`	Variable defining the clustering (if not given in the formula)
`var.formula`	Formula specifying the variance component structure (if not given via the cluster special function in the formula) using a linear model with log-link.
`cuts`	Cut points defining the piecewise constant hazard
`type`	when equal to `two.stage`, the Clayton-Oakes-Glidden estimator will be calculated via the `timereg` package
`start`	Optional starting values
`control`	Control parameters to the optimization routine
`var.invlink`	Inverse link function for variance structure model
`...`	Additional arguments

Author(s)

Klaus K. Holst

Examples

```
set.seed(1)
d <- subset(simClaytonOakes(500,4,2,1,stoptime=2,left=2),truncated)
e <- ClaytonOakes(survival::Surv(lefttime,time,status)~x+cluster(~1,cluster),
                  cuts=c(0,0.5,1,2),data=d)
e

d2 <- simClaytonOakes(500,4,2,1,stoptime=2,left=0)
d2$z <- rep(1,nrow(d2)); d2$z[d2$cluster%in%sample(d2$cluster,100)] <- 0
## Marginal=Cox Proportional Hazards model:
ts <- ClaytonOakes(survival::Surv(time,status)~timereg::prop(x)+cluster(~1,cluster),
                   data=d2,type="two.stage")
## Marginal=Aalens additive model:
ts2 <- ClaytonOakes(survival::Surv(time,status)~x+cluster(~1,cluster),
                    data=d2,type="two.stage")
## Marginal=Piecewise constant:
e2 <- ClaytonOakes(survival::Surv(time,status)~x+cluster(~-1+factor(z),cluster),
                   cuts=c(0,0.5,1,2),data=d2)
e2


e0 <- ClaytonOakes(survival::Surv(time,status)~cluster(~-1+factor(z),cluster),
                   cuts=c(0,0.5,1,2),data=d2)
ts0 <- ClaytonOakes(survival::Surv(time,status)~cluster(~1,cluster),
                   data=d2,type="two.stage")
plot(ts0)
plot(e0,add=TRUE)

e3 <- ClaytonOakes(survival::Surv(time,status)~x+cluster(~1,cluster),cuts=c(0,0.5,1,2),
                   data=d,var.invlink=identity)
e3
```

`cluster.index` *Finds subjects related to same cluster*

Description

Finds subjects related to same cluster

Usage

```
cluster.index(
  clusters,
  index.type = FALSE,
  num = NULL,
```

```
  Rindex = 0,
  mat = NULL,
  return.all = FALSE,
  code.na = NA
)
```

Arguments

clusters	list of indeces
index.type	if TRUE then already list of integers of index.type
num	to get numbering according to num-type in separate columns
Rindex	index starts with 1, in C is it is 0
mat	to return matrix of indeces
return.all	return all arguments
code.na	how to code missing values

Author(s)

Klaus Holst, Thomas Scheike

References

Cluster indeces

See Also

familycluster.index familyclusterWithProbands.index

Examples

```
i<-c(1,1,2,2,1,3)
d<- cluster.index(i)
print(d)

type<-c("m","f","m","c","c","c")
d<- cluster.index(i,num=type,Rindex=1)
print(d)
```

---

concordanceCor *Concordance Computes concordance and casewise concordance*

Description

Concordance for Twins

Usage

```
concordanceCor(
  object,
  cif1,
  cif2 = NULL,
  messages = TRUE,
  model = NULL,
  coefs = NULL,
  ...
)
```

Arguments

object	Output from the cor.cif, rr.cif or or.cif function
cif1	Marginal cumulative incidence
cif2	Marginal cumulative incidence of other cause (cause2) if it is different from cause1
messages	To print messages
model	Specfifies wich model that is considered if object not given.
coefs	Specfifies dependence parameters if object is not given.
...	Extra arguments, not used.

Details

The concordance is the probability that both twins have experienced the event of interest and is defined as

$$cor(t) = P(T_1 \leq t, \epsilon_1 = 1, T_2 \leq t, \epsilon_2 = 1)$$

Similarly, the casewise concordance is

$$casewise(t) = \frac{cor(t)}{P(T_1 \leq t, \epsilon_1 = 1)}$$

that is the probability that twin "2" has the event given that twins "1" has.

Author(s)

Thomas Scheike

References

Estimating twin concordance for bivariate competing risks twin data Thomas H. Scheike, Klaus K. Holst and Jacob B. Hjelmborg, Statistics in Medicine 2014, 1193-1204

Estimating Twin Pair Concordance for Age of Onset. Thomas H. Scheike, Jacob V B Hjelmborg, Klaus K. Holst, 2015 in Behavior genetics DOI:10.1007/s10519-015-9729-3

`cor.cif` *Cross-odds-ratio, OR or RR risk regression for competing risks*

Description

Fits a parametric model for the log-cross-odds-ratio for the predictive effect of for the cumulative incidence curves for T_1 experiencing cause i given that T_2 has experienced a cause k :

$$\log(COR(i|k)) = h(\theta, z_1, i, z_2, k, t) =_{default} \theta^T z =$$

with the log cross odds ratio being

$$COR(i|k) = \frac{O(T_1 \leq t, cause_1 = i | T_2 \leq t, cause_2 = k)}{O(T_1 \leq t, cause_1 = i)}$$

the conditional odds divided by the unconditional odds, with the odds being, respectively

$$O(T_1 \leq t, cause_1 = i | T_2 \leq t, cause_1 = k) = \frac{P_x(T_1 \leq t, cause_1 = i | T_2 \leq t, cause_2 = k)}{P_x((T_1 \leq t, cause_1 = i)^c | T_2 \leq t, cause_2 = k)}$$

and

$$O(T_1 \leq t, cause_1 = i) = \frac{P_x(T_1 \leq t, cause_1 = i)}{P_x((T_1 \leq t, cause_1 = i)^c)}.$$

Here B^c is the complement event of B, P_x is the distribution given covariates (x are subject specific and z are cluster specific covariates), and $h()$ is a function that is the simple identity $\theta^T z$ by default.

Usage

```
cor.cif(
  cif,
  data,
  cause = NULL,
  times = NULL,
  cause1 = 1,
  cause2 = 1,
  cens.code = NULL,
  cens.model = "KM",
  Nit = 40,
  detail = 0,
  clusters = NULL,
  theta = NULL,
  theta.des = NULL,
  step = 1,
  sym = 0,
  weights = NULL,
  par.func = NULL,
  dpar.func = NULL,
  dimpar = NULL,
```

```
  score.method = "nlminb",
  same.cens = FALSE,
  censoring.weights = NULL,
  silent = 1,
  ...
)
```

Arguments

cif	a model object from the timereg::comp.risk function with the marginal cumulative incidence of cause1, i.e., the event of interest, and whose odds the comparision is compared to the conditional odds given cause2
data	a data.frame with the variables.
cause	specifies the causes related to the death times, the value cens.code is the censoring value. When missing it comes from marginal cif.
times	time-vector that specifies the times used for the estimating euqations for the cross-odds-ratio estimation.
cause1	specificies the cause considered.
cause2	specificies the cause that is conditioned on.
cens.code	specificies the code for the censoring if NULL then uses the one from the marginal cif model.
cens.model	specified which model to use for the ICPW, KM is Kaplan-Meier alternatively it may be "cox"
Nit	number of iterations for Newton-Raphson algorithm.
detail	if 0 no details are printed during iterations, if 1 details are given.
clusters	specifies the cluster structure.
theta	specifies starting values for the cross-odds-ratio parameters of the model.
theta.des	specifies a regression design for the cross-odds-ratio parameters.
step	specifies the step size for the Newton-Raphson algorithm.
sym	specifies if symmetry is used in the model.
weights	weights for estimating equations.
par.func	parfunc
dpar.func	dparfunc
dimpar	dimpar
score.method	"nlminb", can also use "nr".
same.cens	if true then censoring within clusters are assumed to be the same variable, default is independent censoring.
censoring.weights	these probabilities are used for the bivariate censoring dist.
silent	1 to suppress output about convergence related issues.
...	Not used.

Details

The OR dependence measure is given by

$$OR(i,k) = \log(\frac{O(T_1 \leq t, cause_1 = i | T_2 \leq t, cause_2 = k)}{O(T_1 \leq t, cause_1 = i) | T_2 \leq t, cause_2 = k)}$$

This measure is numerically more stabile than the COR measure, and is symetric in i,k.

The RR dependence measure is given by

$$RR(i,k) = \log(\frac{P(T_1 \leq t, cause_1 = i, T_2 \leq t, cause_2 = k)}{P(T_1 \leq t, cause_1 = i) P(T_2 \leq t, cause_2 = k)}$$

This measure is numerically more stabile than the COR measure, and is symetric in i,k.

The model is fitted under symmetry (sym=1), i.e., such that it is assumed that T_1 and T_2 can be interchanged and leads to the same cross-odd-ratio (i.e. $COR(i|k) = COR(k|i)$), as would be expected for twins or without symmetry as might be the case with mothers and daughters (sym=0).

$h()$ may be specified as an R-function of the parameters, see example below, but the default is that it is simply $\theta^T z$.

Value

returns an object of type 'cor'. With the following arguments:

`theta`	estimate of proportional odds parameters of model.
`var.theta`	variance for gamma.
`hess`	the derivative of the used score.
`score`	scores at final stage.
`score`	scores at final stage.
`theta.iid`	matrix of iid decomposition of parametric effects.

Author(s)

Thomas Scheike

References

Cross odds ratio Modelling of dependence for Multivariate Competing Risks Data, Scheike and Sun (2012), Biostatistics.

A Semiparametric Random Effects Model for Multivariate Competing Risks Data, Scheike, Zhang, Sun, Jensen (2010), Biometrika.

Examples

```
library("timereg")
data(multcif);
multcif$cause[multcif$cause==0] <- 2
zyg <- rep(rbinom(200,1,0.5),each=2)
theta.des <- model.matrix(~-1+factor(zyg))
```

```
times=seq(0.05,1,by=0.05) # to speed up computations use only these time-points
add <- timereg::comp.risk(Event(time,cause)~+1+cluster(id),data=multcif,cause=1,
               n.sim=0,times=times,model="fg",max.clust=NULL)
add2 <- timereg::comp.risk(Event(time,cause)~+1+cluster(id),data=multcif,cause=2,
               n.sim=0,times=times,model="fg",max.clust=NULL)

out1 <- cor.cif(add,data=multcif,cause1=1,cause2=1)
summary(out1)

out2 <- cor.cif(add,data=multcif,cause1=1,cause2=1,theta.des=theta.des)
summary(out2)

##out3 <- cor.cif(add,data=multcif,cause1=1,cause2=2,cif2=add2)
##summary(out3)
############################################################
# investigating further models using parfunc and dparfunc
############################################################
 ## Reduce Ex.Timings
set.seed(100)
prt<-simnordic.random(2000,cordz=2,cormz=5)
prt$status <-prt$cause
table(prt$status)

times <- seq(40,100,by=10)
cifmod <- timereg::comp.risk(Event(time,cause)~+1+cluster(id),data=prt,
                   cause=1,n.sim=0,
                   times=times,conservative=1,max.clust=NULL,model="fg")
theta.des <- model.matrix(~-1+factor(zyg),data=prt)

parfunc <- function(par,t,pardes)
{
par <- pardes %*% c(par[1],par[2]) +
       pardes %*% c( par[3]*(t-60)/12,par[4]*(t-60)/12)
par
}
head(parfunc(c(0.1,1,0.1,1),50,theta.des))

dparfunc <- function(par,t,pardes)
{
dpar <- cbind(pardes, t(t(pardes) * c( (t-60)/12,(t-60)/12)) )
dpar
}
head(dparfunc(c(0.1,1,0.1,1),50,theta.des))

names(prt)
or1 <- or.cif(cifmod,data=prt,cause1=1,cause2=1,theta.des=theta.des,
              same.cens=TRUE,theta=c(0.6,1.1,0.1,0.1),
              par.func=parfunc,dpar.func=dparfunc,dimpar=4,
              score.method="nr",detail=1)
summary(or1)

 cor1 <- cor.cif(cifmod,data=prt,cause1=1,cause2=1,theta.des=theta.des,
```

```
                same.cens=TRUE,theta=c(0.5,1.0,0.1,0.1),
                par.func=parfunc,dpar.func=dparfunc,dimpar=4,
                control=list(trace=TRUE),detail=1)
summary(cor1)

### piecewise contant OR model
gparfunc <- function(par,t,pardes)
{
cuts <- c(0,80,90,120)
grop <- diff(t<cuts)
paru  <- (pardes[,1]==1) * sum(grop*par[1:3]) +
    (pardes[,2]==1) * sum(grop*par[4:6])
paru
}

dgparfunc <- function(par,t,pardes)
{
cuts <- c(0,80,90,120)
grop <- diff(t<cuts)
par1 <- matrix(c(grop),nrow(pardes),length(grop),byrow=TRUE)
parmz <- par1* (pardes[,1]==1)
pardz <- (pardes[,2]==1) * par1
dpar <- cbind( parmz,pardz)
dpar
}
head(dgparfunc(rep(0.1,6),50,theta.des))
head(gparfunc(rep(0.1,6),50,theta.des))

or1g <- or.cif(cifmod,data=prt,cause1=1,cause2=1,
               theta.des=theta.des, same.cens=TRUE,
               par.func=gparfunc,dpar.func=dgparfunc,
               dimpar=6,score.method="nr",detail=1)
summary(or1g)
names(or1g)
head(or1g$theta.iid)
```

`count.history` *Counts the number of previous events of two types for recurrent events processes*

Description

Counts the number of previous events of two types for recurrent events processes

Usage

```
count.history(
  data,
  status = "status",
```

```
  id = "id",
  types = 1:2,
  names.count = "Count",
  lag = TRUE,
  multitype = FALSE
)
```

Arguments

data	data-frame
status	name of status
id	id
types	types of the events (code) related to status
names.count	name of Counts, for example Count1 Count2 when types=c(1,2)
lag	if true counts previously observed, and if lag=FALSE counts up to know
multitype	if multitype then count number of types also when types=c(1,2) for example

Author(s)

Thomas Scheike

Examples

```
######################################
## getting some rates to mimick
######################################

data(base1cumhaz)
data(base4cumhaz)
data(drcumhaz)
dr <- drcumhaz
base1 <- base1cumhaz
base4 <- base4cumhaz

#########################################################################
### simulating simple model that mimicks data
### now with two event types and second type has same rate as death rate
#########################################################################

rr <- simRecurrentII(1000,base1,base4,death.cumhaz=dr)
rr <-  count.history(rr)
dtable(rr,~"Count*"+status,level=1)
```

`covarianceRecurrent` *Estimation of covariance for bivariate recurrent events with terminal event*

Description

Estimation of probability of more that k events for recurrent events process where there is terminal event

Usage

```
covarianceRecurrent(
  data,
  type1,
  type2,
  status = "status",
  death = "death",
  start = "start",
  stop = "stop",
  id = "id",
  names.count = "Count"
)
```

Arguments

`data`	data-frame
`type1`	type of first event (code) related to status
`type2`	type of second event (code) related to status
`status`	name of status
`death`	name of death indicator
`start`	start stop call of Hist() of prodlim
`stop`	start stop call of Hist() of prodlim
`id`	id
`names.count`	name of count for number of previous event of different types, here generated by count.history()

Author(s)

Thomas Scheike

References

Scheike, Eriksson, Tribler (2019) The mean, variance and correlation for bivariate recurrent events with a terminal event, JRSS-C

Examples

```
#######################################
## getting some data to work on
#######################################
data(base1cumhaz)
data(base4cumhaz)
data(drcumhaz)
dr <- drcumhaz
base1 <- base1cumhaz
base4 <- base4cumhaz
rr <- simRecurrentII(1000,base1,cumhaz2=base4,death.cumhaz=dr)
rr <- count.history(rr)
rr$strata <- 1
dtable(rr,~death+status)

covrp <- covarianceRecurrent(rr,1,2,status="status",death="death",
                        start="entry",stop="time",id="id",names.count="Count")
par(mfrow=c(1,3))
plot(covrp)

### with strata, each strata in matrix column, provides basis for fast Bootstrap
covrpS <- covarianceRecurrentS(rr,1,2,status="status",death="death",
        start="entry",stop="time",strata="strata",id="id",names.count="Count")
```

---

daggregate *aggregating for for data frames*

Description

aggregating for for data frames

Usage

```
daggregate(
  data,
  y = NULL,
  x = NULL,
  subset,
  ...,
  fun = "summary",
  regex = mets.options()$regex,
  missing = FALSE,
  remove.empty = FALSE,
  matrix = FALSE,
  silent = FALSE,
  na.action = na.pass,
  convert = NULL
)
```

Arguments

data	data.frame
y	name of variable, or formula, or names of variables on data frame.
x	name of variable, or formula, or names of variables on data frame.
subset	subset expression
...	additional arguments to lower level functions
fun	function defining aggregation
regex	interpret x,y as regular expressions
missing	Missing used in groups (x)
remove.empty	remove empty groups from output
matrix	if TRUE a matrix is returned instead of an array
silent	suppress messages
na.action	How model.frame deals with 'NA's
convert	if TRUE try to coerce result into matrix. Can also be a user-defined function

Examples

```
data("sTRACE",package="timereg")
daggregate(iris, "^.e.al", x="Species", fun=cor, regex=TRUE)
daggregate(iris, Sepal.Length+Petal.Length ~Species, fun=summary)
daggregate(iris, log(Sepal.Length)+I(Petal.Length>1.5) ~ Species,
                 fun=summary)
daggregate(iris, "*Length*", x="Species", fun=head)
daggregate(iris, "^.e.al", x="Species", fun=tail, regex=TRUE)
daggregate(sTRACE, status~ diabetes, fun=table)
daggregate(sTRACE, status~ diabetes+sex, fun=table)
daggregate(sTRACE, status + diabetes+sex ~ vf+I(wmi>1.4), fun=table)
daggregate(iris, "^.e.al", x="Species",regex=TRUE)
dlist(iris,Petal.Length+Sepal.Length ~ Species |Petal.Length>1.3 & Sepal.Length>5,
            n=list(1:3,-(3:1)))
daggregate(iris, I(Sepal.Length>7)~Species | I(Petal.Length>1.5))
daggregate(iris, I(Sepal.Length>7)~Species | I(Petal.Length>1.5),
                 fun=table)

dsum(iris, .~Species, matrix=TRUE, missing=TRUE)

par(mfrow=c(1,2))
data(iris)
drename(iris) <- ~.
daggregate(iris,'sepal*'~species|species!="virginica",fun=plot)
daggregate(iris,'sepal*'~I(as.numeric(species))|I(as.numeric(species))!=1,fun=summary)

dnumeric(iris) <- ~species
daggregate(iris,'sepal*'~species.n|species.n!=1,fun=summary)
```

Dbvn *Derivatives of the bivariate normal cumulative distribution function*

Description

Derivatives of the bivariate normal cumulative distribution function

Usage

```
Dbvn(p,design=function(p,...) {
     return(list(mu=cbind(p[1],p[1]),
               dmu=cbind(1,1),
               S=matrix(c(p[2],p[3],p[3],p[4]),ncol=2),
               dS=rbind(c(1,0,0,0),c(0,1,1,0),c(0,0,0,1)))  )},
     Y=cbind(0,0))
```

Arguments

p	Parameter vector
design	Design function with defines mean, derivative of mean, variance, and derivative of variance with respect to the parameter p
Y	column vector where the CDF is evaluated

Author(s)

Klaus K. Holst

dby *Calculate summary statistics grouped by*

Description

Calculate summary statistics grouped by variable

Usage

```
dby(
  data,
  INPUT,
  ...,
  ID = NULL,
  ORDER = NULL,
  SUBSET = NULL,
  SORT = 0,
  COMBINE = !REDUCE,
```

```
  NOCHECK = FALSE,
  ARGS = NULL,
  NAMES,
  COLUMN = FALSE,
  REDUCE = FALSE,
  REGEX = mets.options()$regex,
  ALL = TRUE
)
```

Arguments

data	Data.frame
INPUT	Input variables (character or formula)
...	functions
ID	id variable
ORDER	(optional) order variable
SUBSET	(optional) subset expression
SORT	sort order (id+order variable)
COMBINE	If TRUE result is appended to data
NOCHECK	No sorting or check for missing data
ARGS	Optional list of arguments to functions (...)
NAMES	Optional vector of column names
COLUMN	If TRUE do the calculations for each column
REDUCE	Reduce number of redundant rows
REGEX	Allow regular expressions
ALL	if FALSE only the subset will be returned

Details

Calculate summary statistics grouped by

dby2 for column-wise calculations

Author(s)

Klaus K. Holst and Thomas Scheike

Examples

```
n <- 4
k <- c(3,rbinom(n-1,3,0.5)+1)
N <- sum(k)
d <- data.frame(y=rnorm(N),x=rnorm(N),id=rep(seq(n),k),num=unlist(sapply(k,seq)))
d2 <- d[sample(nrow(d)),]

dby(d2, y~id, mean)
```

```
dby(d2, y~id + order(num), cumsum)

dby(d,y ~ id + order(num), dlag)
dby(d,y ~ id + order(num), dlag, ARGS=list(k=1:2))
dby(d,y ~ id + order(num), dlag, ARGS=list(k=1:2), NAMES=c("l1","l2"))

dby(d, y~id + order(num), mean=mean, csum=cumsum, n=length)
dby(d2, y~id + order(num), a=cumsum, b=mean, N=length, l1=function(x) c(NA,x)[-length(x)])

dby(d, y~id + order(num), nn=seq_along, n=length)
dby(d, y~id + order(num), nn=seq_along, n=length)

d <- d[,1:4]
dby(d, x<0) <- list(z=mean)
d <- dby(d, is.na(z), z=1)

f <- function(x) apply(x,1,min)
dby(d, y+x~id, min=f)

dby(d,y+x~id+order(num), function(x) x)

f <- function(x) { cbind(cumsum(x[,1]),cumsum(x[,2]))/sum(x)}
dby(d, y+x~id, f)

## column-wise
a <- d
dby2(a, mean, median, REGEX=TRUE) <- '^[y|x]'~id
a
## wildcards
dby2(a,'y*'+'x*'~id,mean)


## subset
dby(d, x<0) <- list(z=NA)
d
dby(d, y~id|x>-1, v=mean,z=1)
dby(d, y+x~id|x>-1, mean, median, COLUMN=TRUE)

dby2(d, y+x~id|x>0, mean, REDUCE=TRUE)

dby(d,y~id|x<0,mean,ALL=FALSE)

a <- iris
a <- dby(a,y=1)
dby(a,Species=="versicolor") <- list(y=2)
```

---

dcor *summary, tables, and correlations for data frames*

Description

summary, tables, and correlations for data frames

Usage

```
dcor(data, y = NULL, x = NULL, use = "pairwise.complete.obs", ...)
```

Arguments

data	if x is formula or names for data frame then data frame is needed.
y	name of variable, or fomula, or names of variables on data frame.
x	possible group variable
use	how to handle missing values
...	Optional additional arguments

Author(s)

Klaus K. Holst and Thomas Scheike

Examples

```
data("sTRACE",package="timereg")
dt<- sTRACE
dt$time2 <- dt$time^2
dt$wmi2 <- dt$wmi^2
head(dt)

dcor(dt)

dcor(dt,~time+wmi)
dcor(dt,~time+wmi,~vf+chf)
dcor(dt,time+wmi~vf+chf)

dcor(dt,c("time*","wmi*"),~vf+chf)
```

---

dcut *Cutting, sorting, rm (removing), rename for data frames*

Description

Cut variables, if breaks are given these are used, otherwise cuts into using group size given by probs, or equispace groups on range. Default is equally sized groups if possible

Usage

```
dcut(
  data,
  y = NULL,
  x = NULL,
  breaks = 4,
  probs = NULL,
```

```
  equi = FALSE,
  regex = mets.options()$regex,
  sep = NULL,
  na.rm = TRUE,
  labels = NULL,
  all = FALSE,
  ...
)
```

Arguments

data	if x is formula or names for data frame then data frame is needed.
y	name of variable, or fomula, or names of variables on data frame.
x	name of variable, or fomula, or names of variables on data frame.
breaks	number of breaks, for variables or vector of break points,
probs	groups defined from quantiles
equi	for equi-spaced breaks
regex	for regular expressions.
sep	seperator for naming of cut names.
na.rm	to remove NA for grouping variables.
labels	to use for cut groups
all	to do all variables, even when breaks are not unique
...	Optional additional arguments

Author(s)

Klaus K. Holst and Thomas Scheike

Examples

```
data("sTRACE",package="timereg")
sTRACE$age2 <- sTRACE$age^2
sTRACE$age3 <- sTRACE$age^3

mm <- dcut(sTRACE,~age+wmi)
head(mm)

mm <- dcut(sTRACE,catage4+wmi4~age+wmi)
head(mm)

mm <- dcut(sTRACE,~age+wmi,breaks=c(2,4))
head(mm)

mm <- dcut(sTRACE,c("age","wmi"))
head(mm)

mm <- dcut(sTRACE,~.)
```

```
head(mm)

mm <- dcut(sTRACE,c("age","wmi"),breaks=c(2,4))
head(mm)

gx <- dcut(sTRACE$age)
head(gx)


## Removes all cuts variables with these names wildcards
mm1 <- drm(mm,c("*.2","*.4"))
head(mm1)

## wildcards, for age, age2, age4 and wmi
head(dcut(mm,c("a*","?m*")))

## with direct asignment
drm(mm) <- c("*.2","*.4")
head(mm)

dcut(mm) <- c("age","*m*")
dcut(mm) <- ageg1+wmig1~age+wmi
head(mm)

############################
## renaming
############################

head(mm)
drename(mm, ~Age+Wmi) <- c("wmi","age")
head(mm)
mm1 <- mm

## all names to lower
drename(mm1) <- ~.
head(mm1)

## A* to lower
mm2 <-  drename(mm,c("A*","W*"))
head(mm2)
drename(mm) <- "A*"
head(mm)

dd <- data.frame(A_1=1:2,B_1=1:2)
funn <- function(x) gsub("_",".",x)
drename(dd) <- ~.
drename(dd,fun=funn) <- ~.
names(dd)
```

---

dermalridges *Dermal ridges data (families)*

Description

Data on dermal ridge counts in left and right hand in (nuclear) families

Format

Data on 50 families with ridge counts in left and right hand for moter, father and each child. Family id in 'family' and gender and child number in 'sex' and 'child'.

Source

Sarah B. Holt (1952). Genetics of dermal ridges: bilateral asymmetry in finger ridge-counts. Annals of Eugenics 17 (1), pp.211–231. DOI: 10.1111/j.1469-1809.1952.tb02513.x

Examples

```
data(dermalridges)
fast.reshape(dermalridges,id="family",varying=c("child.left","child.right","sex"))
```

---

dermalridgesMZ *Dermal ridges data (monozygotic twins)*

Description

Data on dermal ridge counts in left and right hand in (nuclear) families

Format

Data on dermal ridge counts (left and right hand) in 18 monozygotic twin pairs.

Source

Sarah B. Holt (1952). Genetics of dermal ridges: bilateral asymmetry in finger ridge-counts. Annals of Eugenics 17 (1), pp.211–231. DOI: 10.1111/j.1469-1809.1952.tb02513.x

Examples

```
data(dermalridgesMZ)
fast.reshape(dermalridgesMZ,id="id",varying=c("left","right"))
```

diabetes *The Diabetic Retinopathy Data*

Description

The data was colleceted to test a laser treatment for delaying blindness in patients with dibetic retinopathy. The subset of 197 patiens given in Huster et al. (1989) is used.

Format

This data frame contains the following columns:

id a numeric vector. Patient code.

agedx a numeric vector. Age of patient at diagnosis.

time a numeric vector. Survival time: time to blindness or censoring.

status a numeric vector code. Survival status. 1: blindness, 0: censored.

trteye a numeric vector code. Random eye selected for treatment. 1: left eye 2: right eye.

treat a numeric vector. 1: treatment 0: untreated.

adult a numeric vector code. 1: younger than 20, 2: older than 20.

Source

Huster W.J. and Brookmeyer, R. and Self. S. (1989) MOdelling paired survival data with covariates, Biometrics 45, 145-56.

Examples

```
data(diabetes)
names(diabetes)
```

divide.conquer *Split a data set and run function*

Description

Split a data set and run function

Usage

```
divide.conquer(func = NULL, data, size, splits, id = NULL, ...)
```

Arguments

func	called function
data	data-frame
size	size of splits
splits	number of splits (ignored if size is given)
id	optional cluster variable
...	Additional arguments to lower level functions

Author(s)

Thomas Scheike, Klaus K. Holst

Examples

```
## avoid dependency on timereg
## library(timereg)
## data(TRACE)
## res <- divide.conquer(prop.odds,TRACE,
##       formula=Event(time,status==9)~chf+vf+age,n.sim=0,size=200)
```

---

divide.conquer.timereg

Split a data set and run function from timereg and aggregate

Description

Split a data set and run function of cox-aalen type and aggregate results

Usage

```
divide.conquer.timereg(func = NULL, data, size, ...)
```

Arguments

func	called function
data	data-frame
size	size of splits
...	Additional arguments to lower level functions

Author(s)

Thomas Scheike, Klaus K. Holst

Examples

```
## library(timereg)
## data(TRACE)
## a <- divide.conquer.timereg(prop.odds,TRACE,
##                             formula=Event(time,status==9)~chf+vf+age,n.sim=0,size=200)
## coef(a)
## a2 <- divide.conquer.timereg(prop.odds,TRACE,
##                             formula=Event(time,status==9)~chf+vf+age,n.sim=0,size=500)
## coef(a2)
##
##if (interactive()) {
##par(mfrow=c(1,1))
##plot(a,xlim=c(0,8),ylim=c(0,0.01))
##par(new=TRUE)
##plot(a2,xlim=c(0,8),ylim=c(0,0.01))
##}
```

---

dlag *Lag operator*

Description

Lag operator

Usage

```
dlag(data, x, k = 1, combine = TRUE, simplify = TRUE, names, ...)
```

Arguments

data	data.frame or vector
x	optional column names or formula
k	lag (vector of integers)
combine	combine results with original data.frame
simplify	Return vector if possible
names	optional new column names
...	additional arguments to lower level functions

Examples

```
d <- data.frame(y=1:10,x=c(10:1))
dlag(d,k=1:2)
dlag(d,~x,k=0:1)
dlag(d$x,k=1)
dlag(d$x,k=-1:2, names=letters[1:4])
```

doubleFGR *Double CIF Fine-Gray model with two causes*

Description

Estimation based on derived hazards and recursive estimating equations. fits two parametrizations 1)

$$F_1(t,X) = 1 - \exp(-\exp(X^T\beta)\Lambda_1(t))$$

and

$$F_2(t,X_2) = 1 - \exp(-\exp(X_2^T\beta_2)\Lambda_2(t))$$

or restricted version 2)

$$F_1(t,X) = 1 - \exp(-\exp(X^T\beta)\Lambda_1(t))$$

and

$$F_2(t,X_2,X) = (1 - \exp(-\exp(X_2^T\beta_2)\Lambda_2(t)))(1 - F_1(\infty,X))$$

Usage

```
doubleFGR(formula, data, offset = NULL, weights = NULL, X2 = NULL, ...)
```

Arguments

formula	formula with 'Event'
data	data frame
offset	offsets for cox model
weights	weights for Cox score equations
X2	specifies the regression design for second CIF model
...	Additional arguments to lower level funtions

Author(s)

Thomas Scheike

Examples

```
res <- 0
data(bmt)
bmt$age2 <- bmt$age
newdata <- bmt[1:19,]
if (interactive()) par(mfrow=c(5,3))

## same X1 and X2
pr2 <- doubleFGR(Event(time,cause)~age+platelet,data=bmt,restrict=res)
if (interactive()) {
  bplotdFG(pr2,cause=1)
  bplotdFG(pr2,cause=2,add=TRUE)
```

```
}
pp21 <- predictdFG(pr2,newdata=newdata)
pp22 <- predictdFG(pr2,newdata=newdata,cause=2)
if (interactive()) {
  plot(pp21)
  plot(pp22,add=TRUE,col=2)
}
pp21 <- predictdFG(pr2)
pp22 <- predictdFG(pr2,cause=2)
if (interactive()) {
  plot(pp21)
  plot(pp22,add=TRUE,col=2)
}

pr2 <- doubleFGR(Event(time,cause)~strata(platelet),data=bmt,restrict=res)
if (interactive()) {
  bplotdFG(pr2,cause=1)
  bplotdFG(pr2,cause=2,add=TRUE)
}
pp21 <- predictdFG(pr2,newdata=newdata)
pp22 <- predictdFG(pr2,,newdata=newdata,cause=2)
if (interactive()) {
  plot(pp21)
  plot(pp22,add=TRUE,col=2)
}
pp21 <- predictdFG(pr2)
pp22 <- predictdFG(pr2,cause=2)
if (interactive()) {
  plot(pp21)
  plot(pp22,add=TRUE,col=2)
}

## different X1 and X2
pr2 <- doubleFGR(Event(time,cause)~age+platelet+age2,data=bmt,X2=3,restrict=res)
if (interactive()) {
  bplotdFG(pr2,cause=1)
  bplotdFG(pr2,cause=2,add=TRUE)
}
pp21 <- predictdFG(pr2,newdata=newdata)
pp22 <- predictdFG(pr2,newdata=newdata,cause=2)
if (interactive()) {
  plot(pp21)
  plot(pp22,add=TRUE,col=2)
}
pp21 <- predictdFG(pr2)
pp22 <- predictdFG(pr2,cause=2)
if (interactive()) {
  plot(pp21)
  plot(pp22,add=TRUE,col=2)
}

### uden X1
pr2 <- doubleFGR(Event(time,cause)~age+platelet,data=bmt,X2=1:2,restrict=res)
```

```
if (interactive()) {
  bplotdFG(pr2,cause=1)
  bplotdFG(pr2,cause=2,add=TRUE)
}
pp21 <- predictdFG(pr2,newdata=newdata)
pp22 <- predictdFG(pr2,newdata=newdata,cause=2)
if (interactive()) {
  plot(pp21)
  plot(pp22,add=TRUE,col=2)
}
pp21 <- predictdFG(pr2)
p22 <- predictdFG(pr2,cause=2)
if (interactive()) {
  plot(pp21)
  plot(pp22,add=TRUE,col=2)
}

### without X2
pr2 <- doubleFGR(Event(time,cause)~age+platelet,data=bmt,X2=0,restrict=res)
if (interactive()) {
  bplotdFG(pr2,cause=1)
  bplotdFG(pr2,cause=2,add=TRUE)
}
pp21 <- predictdFG(pr2,newdata=newdata)
pp22 <- predictdFG(pr2,newdata=newdata,cause=2)
if (interactive()) {
  plot(pp21)
  plot(pp22,add=TRUE,col=2)
}
pp21 <- predictdFG(pr2)
pp22 <- predictdFG(pr2,cause=2)
if (interactive()) {
  plot(pp21)
  plot(pp22,add=TRUE,col=2)
}
```

---

dprint *list, head, print, tail*

Description

listing for data frames

Usage

```
dprint(data, y = NULL, n = 0, ..., x = NULL)
```

Arguments

data	if x is formula or names for data frame then data frame is needed.
y	name of variable, or fomula, or names of variables on data frame.
n	Index of observations to print (default c(1:nfirst, n-nlast:nlast)
...	Optional additional arguments (nfirst,nlast, and print options)
x	possible group variable

Author(s)

Klaus K. Holst and Thomas Scheike

Examples

```
m <- lava::lvm(letters)
d <- lava::sim(m, 20)

dlist(d,~a+b+c)
dlist(d,~a+b+c|a<0 & b>0)
## listing all :
dlist(d,~a+b+c|a<0 & b>0,n=0)
dlist(d,a+b+c~I(d>0)|a<0 & b>0)
dlist(d,.~I(d>0)|a<0 & b>0)
dlist(d,~a+b+c|a<0 & b>0, nlast=0)
dlist(d,~a+b+c|a<0 & b>0, nfirst=3, nlast=3)
dlist(d,~a+b+c|a<0 & b>0, 1:5)
dlist(d,~a+b+c|a<0 & b>0, -(5:1))
dlist(d,~a+b+c|a<0 & b>0, list(1:5,50:55,-(5:1)))
dprint(d,a+b+c ~ I(d>0) |a<0 & b>0, list(1:5,50:55,-(5:1)))
```

---

drcumhaz *Rate for leaving HPN program for patients of Copenhagen*

Description

Rate for leaving HPN program for patients of Copenhagen

Source

Estimated data

dreg *Regression for data frames with dutility call*

Description

Regression for data frames with dutility call

Usage

```
dreg(
  data,
  y,
  x = NULL,
  z = NULL,
  x.oneatatime = TRUE,
  x.base.names = NULL,
  z.arg = c("clever", "base", "group", "condition"),
  fun. = lm,
  summary. = summary,
  regex = FALSE,
  convert = NULL,
  doSummary = TRUE,
  special = NULL,
  equal = TRUE,
  test = 1,
  ...
)
```

Arguments

data	data frame
y	name of variable, or fomula, or names of variables on data frame.
x	name of variable, or fomula, or names of variables on data frame.
z	name of variable, or fomula, or names of variables on data frame.
x.oneatatime	x's one at a time
x.base.names	base covarirates
z.arg	what is Z, c("clever","base","group","condition"), clever decides based on type of Z, base means that Z is used as fixed baseline covaraites for all X, group means the analyses is done based on groups of Z, and condition means that Z specifies a condition on the data
fun.	function lm is default
summary.	summary to use
regex	regex
convert	convert

doSummary	doSummary or not
special	special's
equal	to do pairwise stuff
test	development argument
...	Additional arguments for fun

Author(s)

Klaus K. Holst, Thomas Scheike

Examples

```
##'
data(iris)
dat <- iris
drename(dat) <- ~.
names(dat)
set.seed(1)
dat$time <- runif(nrow(dat))
dat$time1 <- runif(nrow(dat))
dat$status <- rbinom(nrow(dat),1,0.5)
dat$S1 <- with(dat, Surv(time,status))
dat$S2 <- with(dat, Surv(time1,status))
dat$id <- 1:nrow(dat)

mm <- dreg(dat, "*.length"~"*.width"|I(species=="setosa" & status==1))
mm <- dreg(dat, "*.length"~"*.width"|species+status)
mm <- dreg(dat, "*.length"~"*.width"|species)
mm <- dreg(dat, "*.length"~"*.width"|species+status,z.arg="group")

 ## Reduce Ex.Timings
y <- "S*"~"*.width"
xs <- dreg(dat, y, fun.=phreg)
xs <- dreg(dat, y, fun.=survdiff)

y <- "S*"~"*.width"
xs <- dreg(dat, y, x.oneatatime=FALSE, fun.=phreg)

## under condition
y <- S1~"*.width"|I(species=="setosa" & sepal.width>3)
xs <- dreg(dat, y, z.arg="condition", fun.=phreg)
xs <- dreg(dat, y, fun.=phreg)

## under condition
y <- S1~"*.width"|species=="setosa"
xs <- dreg(dat, y, z.arg="condition", fun.=phreg)
xs <- dreg(dat, y, fun.=phreg)

## with baseline  after |
y <- S1~"*.width"|sepal.length
xs <- dreg(dat, y, fun.=phreg)
```

```
## by group by species, not working
y <- S1~"*.width"|species
ss <- split(dat, paste(dat$species, dat$status))

xs <- dreg(dat, y, fun.=phreg)

## species as base, species is factor so assumes that this is grouping
y <- S1~"*.width"|species
xs <- dreg(dat, y, z.arg="base", fun.=phreg)

##  background var after | and then one of x's at at time
y <- S1~"*.width"|status+"sepal*"
xs <- dreg(dat, y, fun.=phreg)

##  background var after | and then one of x's at at time
##y <- S1~"*.width"|status+"sepal*"
##xs <- dreg(dat, y, x.oneatatime=FALSE, fun.=phreg)
##xs <- dreg(dat, y, fun.=phreg)

##  background var after | and then one of x's at at time
##y <- S1~"*.width"+factor(species)
##xs <- dreg(dat, y, fun.=phreg)
##xs <- dreg(dat, y, fun.=phreg, x.oneatatime=FALSE)

y <- S1~"*.width"|factor(species)
xs <- dreg(dat, y, z.arg="base", fun.=phreg)

y <- S1~"*.width"|cluster(id)+factor(species)
xs <- dreg(dat, y, z.arg="base", fun.=phreg)
xs <- dreg(dat, y, z.arg="base", fun.=coxph)

## under condition with groups
y <- S1~"*.width"|I(sepal.length>4)
xs <- dreg(subset(dat, species=="setosa"), y,z.arg="group",fun.=phreg)

## under condition with groups
y <- S1~"*.width"+I(log(sepal.length))|I(sepal.length>4)
xs <- dreg(subset(dat, species=="setosa"), y,z.arg="group",fun.=phreg)

y <- S1~"*.width"+I(dcut(sepal.length))|I(sepal.length>4)
xs <- dreg(subset(dat,species=="setosa"), y,z.arg="group",fun.=phreg)

ff <- function(formula,data,...) {
 ss <- survfit(formula,data,...)
 kmplot(ss,...)
 return(ss)
}

if (interactive()) {
dcut(dat) <- ~"*.width"
y <- S1~"*.4"|I(sepal.length>4)
par(mfrow=c(1, 2))
```

```
xs <- dreg(dat, y, fun.=ff)
}
```

`drelevel` *relev levels for data frames*

Description

levels shows levels for variables in data frame, relevel relevels a factor in data.frame

Usage

```
drelevel(
  data,
  y = NULL,
  x = NULL,
  ref = NULL,
  newlevels = NULL,
  regex = mets.options()$regex,
  sep = NULL,
  overwrite = FALSE,
  ...
)
```

Arguments

`data`	if x is formula or names for data frame then data frame is needed.
`y`	name of variable, or fomula, or names of variables on data frame.
`x`	name of variable, or fomula, or names of variables on data frame.
`ref`	new reference variable
`newlevels`	to combine levels of factor in data frame
`regex`	for regular expressions.
`sep`	seperator for naming of cut names.
`overwrite`	to overwrite variable
`...`	Optional additional arguments

Author(s)

Klaus K. Holst and Thomas Scheike

Examples

```
data(mena)
dstr(mena)
dfactor(mena)  <- ~twinnum
dnumeric(mena) <- ~twinnum.f

dstr(mena)

mena2 <- drelevel(mena,"cohort",ref="(1980,1982]")
mena2 <- drelevel(mena,~cohort,ref="(1980,1982]")
mena2 <- drelevel(mena,cohortII~cohort,ref="(1980,1982]")
dlevels(mena)
dlevels(mena2)
drelevel(mena,ref="(1975,1977]")  <-  ~cohort
drelevel(mena,ref="(1980,1982]")  <-  ~cohort
dlevels(mena,"coh*")
dtable(mena,"coh*",level=1)

### level 1 of zyg as baseline for new variable
drelevel(mena,ref=1) <- ~zyg
drelevel(mena,ref=c("DZ","[1973,1975]")) <- ~ zyg+cohort
drelevel(mena,ref=c("DZ","[1973,1975]")) <- zygdz+cohort.early~ zyg+cohort
### level 2 of zyg and cohort as baseline for new variables
drelevel(mena,ref=2) <- ~ zyg+cohort
dlevels(mena)

###################### combining factor levels with newlevels argument

dcut(mena,labels=c("I","II","III","IV")) <- cat4~agemena
dlevels(drelevel(mena,~cat4,newlevels=1:3))
dlevels(drelevel(mena,ncat4~cat4,newlevels=3:2))
drelevel(mena,newlevels=3:2) <- ncat4~cat4
dlevels(mena)

dlevels(drelevel(mena,nca4~cat4,newlevels=list(c(1,4),2:3)))

drelevel(mena,newlevels=list(c(1,4),2:3)) <- nca4..2 ~ cat4
dlevels(mena)

drelevel(mena,newlevels=list("I-III"=c("I","II","III"),"IV"="IV")) <- nca4..3 ~ cat4
dlevels(mena)

drelevel(mena,newlevels=list("I-III"=c("I","II","III"))) <- nca4..4 ~ cat4
dlevels(mena)

drelevel(mena,newlevels=list(group1=c("I","II","III"))) <- nca4..5 ~ cat4
dlevels(mena)

drelevel(mena,newlevels=list(g1=c("I","II","III"),g2="IV")) <- nca4..6 ~ cat4
dlevels(mena)
```

dsort *Sort data frame*

Description

Sort data according to columns in data frame

Usage

```
dsort(data, x, ..., decreasing = FALSE, return.order = FALSE)
```

Arguments

data	Data frame
x	variable to order by
...	additional variables to order by
decreasing	sort order (vector of length x)
return.order	return order

Value

data.frame

Examples

```
data(data="hubble",package="lava")
dsort(hubble, "sigma")
dsort(hubble, hubble$sigma,"v")
dsort(hubble,~sigma+v)
dsort(hubble,~sigma-v)

## with direct asignment
dsort(hubble) <- ~sigma-v
```

dspline *Simple linear spline*

Description

Constructs simple linear spline on a data frame using the formula syntax of dutils that is adds (x-cuti)* (x>cuti) to the data-set for each knot of the spline. The full spline is thus given by x and spline variables added to the data-set.

Usage

```
dspline(
  data,
  y = NULL,
  x = NULL,
  breaks = 4,
  probs = NULL,
  equi = FALSE,
  regex = mets.options()$regex,
  sep = NULL,
  na.rm = TRUE,
  labels = NULL,
  all = FALSE,
  ...
)
```

Arguments

data	if x is formula or names for data frame then data frame is needed.
y	name of variable, or fomula, or names of variables on data frame.
x	name of variable, or fomula, or names of variables on data frame.
breaks	number of breaks, for variables or vector of break points,
probs	groups defined from quantiles
equi	for equi-spaced breaks
regex	for regular expressions.
sep	seperator for naming of cut names.
na.rm	to remove NA for grouping variables.
labels	to use for cut groups
all	to do all variables, even when breaks are not unique
...	Optional additional arguments

Author(s)

Thomas Scheike

Examples

```
data(TRACE)
TRACE <- dspline(TRACE,~wmi,breaks=c(1,1.3,1.7))
cca <- coxph(Surv(time,status==9)~age+vf+chf+wmi,data=TRACE)
cca2 <- coxph(Surv(time,status==9)~age+wmi+vf+chf+wmi.spline1+wmi.spline2+wmi.spline3,data=TRACE)
anova(cca,cca2)

nd=data.frame(age=50,vf=0,chf=0,wmi=seq(0.4,3,by=0.01))
nd <- dspline(nd,~wmi,breaks=c(1,1.3,1.7))
pl <- predict(cca2,newdata=nd)
```

```
plot(nd$wmi,pl,type="l")
```

`dtable` *tables for data frames*

Description

tables for data frames

Usage

```
dtable(
  data,
  y = NULL,
  x = NULL,
  ...,
  level = -1,
  response = NULL,
  flat = TRUE,
  total = FALSE,
  prop = FALSE,
  summary = NULL
)
```

Arguments

`data`	if x is formula or names for data frame then data frame is needed.
`y`	name of variable, or fomula, or names of variables on data frame.
`x`	name of variable, or fomula, or names of variables on data frame.
`...`	Optional additional arguments
`level`	1 for all marginal tables, 2 for all 2 by 2 tables, and null for the full table, possible versus group variable
`response`	For level=2, only produce tables with columns given by 'response' (index)
`flat`	produce flat tables
`total`	add total counts/proportions
`prop`	Proportions instead of counts (vector of margins)
`summary`	summary function

Author(s)

Klaus K. Holst and Thomas Scheike

Examples

```
data("sTRACE",package="timereg")

dtable(sTRACE,~status)
dtable(sTRACE,~status+vf)
dtable(sTRACE,~status+vf,level=1)
dtable(sTRACE,~status+vf,~chf+diabetes)

dtable(sTRACE,c("*f*","status"),~diabetes)
dtable(sTRACE,c("*f*","status"),~diabetes, level=2)
dtable(sTRACE,c("*f*","status"),level=1)

dtable(sTRACE,~"*f*"+status,level=1)
dtable(sTRACE,~"*f*"+status+I(wmi>1.4)|age>60,level=2)
dtable(sTRACE,"*f*"+status~I(wmi>0.5)|age>60,level=1)
dtable(sTRACE,status~dcut(age))

dtable(sTRACE,~status+vf+sex|age>60)
dtable(sTRACE,status+vf+sex~+1|age>60, level=2)
dtable(sTRACE,.~status+vf+sex|age>60,level=1)
dtable(sTRACE,status+vf+sex~diabetes|age>60)
dtable(sTRACE,status+vf+sex~diabetes|age>60, flat=FALSE)

dtable(sTRACE,status+vf+sex~diabetes|age>60, level=1)
dtable(sTRACE,status+vf+sex~diabetes|age>60, level=2)

dtable(sTRACE,status+vf+sex~diabetes|age>60, level=2, prop=1, total=TRUE)
dtable(sTRACE,status+vf+sex~diabetes|age>60, level=2, prop=2, total=TRUE)
dtable(sTRACE,status+vf+sex~diabetes|age>60, level=2, prop=1:2, summary=summary)
```

`dtransform` *Transform that allows condition*

Description

Defines new variables under condition for data frame

Usage

```
dtransform(data, ...)
```

Arguments

`data`	is data frame
`...`	new variable definitions including possible if condition

Examples

```
data(mena)

xx <- dtransform(mena,ll=log(agemena)+twinnum)

xx <- dtransform(mena,ll=log(agemena)+twinnum,agemena<15)
xx <- dtransform(xx  ,ll=100+agemena,ll2=1000,agemena>15)
dsummary(xx,ll+ll2~I(agemena>15))
```

`easy.binomial.twostage`

Fits two-stage binomial for describing depdendence in binomial data using marginals that are on logistic form using the binomial.twostage funcion, but call is different and easier and the data manipulation is build into the function. Useful in particular for family design data.

Description

If clusters contain more than two times, the algoritm uses a compososite likelihood based on the pairwise bivariate models.

Usage

```
easy.binomial.twostage(
  margbin = NULL,
  data = parent.frame(),
  method = "nr",
  response = "response",
  id = "id",
  Nit = 60,
  detail = 0,
  silent = 1,
  weights = NULL,
  control = list(),
  theta = NULL,
  theta.formula = NULL,
  desnames = NULL,
  deshelp = 0,
  var.link = 1,
  iid = 1,
  step = 1,
  model = "plackett",
  marginal.p = NULL,
  strata = NULL,
  max.clust = NULL,
  se.clusters = NULL
)
```

Arguments

margbin	Marginal binomial model
data	data frame
method	Scoring method
response	name of response variable in data frame
id	name of cluster variable in data frame
Nit	Number of iterations
detail	Detail for more output for iterations
silent	Debug information
weights	Weights for log-likelihood, can be used for each type of outcome in 2x2 tables.
control	Optimization arguments
theta	Starting values for variance components
theta.formula	design for depedence, either formula or design function
desnames	names for dependence parameters
deshelp	if 1 then prints out some data sets that are used, on on which the design function operates
var.link	Link function for variance
iid	Calculate i.i.d. decomposition
step	Step size
model	model
marginal.p	vector of marginal probabilities
strata	strata for fitting
max.clust	max clusters used for i.i.d. decompostion
se.clusters	clusters for iid decomposition for roubst standard errors

Details

The reported standard errors are based on the estimated information from the likelihood assuming that the marginals are known. This gives correct standard errors in the case of the plackett distribution (OR model for dependence), but incorrect for the clayton-oakes types model. The OR model is often known as the ALR model. Our fitting procedures gives correct standard errors due to the ortogonality and is fast.

Examples

```
data(twinstut)
twinstut0 <- subset(twinstut, tvparnr<4000)
twinstut <- twinstut0
twinstut$binstut <- (twinstut$stutter=="yes")*1
theta.des <- model.matrix( ~-1+factor(zyg),data=twinstut)
margbin <- glm(binstut~factor(sex)+age,data=twinstut,family=binomial())
bin <- binomial.twostage(margbin,data=twinstut,var.link=1,
         clusters=twinstut$tvparnr,theta.des=theta.des,detail=0,
```

```
                method="nr")
summary(bin)
lava::estimate(coef=bin$theta,vcov=bin$var.theta,f=function(p) exp(p))

twinstut$cage <- scale(twinstut$age)
theta.des <- model.matrix( ~-1+factor(zyg)+cage,data=twinstut)
bina <- binomial.twostage(margbin,data=twinstut,var.link=1,
         clusters=twinstut$tvparnr,theta.des=theta.des,detail=0)
summary(bina)

theta.des <- model.matrix( ~-1+factor(zyg)+factor(zyg)*cage,data=twinstut)
bina <- binomial.twostage(margbin,data=twinstut,var.link=1,
         clusters=twinstut$tvparnr,theta.des=theta.des)
summary(bina)

out <- easy.binomial.twostage(stutter~factor(sex)+age,data=twinstut,
                              response="binstut",id="tvparnr",var.link=1,
          theta.formula=~-1+factor(zyg1))
summary(out)

## refers to zygosity of first subject in eash pair : zyg1
## could also use zyg2 (since zyg2=zyg1 within twinpair's))
## do not run t save time
# desfs <- function(x,num1="zyg1",namesdes=c("mz","dz","os"))
#     c(x[num1]=="mz",x[num1]=="dz",x[num1]=="os")*1
#
#out3 <- easy.binomial.twostage(binstut~factor(sex)+age,
#                               data=twinstut, response="binstut",id="tvparnr",
#                               var.link=1,theta.formula=desfs,
#                               desnames=c("mz","dz","os"))
#summary(out3)

 ## Reduce Ex.Timings
n <- 1000
set.seed(100)
dd <- simBinFam(n,beta=0.3)
binfam <- fast.reshape(dd,varying=c("age","x","y"))
## mother, father, children  (ordered)
head(binfam)

########### ########### ########### ########### ########### ###########
####  simple analyses of binomial family data
########### ########### ########### ########### ########### ###########
desfs <- function(x,num1="num1",num2="num2")
{
     pp <- 1*(((x[num1]=="m")*(x[num2]=="f"))|(x[num1]=="f")*(x[num2]=="m"))
     pc <- (x[num1]=="m" | x[num1]=="f")*(x[num2]=="b1" | x[num2]=="b2")*1
     cc <- (x[num1]=="b1")*(x[num2]=="b1" | x[num2]=="b2")*1
     c(pp,pc,cc)
}

ud <- easy.binomial.twostage(y~+1,data=binfam,
     response="y",id="id",
```

```
     theta.formula=desfs,desnames=c("pp","pc","cc"))
summary(ud)

udx <- easy.binomial.twostage(y~+x,data=binfam,
     response="y",id="id",
     theta.formula=desfs,desnames=c("pp","pc","cc"))
summary(udx)

########### ########### ########### ########### ########### ###########
####  now allowing parent child POR to be different for mother and father
########### ########### ########### ########### ########### ###########

desfsi <- function(x,num1="num1",num2="num2")
{
    pp <- (x[num1]=="m")*(x[num2]=="f")*1
    mc <- (x[num1]=="m")*(x[num2]=="b1" | x[num2]=="b2")*1
    fc <- (x[num1]=="f")*(x[num2]=="b1" | x[num2]=="b2")*1
    cc <- (x[num1]=="b1")*(x[num2]=="b1" | x[num2]=="b2")*1
    c(pp,mc,fc,cc)
}

udi <- easy.binomial.twostage(y~+1,data=binfam,
     response="y",id="id",
     theta.formula=desfsi,desnames=c("pp","mother-child","father-child","cc"))
summary(udi)

##now looking to see if interactions with age or age influences marginal models
##converting factors to numeric to make all involved covariates numeric
##to use desfai2 rather then desfai that works on binfam

nbinfam <- binfam
nbinfam$num <- as.numeric(binfam$num)
head(nbinfam)

desfsai <- function(x,num1="num1",num2="num2")
{
    pp <- (x[num1]=="m")*(x[num2]=="f")*1
### av age for pp=1 i.e parent pairs
    agepp <- ((as.numeric(x["age1"])+as.numeric(x["age2"]))/2-30)*pp
    mc <- (x[num1]=="m")*(x[num2]=="b1" | x[num2]=="b2")*1
    fc <- (x[num1]=="f")*(x[num2]=="b1" | x[num2]=="b2")*1
    cc <- (x[num1]=="b1")*(x[num2]=="b1" | x[num2]=="b2")*1
    agecc <- ((as.numeric(x["age1"])+as.numeric(x["age2"]))/2-12)*cc
    c(pp,agepp,mc,fc,cc,agecc)
}

desfsai2 <- function(x,num1="num1",num2="num2")
{
    pp <- (x[num1]==1)*(x[num2]==2)*1
    agepp <- (((x["age1"]+x["age2"]))/2-30)*pp ### av age for pp=1 i.e parent pairs
    mc <- (x[num1]==1)*(x[num2]==3 | x[num2]==4)*1
    fc <- (x[num1]==2)*(x[num2]==3 | x[num2]==4)*1
    cc <- (x[num1]==3)*(x[num2]==3 | x[num2]==4)*1
```

```
    agecc <- ((x["age1"]+x["age2"])/2-12)*cc ### av age for children
    c(pp,agepp,mc,fc,cc,agecc)
}

udxai2 <- easy.binomial.twostage(y~+x+age,data=binfam,
     response="y",id="id",
     theta.formula=desfsai,
     desnames=c("pp","pp-age","mother-child","father-child","cc","cc-age"))
summary(udxai2)
```

`Effbinreg` *Efficient IPCW for binary data*

Description

Simple version of comp.risk function of timereg for just one time-point thus fitting the model

$$E(T \leq t|X) = expit(X^T beta)$$

Usage

```
Effbinreg(
  formula,
  data,
  cause = 1,
  time = NULL,
  beta = NULL,
  offset = NULL,
  weights = NULL,
  cens.weights = NULL,
  cens.model = ~+1,
  se = TRUE,
  kaplan.meier = TRUE,
  cens.code = 0,
  no.opt = FALSE,
  method = "nr",
  augmentation = NULL,
  h = NULL,
  MCaugment = NULL,
  ...
)
```

Arguments

`formula`	formula with outcome (see `coxph`)
`data`	data frame
`cause`	cause of interest

time	time of interest
beta	starting values
offset	offsets for partial likelihood
weights	for score equations
cens.weights	censoring weights
cens.model	only stratified cox model without covariates
se	to compute se's based on IPCW
kaplan.meier	uses Kaplan-Meier for IPCW in contrast to exp(-Baseline)
cens.code	gives censoring code
no.opt	to not optimize
method	for optimization
augmentation	to augment binomial regression
h	h for estimating equation
MCaugment	iid of h and censoring model
...	Additional arguments to lower level funtions
model	exp or linear

Details

Based on binomial regresion IPCW response estimating equation:

$$X(\Delta(T \leq t)/G_c(T_i-) - expit(X^T beta)) = 0$$

for IPCW adjusted responses.

Based on binomial regresion IPCW response estimating equation:

$$h(X)X(\Delta(T \leq t)/G_c(T_i-) - expit(X^T beta)) = 0$$

for IPCW adjusted responses where h is given as an argument together with iid of censoring with h. By using appropriately the h argument we can also do the efficient IPCW estimator estimator this works the prepsurv and prepcif for survival or competing risks data. In this case also the censoring martingale should be given for variance calculation and this also comes out of the prepsurv or prepcif functions. (Experimental version at this stage).

Variance is based on

$$\sum w_i^2$$

also with IPCW adjustment, and naive.var is variance under known censoring model.

Censoring model may depend on strata.

Author(s)

Thomas Scheike

EVaddGam *Relative risk for additive gamma model*

Description

Computes the relative risk for additive gamma model at time 0

Usage

```
EVaddGam(theta, x1, x2, thetades, ags)
```

Arguments

theta	theta
x1	x1
x2	x2
thetades	thetades
ags	ags

Author(s)

Thomas Scheike

References

Eriksson and Scheike (2015), Additive Gamma frailty models for competing risks data, Biometrics (2015)

Examples

```
lam0 <- c(0.5,0.3)
pars <- c(1,1,1,1,0,1)
## genetic random effects, cause1, cause2 and overall
parg <- pars[c(1,3,5)]
## environmental random effects, cause1, cause2 and overall
parc <- pars[c(2,4,6)]

## simulate competing risks with two causes with hazards 0.5 and 0.3
## ace for each cause, and overall ace
out <- simCompete.twin.ace(10000,parg,parc,0,2,lam0=lam0,overall=1,all.sum=1)

## setting up design for running the model
mm <- familycluster.index(out$cluster)
head(mm$familypairindex,n=10)
pairs <- matrix(mm$familypairindex,ncol=2,byrow=TRUE)
tail(pairs,n=12)
#
kinship <- (out[pairs[,1],"zyg"]=="MZ")+ (out[pairs[,1],"zyg"]=="DZ")*0.5
```

```
# dout <- make.pairwise.design.competing(pairs,kinship,
#          type="ace",compete=length(lam0),overall=1)
# head(dout$ant.rvs)
## MZ
# dim(dout$theta.des)
# dout$random.design[,,1]
## DZ
# dout$theta.des[,,nrow(pairs)]
# dout$random.design[,,nrow(pairs)]
#
# thetades <- dout$theta.des[,,1]
# x <- dout$random.design[,,1]
# x
##EVaddGam(rep(1,6),x[1,],x[3,],thetades,matrix(1,18,6))

# thetades <- dout$theta.des[,,nrow(out)/2]
# x <- dout$random.design[,,nrow(out)/2]
##EVaddGam(rep(1,6),x[1,],x[4,],thetades,matrix(1,18,6))
```

`eventpois` *Extract survival estimates from lifetable analysis*

Description

Summary for survival analyses via the 'lifetable' function

Usage

```
eventpois(
  object,
  ...,
  timevar,
  time,
  int.len,
  confint = FALSE,
  level = 0.95,
  individual = FALSE,
  length.out = 25
)
```

Arguments

`object`	glm object (poisson regression)
`...`	Contrast arguments
`timevar`	Name of time variable
`time`	Time points (optional)
`int.len`	Time interval length (optional)

confint	If TRUE confidence limits are supplied
level	Level of confidence limits
individual	Individual predictions
length.out	Length of time vector

Details

Summary for survival analyses via the 'lifetable' function

Author(s)

Klaus K. Holst

`EventSplit` *Event split with two time-scales, time and gaptime*

Description

splits after cut times for the two time-scales.

Usage

```
EventSplit(
  data,
  time = "time",
  status = "status",
  entry = "start",
  cuts = "cuts",
  name.id = "id",
  gaptime = NULL,
  gaptime.entry = NULL,
  cuttime = c("time", "gaptime"),
  cens.code = 0,
  order.id = TRUE
)
```

Arguments

data	data to be split
time	time variable.
status	status variable.
entry	name of entry variable.
cuts	cuts variable or numeric cut (only one value)
name.id	name of id variable.
gaptime	gaptime variable.

gaptime.entry	name of entry variable for gaptime.
cuttime	to cut after time or gaptime
cens.code	code for the censoring.
order.id	order data after id and start.

Author(s)

Thomas Scheike

Examples

```
rr  <- data.frame(time=c(500,1000),start=c(0,500),status=c(1,1),id=c(1,1))
rr$gaptime <-  rr$time-rr$start
rr$gapstart <- 0

rr1 <- EventSplit(rr,cuts=600,cuttime="time",  gaptime="gaptime",gaptime.entry="gapstart")
rr2 <- EventSplit(rr1,cuts=100,cuttime="gaptime",gaptime="gaptime",gaptime.entry="gapstart")

dlist(rr1,start-time+status+gapstart+gaptime~id)
dlist(rr2,start-time+status+gapstart+gaptime~id)
```

---

familycluster.index *Finds all pairs within a cluster (family)*

Description

Finds all pairs within a cluster (family)

Usage

```
familycluster.index(clusters, index.type = FALSE, num = NULL, Rindex = 1)
```

Arguments

clusters	list of indeces
index.type	argument of cluster index
num	num
Rindex	index starts with 1 in R, and 0 in C

Author(s)

Klaus Holst, Thomas Scheike

References

Cluster indeces

See Also

cluster.index familyclusterWithProbands.index

Examples

```
i<-c(1,1,2,2,1,3)
d<- familycluster.index(i)
print(d)
```

`familyclusterWithProbands.index` *Finds all pairs within a cluster (famly) with the proband (case/control)*

Description

second column of pairs are the probands and the first column the related subjects

Usage

```
familyclusterWithProbands.index(
  clusters,
  probands,
  index.type = FALSE,
  num = NULL,
  Rindex = 1
)
```

Arguments

`clusters`	list of indeces giving the clusters (families)
`probands`	list of 0,1 where 1 specifices which of the subjects that are probands
`index.type`	argument passed to other functions
`num`	argument passed to other functions
`Rindex`	index starts with 1, in C is it is 0

Author(s)

Klaus Holst, Thomas Scheike

References

Cluster indeces

See Also

familycluster.index cluster.index

Examples

```
i<-c(1,1,2,2,1,3)
p<-c(1,0,0,1,0,1)
d<- familyclusterWithProbands.index(i,p)
print(d)
```

`fast.approx` *Fast approximation*

Description

Fast approximation

Usage

```
fast.approx(
  time,
  new.time,
  equal = FALSE,
  type = c("nearest", "right", "left"),
  sorted = FALSE,
  ...
)
```

Arguments

`time`	Original ordered time points
`new.time`	New time points
`equal`	If TRUE a list is returned with additional element
`type`	Type of matching, nearest index, nearest greater than or equal (right), number of elements smaller than y otherwise the closest value above new.time is returned.
`sorted`	Set to true if new.time is already sorted
`...`	Optional additional arguments

Author(s)

Klaus K. Holst

Examples

```
id <- c(1,1,2,2,7,7,10,10)
fast.approx(unique(id),id)

t <- 0:6
n <- c(-1,0,0.1,0.9,1,1.1,1.2,6,6.5)
fast.approx(t,n,type="left")
```

fast.pattern *Fast pattern*

Description

Fast pattern

Usage

```
fast.pattern(x, y, categories = 2, ...)
```

Arguments

x	Matrix (binary) of patterns. Optionally if y is also passed as argument, then the pattern matrix is defined as the elements agreeing in the two matrices.
y	Optional matrix argument with same dimensions as x (see above)
categories	Default 2 (binary)
...	Optional additional arguments

Author(s)

Klaus K. Holst

Examples

```
X <- matrix(rbinom(100,1,0.5),ncol=4)
fast.pattern(X)

X <- matrix(rbinom(100,3,0.5),ncol=4)
fast.pattern(X,categories=4)
```

fast.reshape *Fast reshape*

Description

Fast reshape/tranpose of data

Usage

```
fast.reshape(
  data,
  varying,
  id,
  num,
  sep = "",
  keep,
  idname = "id",
  numname = "num",
  factor = FALSE,
  idcombine = TRUE,
  labelnum = FALSE,
  labels,
  regex = mets.options()$regex,
  dropid = FALSE,
  ...
)
```

Arguments

data	data.frame or matrix
varying	Vector of prefix-names of the time varying variables. Optional for Long->Wide reshaping.
id	id-variable. If omitted then reshape Wide->Long.
num	Optional number/time variable
sep	String seperating prefix-name with number/time
keep	Vector of column names to keep
idname	Name of id-variable (Wide->Long)
numname	Name of number-variable (Wide->Long)
factor	If true all factors are kept (otherwise treated as character)
idcombine	If TRUE and id is vector of several variables, the unique id is combined from all the variables. Otherwise the first variable is only used as identifier.
labelnum	If TRUE varying variables in wide format (going from long->wide) are labeled 1,2,3,... otherwise use 'num' variable. In long-format (going from wide->long) varying variables matching 'varying' prefix are only selected if their postfix is a number.
labels	Optional labels for the number variable
regex	Use regular expressions
dropid	Drop id in long format (default FALSE)
...	Optional additional arguments

Author(s)

Thomas Scheike, Klaus K. Holst

Examples

```
m <- lava::lvm(c(y1,y2,y3,y4)~x)
d <- lava::sim(m,5)
d
fast.reshape(d,"y")
fast.reshape(fast.reshape(d,"y"),id="id")

##### From wide-format
(dd <- fast.reshape(d,"y"))
## Same with explicit setting new id and number variable/column names
## and seperator "" (default) and dropping x
fast.reshape(d,"y",idname="a",timevar="b",sep="",keep=c())
## Same with 'reshape' list-syntax
fast.reshape(d,list(c("y1","y2","y3","y4")),labelnum=TRUE)

##### From long-format
fast.reshape(dd,id="id")
## Restrict set up within-cluster varying variables
fast.reshape(dd,"y",id="id")
fast.reshape(dd,"y",id="id",keep="x",sep=".")

#####
x <- data.frame(id=c(5,5,6,6,7),y=1:5,x=1:5,tv=c(1,2,2,1,2))
x
(xw <- fast.reshape(x,id="id"))
(xl <- fast.reshape(xw,c("y","x"),idname="id2",keep=c()))
(xl <- fast.reshape(xw,c("y","x","tv")))
(xw2 <- fast.reshape(xl,id="id",num="num"))
fast.reshape(xw2,c("y","x"),idname="id")

### more generally:
### varying=list(c("ym","yf","yb1","yb2"), c("zm","zf","zb1","zb2"))
### varying=list(c("ym","yf","yb1","yb2")))

##### Family cluster example
d <- mets:::simBinFam(3)
d
fast.reshape(d,var="y")
fast.reshape(d,varying=list(c("ym","yf","yb1","yb2")))

d <- lava::sim(lava::lvm(~y1+y2+ya),10)
d
(dd <- fast.reshape(d,"y"))
fast.reshape(d,"y",labelnum=TRUE)
fast.reshape(dd,id="id",num="num")
fast.reshape(dd,id="id",num="num",labelnum=TRUE)
fast.reshape(d,c(a="y"),labelnum=TRUE) ## New column name


##### Unbalanced data
m <- lava::lvm(c(y1,y2,y3,y4)~ x+z1+z3+z5)
d <- lava::sim(m,3)
```

```
d
fast.reshape(d,c("y","z"))

##### not-varying syntax:
fast.reshape(d,-c("x"))

##### Automatically define varying variables from trailing digits
fast.reshape(d)

##### Prostate cancer example
data(prt)
head(prtw <- fast.reshape(prt,"cancer",id="id"))
ftable(cancer1~cancer2,data=prtw)
rm(prtw)
```

FG_AugmentCifstrata *Augmentation for Fine-Gray model based on stratified NPMLE Cif (Aalen-Johansen)*

Description

Computes the augmentation term for each individual as well as the sum

$$A(\beta) = \int H(t, X, \beta) \frac{F_2^*(t, s)}{S^*(t, s)} \frac{1}{G_c(t)} dM_c$$

with

$$H(t, X, \beta) = \int_t^\infty (X - E(\beta, t)) G_c(t) d\Lambda_1^* i(t, s)$$

using a KM for

$$G_c(t)$$

and a working model for cumulative baseline related to

$$F_1^*(t, s)$$

and

$$s$$

is strata,

$$S^*(t, s) = 1 - F_1^*(t, s) - F_2^*(t, s)$$

, and

$$E(\beta^p, t)$$

is given. Assumes that no strata for baseline of ine-Gay model that is augmented.

Usage

```
FG_AugmentCifstrata(
  formula,
  data = data,
  E = NULL,
  cause = NULL,
  cens.code = 0,
  km = TRUE,
  case.weights = NULL,
  weights = NULL,
  offset = NULL,
  ...
)
```

Arguments

formula	formula with 'Event', strata model for CIF given by strata, and strataC specifies censoring strata
data	data frame
E	from FG-model
cause	of interest
cens.code	code of censoring
km	to use Kaplan-Meier
case.weights	weights for FG score equations (that follow dN_1)
weights	weights for FG score equations
offset	offsets for FG model
...	Additional arguments to lower level funtions

Details

After a couple of iterations we end up with a solution of

$$\int (X - E(\beta))Y_1(t)w(t)dM_1 + A(\beta)$$

the augmented FG-score.

Standard errors computed under assumption of correct

$$G_c$$

model.

Author(s)

Thomas Scheike

Examples

```
set.seed(100)
rho1 <- 0.2; rho2 <- 10
n <- 400
beta=c(0.0,-0.1,-0.5,0.3)
dats <- simul.cifs(n,rho1,rho2,beta,rc=0.2)
dtable(dats,~status)
dsort(dats) <- ~time
fg <- cifreg(Event(time,status)~Z1+Z2,data=dats,cause=1,propodds=NULL)
summary(fg)

fgaugS <- FG_AugmentCifstrata(Event(time,status)~Z1+Z2+strata(Z1,Z2),data=dats,cause=1,E=fg$E)
summary(fgaugS)
fgaugS2 <- FG_AugmentCifstrata(Event(time,status)~Z1+Z2+strata(Z1,Z2),data=dats,cause=1,E=fgaugS$E)
summary(fgaugS2)
```

---

ghaplos *ghaplos haplo-types for subjects of haploX data*

Description

ghaplos haplo-types for subjects of haploX data

Source

Simulated data

---

glm_IPTW *IPTW GLM, Inverse Probaibilty of Treatment Weighted GLM*

Description

Fits GLM model with treatment weights

$$w(A) = \sum_a I(A = a)/P(A = a|X)$$

, computes standard errors via influence functions that are returned as the IID argument. Propensity scores are fitted using either logistic regression (glm) or the multinomial model (mlogit) when more than two categories for treatment. The treatment needs to be a factor and is identified on the rhs of the "treat.model".

Usage

```
glm_IPTW(
  formula,
  data,
  treat.model = NULL,
  family = binomial(),
  id = NULL,
  weights = NULL,
  estpr = 1,
  pi0 = 0.5,
  ...
)
```

Arguments

formula	for glm
data	data frame for risk averaging
treat.model	propensity score model (binary or multinomial)
family	of glm (logistic regression)
id	cluster id for standard errors
weights	may be given, and then uses weights*w(A) as the weights
estpr	to estimate propensity scores and get infuence function contribution to uncertainty
pi0	fixed simple weights
...	arguments for glm call

Details

Also works with cluster argument.

Author(s)

Thomas Scheike

---

gof.phreg *GOF for Cox PH regression*

Description

Cumulative score process residuals for Cox PH regression p-values based on Lin, Wei, Ying resampling.

Usage

```
## S3 method for class 'phreg'
gof(object, n.sim = 1000, silent = 1, robust = NULL, ...)
```

Arguments

object	is phreg object
n.sim	number of simulations for score processes
silent	to show timing estimate will be produced for longer jobs
robust	to control wether robust dM_i(t) or dN_i are used for simulations
...	Additional arguments to lower level funtions

Author(s)

Thomas Scheike and Klaus K. Holst

Examples

```
library(mets)
data(sTRACE)

m1 <- phreg(Surv(time,status==9)~vf+chf+diabetes,data=sTRACE)
gg <- gof(m1)
gg
par(mfrow=c(1,3))
plot(gg)

m1 <- phreg(Surv(time,status==9)~strata(vf)+chf+diabetes,data=sTRACE)
## to get Martingale ~ dN based simulations
gg <- gof(m1)
gg

## to get Martingale robust simulations, specify cluster in  call
sTRACE$id <- 1:500
m1 <- phreg(Surv(time,status==9)~vf+chf+diabetes+cluster(id),data=sTRACE)
gg <- gof(m1)
gg

m1 <- phreg(Surv(time,status==9)~strata(vf)+chf+diabetes+cluster(id),data=sTRACE)
gg <- gof(m1)
gg
```

---

gofG.phreg *Stratified baseline graphical GOF test for Cox covariates in PH regression*

Description

Looks at stratified baseline in Cox model and plots all baselines versus each other to see if lines are straight, with 50 resample versions under the assumptiosn that the stratified Cox is correct

Usage

```
gofG.phreg(x, sim = 0, silent = 1, lm = TRUE, ...)
```

Arguments

x	phreg object
sim	to simulate som variation from cox model to put on graph
silent	to keep it absolutely silent
lm	addd line to plot, regressing the cumulatives on each other
...	Additional arguments to lower level funtions

Author(s)

Thomas Scheike and Klaus K. Holst

Examples

```
data(tTRACE)

m1 <- phreg(Surv(time,status==9)~strata(vf)+chf+wmi,data=tTRACE)
m2 <- phreg(Surv(time,status==9)~vf+strata(chf)+wmi,data=tTRACE)
par(mfrow=c(2,2))

gofG.phreg(m1)
gofG.phreg(m2)

bplot(m1,log="y")
bplot(m2,log="y")
```

---

gofM.phreg *GOF for Cox covariates in PH regression*

Description

Cumulative residuals after model matrix for Cox PH regression p-values based on Lin, Wei, Ying resampling.

Usage

```
gofM.phreg(
  formula,
  data,
  offset = NULL,
  weights = NULL,
  modelmatrix = NULL,
  n.sim = 1000,
  silent = 1,
  ...
)
```

Arguments

formula	formula for cox regression
data	data for model
offset	offset
weights	weights
modelmatrix	matrix for cumulating residuals
n.sim	number of simulations for score processes
silent	to keep it absolutely silent, otherwise timing estimate will be prduced for longer jobs.
...	Additional arguments to lower level funtions

Details

That is, computes

$$U(t) = \int_0^t M^t d\hat{M}$$

and resamples its asymptotic distribution.

This will show if the residuals are consistent with the model. Typically, M will be a design matrix for the continous covariates that gives for example the quartiles, and then the plot will show if for the different quartiles of the covariate the risk prediction is consistent over time (time x covariate interaction).

Author(s)

Thomas Scheike and Klaus K. Holst

Examples

```
library(mets)
data(TRACE)
set.seed(1)
TRACEsam <- blocksample(TRACE,idvar="id",replace=FALSE,100)

dcut(TRACEsam)  <- ~.
mm <- model.matrix(~-1+factor(wmicat.4),data=TRACEsam)
m1 <- gofM.phreg(Surv(time,status==9)~vf+chf+wmi,data=TRACEsam,modelmatrix=mm)
summary(m1)
if (interactive()) {
par(mfrow=c(2,2))
plot(m1)
}

m1 <- gofM.phreg(Surv(time,status==9)~strata(vf)+chf+wmi,data=TRACEsam,modelmatrix=mm)
summary(m1)

## cumulative sums in covariates, via design matrix mm
mm <- cumContr(TRACEsam$wmi,breaks=10,equi=TRUE)
```

```
m1 <- gofM.phreg(Surv(time,status==9)~strata(vf)+chf+wmi,data=TRACEsam,
  modelmatrix=mm,silent=0)
summary(m1)
```

`gofZ.phreg` *GOF for Cox covariates in PH regression*

Description

That is, computes

$$U(z,\tau) = \int_0^\tau M(z)^t d\hat{M}$$

and resamples its asymptotic distribution.

Usage

```
gofZ.phreg(
  formula,
  data,
  vars = NULL,
  offset = NULL,
  weights = NULL,
  breaks = 50,
  equi = FALSE,
  n.sim = 1000,
  silent = 1,
  ...
)
```

Arguments

`formula`	formula for cox regression
`data`	data for model
`vars`	which variables to test for linearity
`offset`	offset
`weights`	weights
`breaks`	number of breaks for cumulatives in covarirate direction
`equi`	equidistant breaks or not
`n.sim`	number of simulations for score processes
`silent`	to keep it absolutely silent, otherwise timing estimate will be prduced for longer jobs.
`...`	Additional arguments to lower level funtions

Details

This will show if the residuals are consistent with the model evaulated in the z covariate. M is here chosen based on a grid (z_1, ..., z_m) and the different columns are $I(Z_i \leq z_l)$. for $l = 1, ..., m$. The process in z is resampled to find extreme values. The time-points of evuluation is by default 50 points, chosen as 2

The p-value is valid but depends on the chosen grid. When the number of break points are high this will give the orginal test of Lin, Wei and Ying for linearity, that is also computed in the timereg package.

Author(s)

Thomas Scheike and Klaus K. Holst

Examples

```
library(mets)
data(TRACE)
set.seed(1)
TRACEsam <- blocksample(TRACE,idvar="id",replace=FALSE,100)

## cumulative sums in covariates, via design matrix mm
 ## Reduce Ex.Timings
m1 <- gofZ.phreg(Surv(time,status==9)~strata(vf)+chf+wmi+age,data=TRACEsam)
summary(m1)
plot(m1,type="z")
```

`Grandom.cif` *Additive Random effects model for competing risks data for polygenetic modelling*

Description

Fits a random effects model describing the dependence in the cumulative incidence curves for subjects within a cluster. Given the gamma distributed random effects it is assumed that the cumulative incidence curves are indpendent, and that the marginal cumulative incidence curves are on additive form

$$P(T \leq t, cause = 1|x, z) = P_1(t, x, z) = 1 - exp(-x^T A(t) - tz^T \beta)$$

Usage

```
Grandom.cif(
  cif,
  data,
  cause = NULL,
  cif2 = NULL,
  times = NULL,
```

```
  cause1 = 1,
  cause2 = 1,
  cens.code = NULL,
  cens.model = "KM",
  Nit = 40,
  detail = 0,
  clusters = NULL,
  theta = NULL,
  theta.des = NULL,
  weights = NULL,
  step = 1,
  sym = 0,
  same.cens = FALSE,
  censoring.weights = NULL,
  silent = 1,
  var.link = 0,
  score.method = "nr",
  entry = NULL,
  estimator = 1,
  trunkp = 1,
  admin.cens = NULL,
  random.design = NULL,
  ...
)
```

Arguments

cif	a model object from the timereg::comp.risk function with the marginal cumulative incidence of cause2, i.e., the event that is conditioned on, and whose odds the comparision is made with respect to
data	a data.frame with the variables.
cause	specifies the causes related to the death times, the value cens.code is the censoring value.
cif2	specificies model for cause2 if different from cause1.
times	time points
cause1	cause of first coordinate.
cause2	cause of second coordinate.
cens.code	specificies the code for the censoring if NULL then uses the one from the marginal cif model.
cens.model	specified which model to use for the ICPW, KM is Kaplan-Meier alternatively it may be "cox"
Nit	number of iterations for Newton-Raphson algorithm.
detail	if 0 no details are printed during iterations, if 1 details are given.
clusters	specifies the cluster structure.
theta	specifies starting values for the cross-odds-ratio parameters of the model.

theta.des	specifies a regression design for the cross-odds-ratio parameters.
weights	weights for score equations.
step	specifies the step size for the Newton-Raphson algorith.m
sym	1 for symmetri and 0 otherwise
same.cens	if true then censoring within clusters are assumed to be the same variable, default is independent censoring.
censoring.weights	Censoring probabilities
silent	debug information
var.link	if var.link=1 then var is on log-scale.
score.method	default uses "nlminb" optimzer, alternatively, use the "nr" algorithm.
entry	entry-age in case of delayed entry. Then two causes must be given.
estimator	estimator
trunkp	gives probability of survival for delayed entry, and related to entry-ages given above.
admin.cens	Administrative censoring
random.design	specifies a regression design of 0/1's for the random effects.
...	extra arguments.

Details

We allow a regression structure for the indenpendent gamma distributed random effects and their variances that may depend on cluster covariates.

random.design specificies the random effects for each subject within a cluster. This is a matrix of 1's and 0's with dimension n x d. With d random effects. For a cluster with two subjects, we let the random.design rows be v_1 and v_2. Such that the random effects for subject 1 is

$$v_1^T(Z_1, ..., Z_d)$$

, for d random effects. Each random effect has an associated parameter $(\lambda_1, ..., \lambda_d)$. By construction subjects 1's random effect are Gamma distributed with mean $\lambda_1/v_1^T\lambda$ and variance $\lambda_1/(v_1^T\lambda)^2$. Note that the random effect $v_1^T(Z_1, ..., Z_d)$ has mean 1 and variance $1/(v_1^T\lambda)$.

The parameters $(\lambda_1, ..., \lambda_d)$ are related to the parameters of the model by a regression construction $pard$ (d x k), that links the d λ parameters with the (k) underlying θ parameters

$$\lambda = pard\theta$$

Value

returns an object of type 'random.cif'. With the following arguments:

theta	estimate of parameters of model.
var.theta	variance for gamma.
hess	the derivative of the used score.
score	scores at final stage.
theta.iid	matrix of iid decomposition of parametric effects.

Author(s)

Thomas Scheike

References

A Semiparametric Random Effects Model for Multivariate Competing Risks Data, Scheike, Zhang, Sun, Jensen (2010), Biometrika.

Cross odds ratio Modelling of dependence for Multivariate Competing Risks Data, Scheike and Sun (2013), Biostatitistics.

Scheike, Holst, Hjelmborg (2014), LIDA, Estimating heritability for cause specific hazards based on twin data

Examples

```
## Reduce Ex.Timings
d <- simnordic.random(5000,delayed=TRUE,
      cordz=1.0,cormz=2,lam0=0.3,country=TRUE)
times <- seq(50,90,by=10)
addm <- timereg::comp.risk(Event(time,cause)~-1+factor(country)+cluster(id),data=d,
times=times,cause=1,max.clust=NULL)

### making group indidcator
mm <- model.matrix(~-1+factor(zyg),d)

out1m<-random.cif(addm,data=d,cause1=1,cause2=1,theta=1,
  theta.des=mm,same.cens=TRUE)
summary(out1m)

## this model can also be formulated as a random effects model
## but with different parameters
out2m<-Grandom.cif(addm,data=d,cause1=1,cause2=1,
   theta=c(0.5,1),step=1.0,
   random.design=mm,same.cens=TRUE)
summary(out2m)
1/out2m$theta
out1m$theta

######################################################################
################### ACE modelling of twin data ######################
######################################################################
### assume that zygbin gives the zygosity of mono and dizygotic twins
### 0 for mono and 1 for dizygotic twins. We now formulate and AC model
zygbin <- d$zyg=="DZ"

n <- nrow(d)
### random effects for each cluster
des.rv <- cbind(mm,(zygbin==1)*rep(c(1,0)),(zygbin==1)*rep(c(0,1)),1)
### design making parameters half the variance for dizygotic components
pardes <- rbind(c(1,0), c(0.5,0),c(0.5,0), c(0.5,0), c(0,1))

outacem <-Grandom.cif(addm,data=d,cause1=1,cause2=1,
```

```
same.cens=TRUE,theta=c(0.35,0.15),
            step=1.0,theta.des=pardes,random.design=des.rv)
 summary(outacem)
```

---

hapfreqs *hapfreqs data set*

Description

hapfreqs data set

Source

Simulated data

---

haplo.surv.discrete *Discrete time to event haplo type analysis*

Description

Can be used for logistic regression when time variable is "1" for all id.

Usage

```
haplo.surv.discrete(
  X = NULL,
  y = "y",
  time.name = "time",
  Haplos = NULL,
  id = "id",
  desnames = NULL,
  designfunc = NULL,
  beta = NULL,
  no.opt = FALSE,
  method = "NR",
  stderr = TRUE,
  designMatrix = NULL,
  response = NULL,
  idhap = NULL,
  design.only = FALSE,
  covnames = NULL,
  fam = binomial,
  weights = NULL,
  offsets = NULL,
```

```
  idhapweights = NULL,
  ...
)
```

Arguments

X	design matrix data-frame (sorted after id and time variable) with id time response and desnames
y	name of response (binary response with logistic link) from X
time.name	to sort after time for X
Haplos	(data.frame with id, haplo1, haplo2 (haplotypes (h)) and p=P(h|G)) haplotypes given as factor.
id	name of id variale from X
desnames	names for design matrix
designfunc	function that computes design given haplotypes h=(h1,h2) x(h)
beta	starting values
no.opt	optimization TRUE/FALSE
method	NR, nlm
stderr	to return only estimate
designMatrix	gives response and designMatrix directly not implemented (mush contain: p, id, idhap)
response	gives response and design directly designMatrix not implemented
idhap	name of id-hap variable to specify different haplotypes for different id
design.only	to return only design matrices for haplo-type analyses.
covnames	names of covariates to extract from object for regression
fam	family of models, now binomial default and only option
weights	weights following id for GLM
offsets	following id for GLM
idhapweights	weights following id-hap for GLM (WIP)
...	Additional arguments to lower level funtions lava::NR optimizer or nlm

Details

Cycle-specific logistic regression of haplo-type effects with known haplo-type probabilities. Given observed genotype G and unobserved haplotypes H we here mix out over the possible haplotypes using that P(H|G) is provided.

$$S(t|x,G)) = E(S(t|x,H)|G) = \sum_{h \in G} P(h|G) S(t|z,h)$$

so survival can be computed by mixing out over possible h given g.

Survival is based on logistic regression for the discrete hazard function of the form

$$logit(P(T = t|T \geq t, x, h)) = \alpha_t + x(h)\beta$$

where x(h) is a regression design of x and haplotypes $h = (h_1, h_2)$

Likelihood is maximized and standard errors assumes that P(H|G) is known.

The design over the possible haplotypes is constructed by merging X with Haplos and can be viewed by design.only=TRUE

Author(s)

Thomas Scheike

Examples

```
## some haplotypes of interest
types <- c("DCGCGCTCACG","DTCCGCTGACG","ITCAGTTGACG","ITCCGCTGAGG")

## some haplotypes frequencies for simulations
data(hapfreqs)

www <-which(hapfreqs$haplotype %in% types)
hapfreqs$freq[www]

baseline=hapfreqs$haplotype[9]
baseline

designftypes <- function(x,sm=0) {# {{{
hap1=x[1]
hap2=x[2]
if (sm==0) y <- 1*( (hap1==types) | (hap2==types))
if (sm==1) y <- 1*(hap1==types) + 1*(hap2==types)
return(y)
}# }}}

tcoef=c(-1.93110204,-0.47531630,-0.04118204,-1.57872602,-0.22176426,-0.13836416,
0.88830288,0.60756224,0.39802821,0.32706859)

data(hHaplos)
data(haploX)

haploX$time <- haploX$times
Xdes <- model.matrix(~factor(time),haploX)
colnames(Xdes) <- paste("X",1:ncol(Xdes),sep="")
X <- dkeep(haploX,~id+y+time)
X <- cbind(X,Xdes)
Haplos <- dkeep(ghaplos,~id+"haplo*"+p)
desnames=paste("X",1:6,sep="")   # six X's related to 6 cycles
out <- haplo.surv.discrete(X=X,y="y",time.name="time",
         Haplos=Haplos,desnames=desnames,designfunc=designftypes)
names(out$coef) <- c(desnames,types)
out$coef
summary(out)
```

haploX *haploX covariates and response for haplo survival discrete survival*

Description

haploX covariates and response for haplo survival discrete survival

Source

Simulated data

interval.logitsurv.discrete *Discrete time to event interval censored data*

Description

$$logit(P(T > t|x)) = log(G(t)) + x\beta$$

$$P(T > t|x) = \frac{1}{1 + G(t)exp(x\beta)}$$

Usage

```
interval.logitsurv.discrete(
  formula,
  data,
  beta = NULL,
  no.opt = FALSE,
  method = "NR",
  stderr = TRUE,
  weights = NULL,
  offsets = NULL,
  exp.link = 1,
  increment = 1,
  ...
)
```

Arguments

formula	formula
data	data
beta	starting values
no.opt	optimization TRUE/FALSE

method	NR, nlm
stderr	to return only estimate
weights	weights following id for GLM
offsets	following id for GLM
exp.link	parametrize increments exp(alpha) > 0
increment	using increments dG(t)=exp(alpha) as parameters
...	Additional arguments to lower level funtions lava::NR optimizer or nlm

Details

This is thus also the cumulative odds model, since

$$P(T \leq t|x) = \frac{G(t)\exp(x\beta)}{1 + G(t)exp(x\beta)}$$

The baseline $G(t)$ is written as $cumsum(exp(\alpha))$ and this is not the standard parametrization that takes log of $G(t)$ as the parameters.

Input are intervals given by]t_l,t_r] where t_r can be infinity for right-censored intervals When truly discrete]0,1] will be an observation at 1, and]j,j+1] will be an observation at j+1

Likelihood is maximized:

$$\prod P(T_i > t_{il}|x) - P(T_i > t_{ir}|x)$$

Author(s)

Thomas Scheike

Examples

```
data(ttpd)
dtable(ttpd,~entry+time2)
out <- interval.logitsurv.discrete(Interval(entry,time2)~X1+X2+X3+X4,ttpd)
summary(out)

pred <- predictlogitSurvd(out,se=FALSE)
plotSurvd(pred)
```

---

ipw *Inverse Probability of Censoring Weights*

Description

Internal function. Calculates Inverse Probability of Censoring Weights (IPCW) and adds them to a data.frame

Usage

```
ipw(
  formula,
  data,
  cluster,
  same.cens = FALSE,
  obs.only = FALSE,
  weight.name = "w",
  trunc.prob = FALSE,
  weight.name2 = "wt",
  indi.weight = "pr",
  cens.model = "aalen",
  pairs = FALSE,
  theta.formula = ~1,
  ...
)
```

Arguments

formula	Formula specifying the censoring model
data	data frame
cluster	clustering variable
same.cens	For clustered data, should same censoring be assumed (bivariate probability calculated as mininum of the marginal probabilities)
obs.only	Return data with uncensored observations only
weight.name	Name of weight variable in the new data.frame
trunc.prob	If TRUE truncation probabilities are also calculated and stored in 'weight.name2' (based on Clayton-Oakes gamma frailty model)
weight.name2	Name of truncation probabilities
indi.weight	Name of individual censoring weight in the new data.frame
cens.model	Censoring model (default Aalens additive model)
pairs	For paired data (e.g. twins) only the complete pairs are returned (With pairs=TRUE)
theta.formula	Model for the dependence parameter in the Clayton-Oakes model (truncation only)
...	Additional arguments to censoring model

Author(s)

Klaus K. Holst

Examples

```
## Not run:
data("prt",package="mets")
prtw <- ipw(Surv(time,status==0)~country, data=prt[sample(nrow(prt),5000),],
```

```
            cluster="id",weight.name="w")
plot(0,type="n",xlim=range(prtw$time),ylim=c(0,1),xlab="Age",ylab="Probability")
count <- 0
for (l in unique(prtw$country)) {
    count <- count+1
    prtw <- prtw[order(prtw$time),]
    with(subset(prtw,country==l),
         lines(time,w,col=count,lwd=2))
}
legend("topright",legend=unique(prtw$country),col=1:4,pch=-1,lty=1)

## End(Not run)
```

---

ipw2 *Inverse Probability of Censoring Weights*

Description

Internal function. Calculates Inverse Probability of Censoring and Truncation Weights and adds them to a data.frame

Usage

```
ipw2(
  data,
  times = NULL,
  entrytime = NULL,
  time = "time",
  cause = "cause",
  same.cens = FALSE,
  cluster = NULL,
  pairs = FALSE,
  strata = NULL,
  obs.only = TRUE,
  cens.formula = NULL,
  cens.code = 0,
  pair.cweight = "pcw",
  pair.tweight = "ptw",
  pair.weight = "weights",
  cname = "cweights",
  tname = "tweights",
  weight.name = "indi.weights",
  prec.factor = 100,
  ...
)
```

Arguments

data	data frame
times	possible time argument for speciying a maximum value of time tau=max(times), to specify when things are considered censored or not.
entrytime	nam of entry-time for truncation.
time	name of time variable on data frame.
cause	name of cause indicator on data frame.
same.cens	For clustered data, should same censoring be assumed and same truncation (bivariate probability calculated as mininum of the marginal probabilities)
cluster	name of clustering variable
pairs	For paired data (e.g. twins) only the complete pairs are returned (With pairs=TRUE)
strata	name of strata variable to get weights stratified.
obs.only	Return data with uncensored observations only
cens.formula	model for Cox models for truncation and right censoring times.
cens.code	censoring.code
pair.cweight	Name of weight variable in the new data.frame for right censorig of pairs
pair.tweight	Name of weight variable in the new data.frame for left truncation of pairs
pair.weight	Name of weight variable in the new data.frame for right censoring and left truncation of pairs
cname	Name of weight variable in the new data.frame for right censoring of individuals
tname	Name of weight variable in the new data.frame for left truncation of individuals
weight.name	Name of weight variable in the new data.frame for right censoring and left truncation of individuals
prec.factor	To let tied censoring and truncation times come after the death times.
...	Additional arguments to censoring model

Author(s)

Thomas Scheike

Examples

```
library("timereg")
set.seed(1)
d <- simnordic.random(5000,delayed=TRUE,ptrunc=0.7,
      cordz=0.5,cormz=2,lam0=0.3,country=FALSE)
d$strata <- as.numeric(d$country)+(d$zyg=="MZ")*4
times <- seq(60,100,by=10)
c1 <- timereg::comp.risk(Event(time,cause)~1+cluster(id),data=d,cause=1,
model="fg",times=times,max.clust=NULL,n.sim=0)
mm=model.matrix(~-1+zyg,data=d)
out1<-random.cif(c1,data=d,cause1=1,cause2=1,same.cens=TRUE,theta.des=mm)
summary(out1)
```

```
pc1 <- predict(c1,X=1,se=0)
plot(pc1)

dl <- d[!d$truncated,]
dl <- ipw2(dl,cluster="id",same.cens=TRUE,time="time",entrytime="entry",cause="cause",
          strata="strata",prec.factor=100)
cl <- timereg::comp.risk(Event(time,cause)~+1+
cluster(id),
data=dl,cause=1,model="fg",
weights=dl$indi.weights,cens.weights=rep(1,nrow(dl)),
           times=times,max.clust=NULL,n.sim=0)
pcl <- predict(cl,X=1,se=0)
lines(pcl$time,pcl$P1,col=2)
mm=model.matrix(~-1+factor(zyg),data=dl)
out2<-random.cif(cl,data=dl,cause1=1,cause2=1,theta.des=mm,
                 weights=dl$weights,censoring.weights=rep(1,nrow(dl)))
summary(out2)
```

---

km *Kaplan-Meier with robust standard errors*

Description

Kaplan-Meier with robust standard errors Robust variance is default variance with the summary.

Usage

```
km(
  formula,
  data = data,
  conf.type = "log",
  conf.int = 0.95,
  robust = TRUE,
  ...
)
```

Arguments

formula	formula with 'Surv' outcome (see coxph)
data	data frame
conf.type	transformation
conf.int	level of confidence intervals
robust	for robust standard errors based on martingales
...	Additional arguments to lower level funtions

Author(s)

Thomas Scheike

Examples

```
data(TRACE)
TRACE$cluster <- sample(1:100,1878,replace=TRUE)
out1 <- km(Surv(time,status==9)~strata(vf,chf),data=TRACE)
out2 <- km(Surv(time,status==9)~strata(vf,chf)+cluster(cluster),data=TRACE)

par(mfrow=c(1,2))
bplot(out1,se=TRUE)
bplot(out2,se=TRUE)
```

---

lifecourse *Life-course plot*

Description

Life-course plot for event life data with recurrent events

Usage

```
lifecourse(
  formula,
  data,
  id = "id",
  group = NULL,
  type = "l",
  lty = 1,
  col = 1:10,
  alpha = 0.3,
  lwd = 1,
  recurrent.col = NULL,
  recurrent.lty = NULL,
  legend = NULL,
  pchlegend = NULL,
  by = NULL,
  status.legend = NULL,
  place.sl = "bottomright",
  xlab = "Time",
  ylab = "",
  add = FALSE,
  ...
)
```

Arguments

formula	Formula (Event(start,slut,status) ~ ...)
data	data.frame
id	Id variable

group	group variable
type	Type (line 'l', stair 's', ...)
lty	Line type
col	Colour
alpha	transparency (0-1)
lwd	Line width
recurrent.col	col of recurrence type
recurrent.lty	lty's of of recurrence type
legend	position of optional id legend
pchlegend	point type legends
by	make separate plot for each level in 'by' (formula, name of column, or vector)
status.legend	Status legend
place.sl	Placement of status legend
xlab	Label of X-axis
ylab	Label of Y-axis
add	Add to existing device
...	Additional arguments to lower level arguments

Author(s)

Thomas Scheike, Klaus K. Holst

Examples

```
data = data.frame(id=c(1,1,1,2,2),start=c(0,1,2,3,4),slut=c(1,2,4,4,7),
                  type=c(1,2,3,2,3),status=c(0,1,2,1,2),group=c(1,1,1,2,2))
ll = lifecourse(Event(start,slut,status)~id,data,id="id")
ll = lifecourse(Event(start,slut,status)~id,data,id="id",recurrent.col="type")

ll = lifecourse(Event(start,slut,status)~id,data,id="id",group=~group,col=1:2)
op <- par(mfrow=c(1,2))
ll = lifecourse(Event(start,slut,status)~id,data,id="id",by=~group)
par(op)
legends=c("censored","pregnant","married")
ll = lifecourse(Event(start,slut,status)~id,data,id="id",group=~group,col=1:2,status.legend=legends)
```

`lifetable.matrix` *Life table*

Description

Create simple life table

Usage

```
## S3 method for class 'matrix'
lifetable(x, strata = list(), breaks = c(),
   weights=NULL, confint = FALSE, ...)

 ## S3 method for class 'formula'
lifetable(x, data=parent.frame(), breaks = c(),
   weights=NULL, confint = FALSE, ...)
```

Arguments

`x`	time formula (Surv) or matrix/data.frame with columns time,status or entry,exit,status
`strata`	strata
`breaks`	time intervals
`weights`	weights variable
`confint`	if TRUE 95% confidence limits are calculated
`...`	additional arguments to lower level functions
`data`	data.frame

Author(s)

Klaus K. Holst

Examples

```
library(timereg)
data(TRACE)

d <- with(TRACE,lifetable(Surv(time,status==9)~sex+vf,breaks=c(0,0.2,0.5,8.5)))
summary(glm(events ~ offset(log(atrisk))+factor(int.end)*vf + sex*vf,
            data=d,poisson))
```

LinSpline *Simple linear spline*

Description

Simple linear spline

Usage

```
LinSpline(x, knots, num = TRUE, name = "Spline")
```

Arguments

x	variable to make into spline
knots	cut points
num	to give names x1 x2 and so forth
name	name of spline expansion name.1 name.2 and so forth

Author(s)

Thomas Scheike

logitSurv *Proportional odds survival model*

Description

Semiparametric Proportional odds model, that has the advantage that

$$logit(S(t|x)) = \log(\Lambda(t)) + x\beta$$

so covariate effects give OR of survival.

Usage

```
logitSurv(formula, data, offset = NULL, weights = NULL, ...)
```

Arguments

formula	formula with 'Surv' outcome (see coxph)
data	data frame
offset	offsets for exp(x beta) terms
weights	weights for score equations
...	Additional arguments to lower level funtions

Details

This is equivalent to using a hazards model

$$Z\lambda(t)\exp(x\beta)$$

where Z is gamma distributed with mean and variance 1.

Author(s)

Thomas Scheike

References

The proportional odds cumulative incidence model for competing risks, Eriksson, Frank and Li, Jianing and Scheike, Thomas and Zhang, Mei-Jie, Biometrics, 2015, 3, 687–695, 71,

Examples

```
data(TRACE)
dcut(TRACE) <- ~.
out1 <- logitSurv(Surv(time,status==9)~vf+chf+strata(wmicat.4),data=TRACE)
summary(out1)
gof(out1)
plot(out1)
```

`mediatorSurv` *Mediation analysis in survival context*

Description

Mediation analysis in survival context with robust standard errors taking the weights into account via influence function computations. Mediator and exposure must be factors. This is based on numerical derivative wrt parameters for weighting. See vignette for more examples.

Usage

```
mediatorSurv(
  survmodel,
  weightmodel,
  data = data,
  wdata = wdata,
  id = "id",
  silent = TRUE,
  ...
)
```

Arguments

survmodel	with mediation model (binreg, aalenMets, phreg)
weightmodel	mediation model
data	for computations
wdata	weighted data expansion for computations
id	name of id variable, important for SE computations
silent	to be silent
...	Additional arguments to survival model

Author(s)

Thomas Scheike

Examples

```
n <- 400
dat <- kumarsimRCT(n,rho1=0.5,rho2=0.5,rct=2,censpar=c(0,0,0,0),
          beta = c(-0.67, 0.59, 0.55, 0.25, 0.98, 0.18, 0.45, 0.31),
    treatmodel = c(-0.18, 0.56, 0.56, 0.54),restrict=1)
dfactor(dat) <- dnr.f~dnr
dfactor(dat) <- gp.f~gp
drename(dat) <- ttt24~"ttt24*"
dat$id <- 1:n
dat$ftime <- 1

weightmodel <- fit <- glm(gp.f~dnr.f+preauto+ttt24,data=dat,family=binomial)
wdata <- medweight(fit,data=dat)

### fitting models with and without mediator
aaMss2 <- binreg(Event(time,status)~gp+dnr+preauto+ttt24+cluster(id),data=dat,time=50,cause=2)
aaMss22 <- binreg(Event(time,status)~dnr+preauto+ttt24+cluster(id),data=dat,time=50,cause=2)

### estimating direct and indirect effects (under strong strong assumptions)
aaMss <- binreg(Event(time,status)~dnr.f0+dnr.f1+preauto+ttt24+cluster(id),
               data=wdata,time=50,weights=wdata$weights,cause=2)
## to compute standard errors , requires numDeriv
library(numDeriv)
ll <- mediatorSurv(aaMss,fit,data=dat,wdata=wdata)
summary(ll)
## not run bootstrap (to save time)
## bll <- BootmediatorSurv(aaMss,fit,data=dat,k.boot=500)
```

medweight *Computes mediation weights*

Description

Computes mediation weights for either binary or multinomial mediators. The important part is that the influence functions can be obtained to compute standard errors.

Usage

```
medweight(
  fit,
  data = data,
  var = NULL,
  name.weight = "weights",
  id.name = "id",
  ...
)
```

Arguments

fit	either glm-binomial or mlogit (mets package)
data	data frame with data
var	is NULL reads mediator and exposure from formulae in the fit.
name.weight	name of weights
id.name	name of id variable, important for SE computations
...	Additional arguments to

Author(s)

Thomas Scheike

melanoma *The Melanoma Survival Data*

Description

The melanoma data frame has 205 rows and 7 columns. It contains data relating to survival of patients after operation for malignant melanoma collected at Odense University Hospital by K.T. Drzewiecki.

Format

This data frame contains the following columns:

no a numeric vector. Patient code.

status a numeric vector code. Survival status. 1: dead from melanoma, 2: alive, 3: dead from other cause.

days a numeric vector. Survival time.

ulc a numeric vector code. Ulceration, 1: present, 0: absent.

thick a numeric vector. Tumour thickness (1/100 mm).

sex a numeric vector code. 0: female, 1: male.

Source

Andersen, P.K., Borgan O, Gill R.D., Keiding N. (1993), *Statistical Models Based on Counting Processes*, Springer-Verlag.

Drzewiecki, K.T., Ladefoged, C., and Christensen, H.E. (1980), Biopsy and prognosis for cutaneous malignant melanoma in clinical stage I. Scand. J. Plast. Reconstru. Surg. 14, 141-144.

Examples

```
data(melanoma)
names(melanoma)
```

---

mena *Menarche data set*

Description

Menarche data set

Source

Simulated data

mets.options *Set global options for* mets

Description

Extract and set global parameters of mets.

Usage

```
mets.options(...)
```

Arguments

...	Arguments

Details

- regex: If TRUE character vectors will be interpreted as regular expressions (dby, dcut, ...)
- silent: Set to FALSE to disable various output messages

Value

list of parameters

Examples

```
## Not run:
mets.options(regex=TRUE)

## End(Not run)
```

migr *Migraine data*

Description

Migraine data

`mlogit` *Multinomial regression based on phreg regression*

Description

Fits multinomial regression model

$$P_i = \frac{\exp(X_i^\beta)}{\sum_{j=1}^{K} \exp(X_j^\beta)}$$

for

$$i = 1, .., K$$

where

$$\beta_1 = 0$$

, such that

$$\sum_j P_j = 1$$

using phreg function. Thefore the ratio

$$\frac{P_i}{P_1} = \exp(X_i^\beta)$$

Usage

```
mlogit(formula, data, offset = NULL, weights = NULL, fix.X = FALSE, ...)
```

Arguments

`formula`	formula with outcome (see `coxph`)
`data`	data frame
`offset`	offsets for partial likelihood
`weights`	for score equations
`fix.X`	to have same coefficients for all categories
`...`	Additional arguments to lower level funtions

Details

Coefficients give log-Relative-Risk relative to baseline group (first level of factor, so that it can reset by relevel command). Standard errors computed based on sandwhich form

$$DU^-1 \sum U_i^2 DU^-1$$

.

Can also get influence functions (possibly robust) via iid() function, response should be a factor.

Can fit cumulative odds model as a special case of interval.logitsurv.discrete

Author(s)

Thomas Scheike

Examples

```
data(bmt)
dfactor(bmt) <- cause1f~cause
drelevel(bmt,ref=3) <- cause3f~cause
dlevels(bmt)

mreg <- mlogit(cause1f~+1,bmt)
summary(mreg)

mreg <- mlogit(cause1f~tcell+platelet,bmt)
summary(mreg)

mreg3 <- mlogit(cause3f~tcell+platelet,bmt)
summary(mreg3)

## inverse information standard errors
lava::estimate(coef=mreg3$coef,vcov=mreg3$II)

## predictions based on seen response or not
newdata <- data.frame(tcell=c(1,1,1),platelet=c(0,1,1),cause1f=c("2","1","0"))
predictmlogit(mreg,newdata,response=FALSE)
predictmlogit(mreg,newdata)
```

---

multcif *Multivariate Cumulative Incidence Function example data set*

Description

Multivariate Cumulative Incidence Function example data set

Source

Simulated data

---

np *np data set*

Description

np data set

Source

Simulated data

npc *For internal use*

Description

For internal use

Author(s)

Klaus K. Holst

phreg *Fast Cox PH regression*

Description

Fast Cox PH regression Robust variance is default variance with the summary.

Usage

```
phreg(formula, data, offset = NULL, weights = NULL, ...)
```

Arguments

formula	formula with 'Surv' outcome (see coxph)
data	data frame
offset	offsets for cox model
weights	weights for Cox score equations
...	Additional arguments to lower level funtions

Details

influence functions (iid) will follow numerical order of given cluster variable so ordering after $id will give iid in order of data-set.

Author(s)

Klaus K. Holst, Thomas Scheike

Examples

```
data(TRACE)
dcut(TRACE) <- ~.
out1 <- phreg(Surv(time,status==9)~vf+chf+strata(wmicat.4),data=TRACE)
out2 <- phreg(Event(time,status)~vf+chf+strata(wmicat.4),data=TRACE)
## tracesim <- timereg::sim.cox(out1,1000)
## sout1 <- phreg(Surv(time,status==1)~vf+chf+strata(wmicat.4),data=tracesim)
## robust standard errors default
summary(out1)
out1 <- phreg(Surv(time,status!=0)~vf+chf+strata(wmicat.4),data=TRACE)
summary(out2)

par(mfrow=c(1,2))
bplot(out1)
## bplot(sout1,se=TRUE)

## computing robust variance for baseline
rob1 <- robust.phreg(out1)
bplot(rob1,se=TRUE,robust=TRUE)

## making iid decomposition of regression parameters
betaiiid <- lava::iid(out1)

## making iid decomposition of baseline at a specific time-point
Aiiid <- mets:::IIDbaseline.phreg(out1,time=30)
```

---

phregR *Fast Cox PH regression and calculations done in R to make play and adjustments easy*

Description

Fast Cox PH regression with R implementation to play and adjust in R function: FastCoxPLstrataR

Usage

```
phregR(formula, data, offset = NULL, weights = NULL, ...)
```

Arguments

formula	formula with 'Surv' outcome (see coxph)
data	data frame
offset	offsets for cox model
weights	weights for Cox score equations
...	Additional arguments to lower level funtions

Details

Robust variance is default variance with the summary.

influence functions (iid) will follow numerical order of given cluster variable so ordering after $id will give iid in order of data-set.

Author(s)

Klaus K. Holst, Thomas Scheike

`phreg_IPTW` *IPTW Cox, Inverse Probaibilty of Treatment Weighted Cox regression*

Description

Fits Cox model with treatment weights

$$w(A) = \sum_a I(A = a)/P(A = a|X)$$

, computes standard errors via influence functions that are returned as the IID argument. Propensity scores are fitted using either logistic regression (glm) or the multinomial model (mlogit) when more than two categories for treatment. The treatment needs to be a factor and is identified on the rhs of the "treat.model".

Usage

```
phreg_IPTW(
  formula,
  data,
  treat.model = NULL,
  weight.var = NULL,
  weights = NULL,
  estpr = 1,
  pi0 = 0.5,
  ...
)
```

Arguments

`formula`	for phreg
`data`	data frame for risk averaging
`treat.model`	propensity score model (binary or multinomial)
`weight.var`	a 1/0 variable that indicates when propensity score is computed over time
`weights`	may be given, and then uses weights*w(A) as the weights
`estpr`	to estimate propensity scores and get infuence function contribution to uncertainty
`pi0`	fixed simple weights
`...`	arguments for phreg call

Details

Also works with cluster argument. Time-dependent propensity score weights can also be computed when weight.var is 1 and then at time of 2nd treatment (A_1) uses weights w_0(A_0) * w_1(A_1) where A_0 is first treatment.

Author(s)

Thomas Scheike

Examples

```
data <- mets:::simLT(0.7,100,beta=0.3,betac=0,ce=1,betao=0.3)
dfactor(data) <- Z.f~Z
out <- phreg_IPTW(Surv(time,status)~Z.f,data=data,treat.model=Z.f~X)
summary(out)
```

---

phreg_rct *Lu-Tsiatis More Efficient Log-Rank for Randomized studies with baseline covariates*

Description

Efficient implementation of the Lu-Tsiatis improvement using baseline covariates, extended to competing risks and recurrent events. Results almost equivalent with the speffSurv function of the speff2trial function in the survival case. A dynamic censoring augmentation regression is also computed to gain even more from the censoring augmentation. Furhter, we also deal with twostage randomizations. The function was implemented to deal with recurrent events (start,stop) + cluster, and more examples in vignette.

Usage

```
phreg_rct(
  formula,
  data,
  cause = 1,
  cens.code = 0,
  typesR = c("R0", "R1", "R01"),
  typesC = c("C", "dynC"),
  augmentR0 = NULL,
  augmentR1 = NULL,
  augmentC = NULL,
  treat.model = ~+1,
  RCT = TRUE,
  weight.var = NULL,
  km = TRUE,
```

```
  level = 0.95,
  cens.model = NULL,
  estpr = 1,
  pi0 = 0.5,
  ...
)
```

Arguments

formula	formula with 'Surv' or 'Event' outcome (see coxph) and treatment (randomization 0/1)
data	data frame
cause	to use for competing risks, recurrent events data
cens.code	to use for competing risks, recurrent events data
typesR	augmentations used for randomization
typesC	augmentations used for censoring
augmentR0	formula for the randomization augmentation (~age+sex)
augmentR1	formula for the randomization augmentation (~age+sex)
augmentC	formula for the censoring augmentation (~age+sex)
treat.model	propensity score model, default is ~+1, assuming RCT study
RCT	if false will use propensity score adjustment
weight.var	in case of twostage randomization, this variable is 1 for the treatment times,
km	use Kaplan-Meier for the censoring weights (stratified on treatment)
level	of confidence intervals
cens.model,	default is censoring model ~strata(treatment) but any model can be used to make censoring martingales
estpr	estimates propensity scores
pi0	possible fixed propoensity scores for randomizations
...	Additional arguments to phreg function

Author(s)

Thomas Scheike

References

Lu, Tsiatis (2008), Improving the efficiency of the log-rank test using auxiliary covariates, Biometrika, 679–694 Scheike (2024), WIP, Two-stage randomization for recurrent events,

Examples

```
## Lu, Tsiatis simulation
data <- mets:::simLT(0.7,100)
dfactor(data) <- Z.f~Z

out <- phreg_rct(Surv(time,status)~Z.f,data=data,augmentR0=~X,augmentC=~factor(Z):X)
summary(out)
```

plack.cif — *plack Computes concordance for or.cif based model, that is Plackett random effects model*

Description

.. content for description (no empty lines) ..

Usage

```
plack.cif(cif1, cif2, object)
```

Arguments

cif1	Cumulative incidence of first argument.
cif2	Cumulative incidence of second argument.
object	or.cif object with dependence parameters.

Author(s)

Thomas Scheike

pmvn — *Multivariate normal distribution function*

Description

Multivariate normal distribution function

Usage

```
pmvn(lower, upper, mu, sigma, cor = FALSE)
```

Arguments

lower	lower limits
upper	upper limits
mu	mean vector
sigma	variance matrix or vector of correlation coefficients
cor	if TRUE sigma is treated as standardized (correlation matrix)

Examples

```
lower <- rbind(c(0,-Inf),c(-Inf,0))
upper <- rbind(c(Inf,0),c(0,Inf))
mu <- rbind(c(1,1),c(-1,1))
sigma <- diag(2)+1
pmvn(lower=lower,upper=upper,mu=mu,sigma=sigma)
```

`predict.phreg` *Predictions from proportional hazards model*

Description

Predictions from proportional hazards model

Usage

```
## S3 method for class 'phreg'
predict(
  object,
  newdata,
  times = NULL,
  individual.time = FALSE,
  tminus = FALSE,
  se = TRUE,
  robust = FALSE,
  conf.type = "log",
  conf.int = 0.95,
  km = FALSE,
  ...
)
```

Arguments

`object`	phreg object
`newdata`	data.frame
`times`	Time where to predict variable, default is all time-points from the object sorted
`individual.time`	to use one (individual) time per subject, and then newdata and times have same length and makes only predictions for these individual times.
`tminus`	to make predictions in T- that is strictly before given times, useful for IPCW techniques
`se`	with standard errors and upper and lower confidence intervals.
`robust`	to get robust se's.
`conf.type`	transformation for suvival estimates, default is log
`conf.int`	significance level

km	to use Kaplan-Meier product-limit for baseline $$S_{s0}(t) = (1 - dA_{s0}(t))$$, otherwise take exp of cumulative baseline.
...	Additional arguments to plot functions

`print.casewise` *prints Concordance test*

Description

prints Concordance test

Usage

```
## S3 method for class 'casewise'
print(x, digits = 3, ...)
```

Arguments

x	output from casewise.test
digits	number of digits
...	Additional arguments to lower level functions

Author(s)

Thomas Scheike

`prob.exceed.recurrent` *Estimation of probability of more that k events for recurrent events process*

Description

Estimation of probability of more that k events for recurrent events process where there is terminal event, based on this also estimate of variance of recurrent events. The estimator is based on cumulative incidence of exceeding "k" events. In contrast the probability of exceeding k events can also be computed as a counting process integral, and this is implemented in prob.exceedRecurrent

Usage

```
prob.exceed.recurrent(
  data,
  type,
  status = "status",
  death = "death",
  start = "start",
  stop = "stop",
  id = "id",
  times = NULL,
  exceed = NULL,
  cifmets = TRUE,
  strata = NULL,
  all.cifs = FALSE,
  ...
)
```

Arguments

data	data-frame
type	type of evnent (code) related to status
status	name of status
death	name of death indicator
start	start stop call of Hist() of prodlim
stop	start stop call of Hist() of prodlim
id	id
times	time at which to get probabilites P(N1(t) >= n)
exceed	n's for which which to compute probabilites P(N1(t) >= n)
cifmets	if true uses cif of mets package rather than prodlim
strata	to stratify according to variable, only for cifmets=TRUE, when strata is given then only consider the output in the all.cifs
all.cifs	if true then returns list of all fitted objects in cif.exceed
...	Additional arguments to lower level funtions

Author(s)

Thomas Scheike

References

Scheike, Eriksson, Tribler (2019) The mean, variance and correlation for bivariate recurrent events with a terminal event, JRSS-C

Examples

```
#######################################
## getting some rates to mimick
#######################################

data(base1cumhaz)
data(base4cumhaz)
data(drcumhaz)
dr <- drcumhaz
base1 <- base1cumhaz
base4 <- base4cumhaz

cor.mat <- corM <- rbind(c(1.0, 0.6, 0.9), c(0.6, 1.0, 0.5), c(0.9, 0.5, 1.0))
rr <- simRecurrentII(1000,base4,cumhaz2=base4,death.cumhaz=dr,cens=2/5000)
rr <-  count.history(rr)
dtable(rr,~death+status)

oo <- prob.exceedRecurrent(rr,1)
bplot(oo)

par(mfrow=c(1,2))
with(oo,plot(time,mu,col=2,type="l"))
###
with(oo,plot(time,varN,type="l"))


### Bivariate probability of exceeding
oo <- prob.exceedBiRecurrent(rr,1,2,exceed1=c(1,5),exceed2=c(1,2))
with(oo, matplot(time,pe1e2,type="s"))
nc <- ncol(oo$pe1e2)
legend("topleft",legend=colnames(oo$pe1e2),lty=1:nc,col=1:nc)



### do not test to avoid dependence on prodlim
### now estimation based on cumualative incidence, but do not test to avoid dependence on prodlim
### library(prodlim)
pp <- prob.exceed.recurrent(rr,1,status="status",death="death",start="entry",stop="time",id="id")
with(pp, matplot(times,prob,type="s"))
###
with(pp, matlines(times,se.lower,type="s"))
with(pp, matlines(times,se.upper,type="s"))
```

`prt` *Prostate data set*

Description

Prostate data set

Source

Simulated data

`random.cif` *Random effects model for competing risks data*

Description

Fits a random effects model describing the dependence in the cumulative incidence curves for subjects within a cluster. Given the gamma distributed random effects it is assumed that the cumulative incidence curves are indpendent, and that the marginal cumulative incidence curves are on the form

$$P(T \leq t, cause = 1|x, z) = P_1(t, x, z) = 1 - exp(-x^T A(t) exp(z^T \beta))$$

We allow a regression structure for the random effects variances that may depend on cluster covariates.

Usage

```
random.cif(
  cif,
  data,
  cause = NULL,
  cif2 = NULL,
  cause1 = 1,
  cause2 = 1,
  cens.code = NULL,
  cens.model = "KM",
  Nit = 40,
  detail = 0,
  clusters = NULL,
  theta = NULL,
  theta.des = NULL,
  sym = 1,
  step = 1,
  same.cens = FALSE,
  var.link = 0,
  score.method = "nr",
  entry = NULL,
  trunkp = 1,
  ...
)
```

Arguments

`cif`	a model object from the comp.risk function with the marginal cumulative incidence of cause2, i.e., the event that is conditioned on, and whose odds the comparision is made with respect to

data	a data.frame with the variables.
cause	specifies the causes related to the death times, the value cens.code is the censoring value.
cif2	specificies model for cause2 if different from cause1.
cause1	cause of first coordinate.
cause2	cause of second coordinate.
cens.code	specificies the code for the censoring if NULL then uses the one from the marginal cif model.
cens.model	specified which model to use for the ICPW, KM is Kaplan-Meier alternatively it may be "cox"
Nit	number of iterations for Newton-Raphson algorithm.
detail	if 0 no details are printed during iterations, if 1 details are given.
clusters	specifies the cluster structure.
theta	specifies starting values for the cross-odds-ratio parameters of the model.
theta.des	specifies a regression design for the cross-odds-ratio parameters.
sym	1 for symmetry 0 otherwise
step	specifies the step size for the Newton-Raphson algorith.m
same.cens	if true then censoring within clusters are assumed to be the same variable, default is independent censoring.
var.link	if var.link=1 then var is on log-scale.
score.method	default uses "nlminb" optimzer, alternatively, use the "nr" algorithm.
entry	entry-age in case of delayed entry. Then two causes must be given.
trunkp	gives probability of survival for delayed entry, and related to entry-ages given above.
...	extra arguments.

Value

returns an object of type 'cor'. With the following arguments:

theta	estimate of proportional odds parameters of model.
var.theta	variance for gamma.
hess	the derivative of the used score.
score	scores at final stage.
score	scores at final stage.
theta.iid	matrix of iid decomposition of parametric effects.

Author(s)

Thomas Scheike

References

A Semiparametric Random Effects Model for Multivariate Competing Risks Data, Scheike, Zhang, Sun, Jensen (2010), Biometrika.

Cross odds ratio Modelling of dependence for Multivariate Competing Risks Data, Scheike and Sun (2012), work in progress.

Examples

```
## Reduce Ex.Timings
d <- simnordic.random(5000,delayed=TRUE,cordz=0.5,cormz=2,lam0=0.3,country=TRUE)
times <- seq(50,90,by=10)
add1 <- timereg::comp.risk(Event(time,cause)~-1+factor(country)+cluster(id),data=d,
times=times,cause=1,max.clust=NULL)

### making group indidcator
mm <- model.matrix(~-1+factor(zyg),d)

out1<-random.cif(add1,data=d,cause1=1,cause2=1,theta=1,same.cens=TRUE)
summary(out1)

out2<-random.cif(add1,data=d,cause1=1,cause2=1,theta=1,
  theta.des=mm,same.cens=TRUE)
summary(out2)

########################################
##### 2 different causes
########################################

add2 <- timereg::comp.risk(Event(time,cause)~-1+factor(country)+cluster(id),data=d,
                times=times,cause=2,max.clust=NULL)
out3 <- random.cif(add1,data=d,cause1=1,cause2=2,cif2=add2,sym=1,same.cens=TRUE)
summary(out3) ## negative dependence

out4 <- random.cif(add1,data=d,cause1=1,cause2=2,cif2=add2,theta.des=mm,sym=1,same.cens=TRUE)
summary(out4) ## negative dependence
```

---

rchaz *Simulation of Piecewise constant hazard model (Cox).*

Description

Simulates data from piecwise constant baseline hazard that can also be of Cox type. Censor data at highest value of the break points.

Usage

```
rchaz(
  cumhazard,
  rr,
  n = NULL,
  entry = NULL,
  cum.hazard = TRUE,
  cause = 1,
  extend = FALSE
)
```

Arguments

cumhazard	cumulative hazard, or piece-constant rates for periods defined by first column of input.
rr	relative risk for simulations, alternatively when rr=1 specify n
n	number of simulation if rr not given
entry	delayed entry time for simuations.
cum.hazard	specifies wheter input is cumulative hazard or rates.
cause	name of cause
extend	to extend piecewise constant with constant rate. Default is average rate over time from cumulative (when TRUE), if numeric then uses given rate.

Details

For a piecewise linear cumulative hazard the inverse is easy to compute with and delayed entry x we compute

$$\Lambda^{-1}(\Lambda(x) + E/RR)$$

, where RR are the relative risks and E is exponential with mean 1. This quantity has survival function

$$P(T > t|T > x) = exp(-RR(\Lambda(t) - \Lambda(x)))$$

.

Author(s)

Thomas Scheike

Examples

```
chaz <-  c(0,1,1.5,2,2.1)
breaks <- c(0,10,   20,  30,   40)
cumhaz <- cbind(breaks,chaz)
n <- 100
X <- rbinom(n,1,0.5)
beta <- 0.2
rrcox <- exp(X * beta)
```

```
pctime <- rchaz(cumhaz,n=1000,cum.hazard=FALSE)
pctimecox <- rchaz(cumhaz,rrcox,cum.hazard=FALSE)
```

---

rchazC *Piecewise constant hazard distribution*

Description

Piecewise constant hazard distribution

Usage

```
rchazC(base1, rr, entry)
```

Arguments

base1	baseline
rr	relative risk terms
entry	entry times for left truncation

---

rcrisk *Simulation of Piecewise constant hazard models with two causes (Cox).*

Description

Simulates data from piecwise constant baseline hazard that can also be of Cox type. Censor data at highest value of the break points for either of the cumulatives.

Usage

```
rcrisk(cumhaz1, cumhaz2, rr1, rr2, n = NULL, cens = NULL, rrc = NULL, ...)
```

Arguments

cumhaz1	cumulative hazard of cause 1
cumhaz2	cumulative hazard of cause 1
rr1	number of simulations or vector of relative risk for simuations.
rr2	number of simulations or vector of relative risk for simuations.
n	number of simulation if rr not given
cens	to censor further , rate or cumumlative hazard
rrc	retlativ risk for censoring.
...	arguments for rchaz

Author(s)

Thomas Scheike

Examples

```
library(mets); data(bmt); library(survival)

cox1 <- phreg(Surv(time,cause==1)~tcell+platelet,data=bmt)
cox2 <- phreg(Surv(time,cause==2)~tcell+platelet,data=bmt)

X1 <- bmt[,c("tcell","platelet")]
n <- 100
xid <- sample(1:nrow(X1),n,replace=TRUE)
Z1 <- X1[xid,]
Z2 <- X1[xid,]
rr1 <- exp(as.matrix(Z1) %*% cox1$coef)
rr2 <- exp(as.matrix(Z2) %*% cox2$coef)

d <-  rcrisk(cox1$cum,cox2$cum,rr1,rr2)
dd <- cbind(d,Z1)

scox1 <- phreg(Surv(time,status==1)~tcell+platelet,data=dd)
scox2 <- phreg(Surv(time,status==2)~tcell+platelet,data=dd)
par(mfrow=c(1,2))
plot(cox1); plot(scox1,add=TRUE)
plot(cox2); plot(scox2,add=TRUE)
cbind(cox1$coef,scox1$coef,cox2$coef,scox2$coef)
```

---

recreg *Recurrent events regression with terminal event*

Description

Fits Ghosh-Lin IPCW Cox-type model

Usage

```
recreg(
  formula,
  data = data,
  cause = 1,
  death.code = c(2),
  cens.code = 0,
  cens.model = ~1,
  weights = NULL,
  offset = NULL,
  Gc = NULL,
  wcomp = NULL,
```

```
  ...
)
```

Arguments

formula	formula with 'Event' outcome
data	data frame
cause	of interest
death.code	codes for death (terminating event)
cens.code	code of censoring (1 default)
cens.model	for stratified Cox model without covariates
weights	weights for score equations
offset	offsets for model
Gc	censoring weights for time argument, default is to calculate these with a Kaplan-Meier estimator, should then give G_c(T_i-)
wcomp	weights for composite outcome, so when cause=c(1,3), we might have wcomp=c(1,2).
...	Additional arguments to lower level funtions

Details

For Cox type model :

$$E(dN_1(t)|X) = \mu_0(t)dtexp(X^T\beta)$$

by solving Cox-type IPCW weighted score equations

$$\int (Z - E(t))w(t)dN_1(t)$$

where

$$w(t) = G(t)(I(T_i \wedge t < C_i)/G_c(T_i \wedge t))$$

and

$$E(t) = S_1(t)/S_0(t)$$

and

$$S_j(t) = \sum X_i^j w_i(t) \exp(X_i^T\beta)$$

.

The iid decomposition of the beta's are on the form

$$\int (Z - E)w(t)dM_1 + \int q(s)/p(s)dM_c$$

and returned as iid.

Events, deaths and censorings are specified via stop start structure and the Event call, that via a status vector and cause (code), censoring-codes (cens.code) and death-codes (death.code) indentifies these. See example and vignette.

Author(s)

Thomas Scheike

Examples

```
## data with no ties
data(base1cumhaz)
data(base4cumhaz)
data(drcumhaz)
Lam1 <- base1cumhaz;  Lam2 <- base4cumhaz;  LamD <- drcumhaz
## simulates recurrent events of types 1 and 2 and with terminal event D and censoring
rr <- simRecurrentII(100,Lam1,cumhaz2=Lam2,death.cumhaz=LamD,cens=3/5000)
rr <- count.history(rr)
rr$cens <- 0
nid <- max(rr$id)
rr$revnr <- revcumsumstrata(rep(1,nrow(rr)),rr$id-1,nid)
rr$x <- rnorm(nid)[rr$id]
rr$statusG <- rr$status
rr <- dtransform(rr,statusG=3,death==1)
dtable(rr,~statusG+status+death)
dcut(rr) <- gx~x

ll <- recreg(Event(start,stop,statusG)~x+cluster(id),data=rr,cause=1,death.code=3)
summary(ll)

## censoring stratified after quartiles of x
lls <- recreg(Event(start, stop, statusG)~x+cluster(id),data=rr,cause=1,
              death.code=3,cens.model=~strata(gx))
summary(lls)
```

`recurrentMarginal` *Fast recurrent marginal mean when death is possible*

Description

Fast Marginal means of recurrent events. Using the Lin and Ghosh (2000) standard errors. Fitting two models for death and recurent events these are combined to prducte the estimator

$$\int_0^t S(u|x=0)dR(u|x=0)$$

the mean number of recurrent events, here

$$S(u|x=0)$$

is the probability of survival for the baseline group, and

$$dR(u|x=0)$$

is the hazard rate of an event among survivors for the baseline. Here

$$S(u|x = 0)$$

is estimated by

$$exp(-\Lambda_d(u|x = 0)$$

with

$$\Lambda_d(u|x = 0)$$

being the cumulative baseline for death.

Usage

```
recurrentMarginal(recurrent, death, fixbeta = NULL, km = TRUE, ...)
```

Arguments

recurrent	phreg object with recurrent events
death	phreg object with deaths
fixbeta	to force the estimation of standard errors to think of regression coefficients as known/fixed
km	if true then uses Kaplan-Meier for death, otherwise exp(- Nelson-Aalen)
...	Additional arguments to lower level funtions

Details

Assumes no ties in the sense that jump times needs to be unique, this is particularly so for the stratified version.

Author(s)

Thomas Scheike

References

Cook, R. J. and Lawless, J. F. (1997) Marginal analysis of recurrent events and a terminating event. Statist. Med., 16, 911–924. Ghosh and Lin (2002) Nonparametric Analysis of Recurrent events and death, Biometrics, 554–562.

Examples

```
data(base1cumhaz)
data(base4cumhaz)
data(drcumhaz)
dr <- drcumhaz
base1 <- base1cumhaz
base4 <- base4cumhaz
rr <- simRecurrent(1000,base1,death.cumhaz=dr)
rr$x <- rnorm(nrow(rr))
```

```
rr$strata <- floor((rr$id-0.01)/500)

##  to fit non-parametric models with just a baseline
xr <- phreg(Surv(entry,time,status)~cluster(id),data=rr)
dr <- phreg(Surv(entry,time,death)~cluster(id),data=rr)
par(mfrow=c(1,3))
bplot(dr,se=TRUE)
title(main="death")
bplot(xr,se=TRUE)
### robust standard errors
rxr <-   robust.phreg(xr,fixbeta=1)
bplot(rxr,se=TRUE,robust=TRUE,add=TRUE,col=4)

## marginal mean of expected number of recurrent events
out <- recurrentMarginal(xr,dr)
bplot(out,se=TRUE,ylab="marginal mean",col=2)

#########################################################################
###   with strata     ###################################################
#########################################################################
xr <- phreg(Surv(entry,time,status)~strata(strata)+cluster(id),data=rr)
dr <- phreg(Surv(entry,time,death)~strata(strata)+cluster(id),data=rr)
par(mfrow=c(1,3))
bplot(dr,se=TRUE)
title(main="death")
bplot(xr,se=TRUE)
rxr <-   robust.phreg(xr,fixbeta=1)
bplot(rxr,se=TRUE,robust=TRUE,add=TRUE,col=1:2)

out <- recurrentMarginal(xr,dr)
bplot(out,se=TRUE,ylab="marginal mean",col=1:2)

#########################################################################
###   cox case        ###################################################
#########################################################################
xr <- phreg(Surv(entry,time,status)~x+cluster(id),data=rr)
dr <- phreg(Surv(entry,time,death)~x+cluster(id),data=rr)
par(mfrow=c(1,3))
bplot(dr,se=TRUE)
title(main="death")
bplot(xr,se=TRUE)
rxr <-   robust.phreg(xr)
bplot(rxr,se=TRUE,robust=TRUE,add=TRUE,col=1:2)

out <- recurrentMarginal(xr,dr)
bplot(out,se=TRUE,ylab="marginal mean",col=1:2)

#########################################################################
###   CIF  ##############################################################
#########################################################################
### use of function to compute cumulative incidence (cif) with robust standard errors
 data(bmt)
 bmt$id <- 1:nrow(bmt)
```

```
xr  <- phreg(Surv(time,cause==1)~cluster(id),data=bmt)
dr  <- phreg(Surv(time,cause!=0)~cluster(id),data=bmt)

out <- recurrentMarginal(xr,dr,km=TRUE)
bplot(out,se=TRUE,ylab="cumulative incidence")
```

`resmean.phreg` *Restricted mean for stratified Kaplan-Meier or Cox model with martingale standard errors*

Description

Restricted mean for stratified Kaplan-Meier or stratified Cox with martingale standard error. Standard error is computed using linear interpolation between standard errors at jump-times. Plots gives restricted mean at all times. Years lost can be computed based on this and decomposed into years lost for different causes using the cif.yearslost function that is based on integrating the cumulative incidence functions. One particular feature of these functions are that the restricted mean and years-lost are computed for all event times as functions and can be plotted/viewed. When times are given and beyond the last event time withn a strata the curves are extrapolated using the estimates of cumulative incidence.

Usage

```
resmean.phreg(x, times = NULL, covs = NULL, ...)
```

Arguments

`x`	phreg object
`times`	possible times for which to report restricted mean
`covs`	possible covariate for Cox model
`...`	Additional arguments to lower level funtions

Author(s)

Thomas Scheike

Examples

```
data(bmt); bmt$time <- bmt$time+runif(408)*0.001
out1 <- phreg(Surv(time,cause!=0)~strata(tcell,platelet),data=bmt)

rm1 <- resmean.phreg(out1,times=10*(1:6))
summary(rm1)
par(mfrow=c(1,2))
plot(rm1,se=1)
plot(rm1,years.lost=TRUE,se=1)
```

```
## years.lost decomposed into causes
drm1 <- cif.yearslost(Event(time,cause)~strata(tcell,platelet),data=bmt,times=10*(1:6))
summary(drm1)
```

`resmeanATE` *Average Treatment effect for Restricted Mean for censored competing risks data using IPCW*

Description

Under the standard causal assumptions we can estimate the average treatment effect E(Y(1) - Y(0)). We need Consistency, ignorability (Y(1), Y(0) indep A given X), and positivity.

Usage

```
resmeanATE(
  formula,
  data,
  outcome = c("rmst", "rmst-cause"),
  model = "exp",
  ...
)
```

Arguments

`formula`	formula with 'Event' outcome
`data`	data-frame
`outcome`	"rmst"=E(min(T, t) | X) , or "rmst-cause"=E(I(epsilon==cause) (t - mint(T,t))) | X)
`model`	possible exp model for relevant mean model that is exp(X^t beta)
`...`	Additional arguments to pass to binregATE

Details

The first covariate in the specification of the competing risks regression model must be the treatment effect that is a factor. If the factor has more than two levels then it uses the mlogit for propensity score modelling. We consider the outcome mint(T;tau) or I(epsion==cause1)(t- min(T;t)) that gives years lost due to cause "cause".

Estimates the ATE using the the standard binary double robust estimating equations that are IPCW censoring adjusted.

Author(s)

Thomas Scheike

Examples

```
library(mets); data(bmt); bmt$event <- bmt$cause!=0; dfactor(bmt) <- tcell~tcell
out <- resmeanATE(Event(time,event)~tcell+platelet,data=bmt,time=40,treat.model=tcell~platelet)
summary(out)

out1 <- resmeanATE(Event(time,cause)~tcell+platelet,data=bmt,cause=1,outcome="rmst-cause",
                   time=40,treat.model=tcell~platelet)
summary(out1)
```

`resmeanIPCW` *Restricted IPCW mean for censored survival data*

Description

Simple and fast version for IPCW regression for just one time-point thus fitting the model

$$E(min(T,t)|X) = exp(X^T beta)$$

or in the case of competing risks data

$$E(I(epsilon = 1)(t - min(T,t))|X) = exp(X^T beta)$$

thus given years lost to cause.

Usage

```
resmeanIPCW(
  formula,
  data,
  cause = 1,
  time = NULL,
  type = c("II", "I"),
  beta = NULL,
  offset = NULL,
  weights = NULL,
  cens.weights = NULL,
  cens.model = ~+1,
  se = TRUE,
  kaplan.meier = TRUE,
  cens.code = 0,
  no.opt = FALSE,
  method = "nr",
  model = "exp",
  augmentation = NULL,
  h = NULL,
  MCaugment = NULL,
  Ydirect = NULL,
  ...
)
```

Arguments

formula	formula with outcome (see coxph)
data	data frame
cause	cause of interest
time	time of interest
type	of estimator
beta	starting values
offset	offsets for partial likelihood
weights	for score equations
cens.weights	censoring weights
cens.model	only stratified cox model without covariates
se	to compute se's based on IPCW
kaplan.meier	uses Kaplan-Meier for IPCW in contrast to exp(-Baseline)
cens.code	gives censoring code
no.opt	to not optimize
method	for optimization
model	exp or linear
augmentation	to augment binomial regression
h	h for estimating equation
MCaugment	iid of h and censoring model
Ydirect	to bypass the construction of the response Y=min(T,tau) and use this instead
...	Additional arguments to lower level funtions

Details

When the status is binary assumes it is a survival setting and default is to consider outcome Y=min(T,t), if status has more than two levels, then computes years lost due to the specified cause, thus

Based on binomial regresion IPCW response estimating equation:

$$X(\Delta(min(T,t))/G_c(min(T_i,t)) - exp(X^T beta)) = 0$$

for IPCW adjusted responses. Here

$$\Delta(min(T,t))I(min(T,t) \leq C)$$

is indicator of being uncensored.

Can also solve the binomial regresion IPCW response estimating equation:

$$h(X)X(\Delta(min(T,t))/G_c(min(T_i,t)) - exp(X^T beta)) = 0$$

for IPCW adjusted responses where h is given as an argument together with iid of censoring with h.

By using appropriately the h argument we can also do the efficient IPCW estimator estimator.

Variance is based on

$$\sum w_i^2$$

also with IPCW adjustment, and naive.var is variance under known censoring model.

When Ydirect is given it solves :

$$X(\Delta(min(T,t))Ydirect/G_c(min(T_i,t)) - exp(X^T beta)) = 0$$

for IPCW adjusted responses.

The actual influence (type="II") function is based on augmenting with

$$X \int_0^t E(Y|T > s)/G_c(s) dM_c(s)$$

and alternatively just solved directly (type="I") without any additional terms.

Censoring model may depend on strata.

Author(s)

Thomas Scheike

Examples

```
data(bmt); bmt$time <- bmt$time+runif(nrow(bmt))*0.001
# E( min(T;t) | X ) = exp( a+b X) with IPCW estimation
out <- resmeanIPCW(Event(time,cause!=0)~tcell+platelet+age,bmt,
                time=50,cens.model=~strata(platelet),model="exp")
summary(out)

 ### same as Kaplan-Meier for full censoring model
bmt$int <- with(bmt,strata(tcell,platelet))
out <- resmeanIPCW(Event(time,cause!=0)~-1+int,bmt,time=30,
                             cens.model=~strata(platelet,tcell),model="lin")
estimate(out)
out1 <- phreg(Surv(time,cause!=0)~strata(tcell,platelet),data=bmt)
rm1 <- resmean.phreg(out1,times=30)
summary(rm1)

## competing risks years-lost for cause 1
out <- resmeanIPCW(Event(time,cause)~-1+int,bmt,time=30,cause=1,
                            cens.model=~strata(platelet,tcell),model="lin")
estimate(out)
## same as integrated cumulative incidence
rmc1 <- cif.yearslost(Event(time,cause)~strata(tcell,platelet),data=bmt,times=30)
summary(rmc1)
```

rpch *Piecewise constant hazard distribution*

Description

Piecewise constant hazard distribution

Usage

```
rpch(n, lambda = 1, breaks = c(0, Inf))
```

Arguments

n	sample size
lambda	rate parameters
breaks	time cut-points

sim.cause.cox *Simulation of cause specific from Cox models.*

Description

Simulates data that looks like fit from cause specific Cox models. Censor data automatically. When censoring is given in the list of causes this will give censoring that looks like the data. Covariates are drawn from data-set with replacement. This gives covariates like the data.

Usage

```
sim.cause.cox(coxs,n,data=NULL,cens=NULL,rrc=NULL,...)
```

Arguments

coxs	list of cox models.
n	number of simulations.
data	to extract covariates for simulations (draws from observed covariates).
cens	specifies censoring model, if NULL then only censoring for each cause at end of last event of this type. if "is.matrix" then uses cumulative. hazard given, if "is.scalar" then uses rate for exponential, and if not given then takes average rate of in simulated data from cox model. But censoring can also be given as a cause.
rrc	possible vector of relative risk for cox-type censoring.
...	arguments for rchaz, for example entry-time

Author(s)

Thomas Scheike

Examples

```
nsim <- 100

data(bmt)
# coxph
cox1 <- coxph(Surv(time,cause==1)~tcell+platelet,data=bmt)
cox2 <- coxph(Surv(time,cause==2)~tcell+platelet,data=bmt)
coxs <- list(cox1,cox2)
dd <- sim.cause.cox(coxs,nsim,data=bmt)
scox1 <- coxph(Surv(time,status==1)~tcell+platelet,data=dd)
scox2 <- coxph(Surv(time,status==2)~tcell+platelet,data=dd)
cbind(cox1$coef,scox1$coef)
cbind(cox2$coef,scox2$coef)

data(bmt)
cox1 <- phreg(Surv(time,cause==1)~tcell+platelet,data=bmt)
cox2 <- phreg(Surv(time,cause==2)~tcell+platelet,data=bmt)
coxs <- list(cox1,cox2)
dd <- sim.cause.cox(coxs,nsim,data=bmt)
scox1 <- phreg(Surv(time,status==1)~tcell+platelet,data=dd)
scox2 <- phreg(Surv(time,status==2)~tcell+platelet,data=dd)
cbind(cox1$coef,scox1$coef)
cbind(cox2$coef,scox2$coef)
par(mfrow=c(1,2))
plot(cox1); plot(scox1,add=TRUE);
plot(cox2); plot(scox2,add=TRUE);

cox1 <- phreg(Surv(time,cause==1)~strata(tcell)+platelet,data=bmt)
cox2 <- phreg(Surv(time,cause==2)~strata(tcell)+platelet,data=bmt)
coxs <- list(cox1,cox2)
dd <- sim.cause.cox(coxs,nsim,data=bmt)
scox1 <- phreg(Surv(time,status==1)~strata(tcell)+platelet,data=dd)
scox2 <- phreg(Surv(time,status==2)~strata(tcell)+platelet,data=dd)
cbind(cox1$coef,scox1$coef)
cbind(cox2$coef,scox2$coef)
par(mfrow=c(1,2))
plot(cox1); plot(scox1,add=TRUE);
plot(cox2); plot(scox2,add=TRUE);
```

---

sim.cif *Simulation of output from Cumulative incidence regression model*

Description

Simulates data that looks like fit from fitted cumulative incidence model

Usage

```
sim.cif(cif,n,data=NULL,Z=NULL,drawZ=TRUE,cens=NULL,rrc=NULL,cumstart=c(0,0),...)
```

Arguments

cif	output form prop.odds.subdist or ccr (cmprsk), can also call invsubdist with with cumulative and linear predictor
n	number of simulations.
data	to extract covariates for simulations (draws from observed covariates).
Z	to use these covariates for simulation rather than drawing new ones.
drawZ	to random sample from Z or not
cens	specifies censoring model, if "is.matrix" then uses cumulative hazard given, if "is.scalar" then uses rate for exponential, and if not given then takes average rate of in simulated data from cox model.
rrc	possible vector of relative risk for cox-type censoring.
cumstart	to start cumulatives at time 0 in 0.
...	arguments for invsubdist

Author(s)

Thomas Scheike

Examples

```
data(bmt)

scif <-  cifreg(Event(time,cause)~tcell+platelet+age,data=bmt,cause=1,prop=NULL)
summary(scif)
plot(scif)
#################################################################
#  simulating several causes with specific cumulatives
#################################################################

cif1 <-  cifreg(Event(time,cause)~tcell+age,data=bmt,cause=1,prop=NULL)
cif2 <-  cifreg(Event(time,cause)~tcell+age,data=bmt,cause=2,prop=NULL)
# dd <- sim.cifsRestrict(list(cif1,cif2),200,data=bmt)
dd <- sim.cifs(list(cif1,cif2),200,data=bmt)
scif1 <-  cifreg(Event(time,cause)~tcell+age,data=dd,cause=1)
scif2 <-  cifreg(Event(time,cause)~tcell+age,data=dd,cause=2)

par(mfrow=c(1,2))
plot(cif1); plot(scif1,add=TRUE,col=2)
plot(cif2); plot(scif2,add=TRUE,col=2)
```

sim.cox *Simulation of output from Cox model.*

Description

Simulates data that looks like fit from Cox model. Censor data automatically for highest value of the event times by using cumulative hazard.

Usage

```
sim.cox(cox,n,data=NULL,cens=NULL,rrc=NULL,entry=NULL,...)
```

Arguments

cox	output form coxph or cox.aalen model fitting cox model.
n	number of simulations.
data	to extract covariates for simulations (draws from observed covariates).
cens	specifies censoring model, if "is.matrix" then uses cumulative hazard given, if "is.scalar" then uses rate for exponential, and if not given then takes average rate of in simulated data from cox model.
rrc	possible vector of relative risk for cox-type censoring.
entry	delayed entry variable for simulation.
...	arguments for rchaz, for example entry-time

Author(s)

Thomas Scheike

Examples

```
data(sTRACE)
cox <-  coxph(Surv(time,status==9)~vf+chf+wmi,data=sTRACE)
sim1 <- sim.cox(cox,1000,data=sTRACE)
cc <- coxph(Surv(time,status)~vf+chf+wmi,data=sim1)
cbind(cox$coef,cc$coef)

cor(sim1[,c("vf","chf","wmi")])
cor(sTRACE[,c("vf","chf","wmi")])

cox <-  phreg(Surv(time, status==9)~vf+chf+wmi,data=sTRACE)
sim3 <- sim.cox(cox,1000,data=sTRACE)
cc <-  phreg(Surv(time, status)~vf+chf+wmi,data=sim3)
cbind(cox$coef,cc$coef)
plot(cox,se=TRUE)
plot(cc,add=TRUE,col=2)
```

```
cox <-  phreg(Surv(time,status==9)~strata(chf)+vf+wmi,data=sTRACE)
sim3 <- sim.cox(cox,100,data=sTRACE)
cc <-   phreg(Surv(time, status)~strata(chf)+vf+wmi,data=sim3)
cbind(cox$coef,cc$coef)
plot(cox)
plot(cc,add=TRUE,col=2)
```

`simAalenFrailty` *Simulate from the Aalen Frailty model*

Description

Simulate observations from Aalen Frailty model with Gamma distributed frailty and constant intensity.

Usage

```
simAalenFrailty(
  n = 5000,
  theta = 0.3,
  K = 2,
  beta0 = 1.5,
  beta = 1,
  cens = 1.5,
  cuts = 0,
  ...
)
```

Arguments

`n`	Number of observations in each cluster
`theta`	Dependence paramter (variance of frailty)
`K`	Number of clusters
`beta0`	Baseline (intercept)
`beta`	Effect (log hazard ratio) of covariate
`cens`	Censoring rate
`cuts`	time cuts
`...`	Additional arguments

Author(s)

Klaus K. Holst

`simClaytonOakes` *Simulate from the Clayton-Oakes frailty model*

Description

Simulate observations from the Clayton-Oakes copula model with piecewise constant marginals.

Usage

```
simClaytonOakes(
  K,
  n,
  eta,
  beta,
  stoptime,
  lam = 1,
  left = 0,
  pairleft = 0,
  trunc.prob = 0.5,
  same = 0
)
```

Arguments

`K`	Number of clusters
`n`	Number of observations in each cluster
`eta`	variance
`beta`	Effect (log hazard ratio) of covariate
`stoptime`	Stopping time
`lam`	constant hazard
`left`	Left truncation
`pairleft`	pairwise (1) left truncation or individual (0)
`trunc.prob`	Truncation probability
`same`	if 1 then left-truncation is same also for univariate truncation

Author(s)

Thomas Scheike and Klaus K. Holst

`simClaytonOakesWei` *Simulate from the Clayton-Oakes frailty model*

Description

Simulate observations from the Clayton-Oakes copula model with Weibull type baseline and Cox marginals.

Usage

```
simClaytonOakesWei(
  K,
  n,
  eta,
  beta,
  stoptime,
  weiscale = 1,
  weishape = 2,
  left = 0,
  pairleft = 0
)
```

Arguments

`K`	Number of clusters
`n`	Number of observations in each cluster
`eta`	1/variance
`beta`	Effect (log hazard ratio) of covariate
`stoptime`	Stopping time
`weiscale`	weibull scale parameter
`weishape`	weibull shape parameter
`left`	Left truncation
`pairleft`	pairwise (1) left truncation or individual (0)

Author(s)

Klaus K. Holst

`simMultistate` *Simulation of illness-death model*

Description

Simulation of illness-death model

Usage

```
simMultistate(
  n,
  cumhaz,
  cumhaz2,
  death.cumhaz,
  death.cumhaz2,
  rr = NULL,
  rr2 = NULL,
  rd = NULL,
  rd2 = NULL,
  gap.time = FALSE,
  max.recurrent = 100,
  dependence = 0,
  var.z = 0.22,
  cor.mat = NULL,
  cens = NULL,
  ...
)
```

Arguments

`n`	number of id's
`cumhaz`	cumulative hazard of going from state 1 to 2.
`cumhaz2`	cumulative hazard of going from state 2 to 1.
`death.cumhaz`	cumulative hazard of death from state 1.
`death.cumhaz2`	cumulative hazard of death from state 2.
`rr`	relative risk adjustment for cumhaz
`rr2`	relative risk adjustment for cumhaz2
`rd`	relative risk adjustment for death.cumhaz
`rd2`	relative risk adjustment for death.cumhaz2
`gap.time`	if true simulates gap-times with specified cumulative hazard
`max.recurrent`	limits number recurrent events to 100

dependence	0:independence; 1:all share same random effect with variance var.z; 2:random effect exp(normal) with correlation structure from cor.mat; 3:additive gamma distributed random effects, z1= (z11+ z12)/2 such that mean is 1 , z2= (z11^cor.mat(1,2)+ z13)/2, z3= (z12^(cor.mat(2,3)+z13^cor.mat(1,3))/2, with z11 z12 z13 are gamma with mean and variance 1 , first random effect is z1 and for N1 second random effect is z2 and for N2 third random effect is for death
var.z	variance of random effects
cor.mat	correlation matrix for var.z variance of random effects
cens	rate of censoring exponential distribution
...	Additional arguments to lower level funtions

Details

simMultistate with different death intensities from states 1 and 2

Must give cumulative hazards on some time-range

Author(s)

Thomas Scheike

Examples

```
########################################
## getting some rates to mimick
########################################
data(base1cumhaz)
data(base4cumhaz)
data(drcumhaz)
dr <- drcumhaz
dr2 <- drcumhaz
dr2[,2] <- 1.5*drcumhaz[,2]
base1 <- base1cumhaz
base4 <- base4cumhaz
cens <- rbind(c(0,0),c(2000,0.5),c(5110,3))

iddata <- simMultistate(10000,base1,base1,dr,dr2,cens=cens)
dlist(iddata,.~id|id<3,n=0)

### estimating rates from simulated data
c0 <- phreg(Surv(start,stop,status==0)~+1,iddata)
c3 <- phreg(Surv(start,stop,status==3)~+strata(from),iddata)
c1 <- phreg(Surv(start,stop,status==1)~+1,subset(iddata,from==2))
c2 <- phreg(Surv(start,stop,status==2)~+1,subset(iddata,from==1))
###
par(mfrow=c(2,3))
bplot(c0)
lines(cens,col=2)
bplot(c3,main="rates 1-> 3 , 2->3")
lines(dr,col=1,lwd=2)
lines(dr2,col=2,lwd=2)
```

```
###
bplot(c1,main="rate 1->2")
lines(base1,lwd=2)
###
bplot(c2,main="rate 2->1")
lines(base1,lwd=2)
```

`simRecurrentII` *Simulation of recurrent events data based on cumulative hazards II*

Description

Simulation of recurrent events data based on cumulative hazards

Usage

```
simRecurrentII(
  n,
  cumhaz,
  cumhaz2,
  death.cumhaz = NULL,
  r1 = NULL,
  r2 = NULL,
  rd = NULL,
  rc = NULL,
  gap.time = FALSE,
  max.recurrent = 100,
  dhaz = NULL,
  haz2 = NULL,
  dependence = 0,
  var.z = 0.22,
  cor.mat = NULL,
  cens = NULL,
  ...
)
```

Arguments

`n`	number of id's
`cumhaz`	cumulative hazard of recurrent events
`cumhaz2`	cumulative hazard of recurrent events of type 2
`death.cumhaz`	cumulative hazard of death
`r1`	potential relative risk adjustment of rate
`r2`	potential relative risk adjustment of rate
`rd`	potential relative risk adjustment of rate

rc	potential relative risk adjustment of rate
gap.time	if true simulates gap-times with specified cumulative hazard
max.recurrent	limits number recurrent events to 100
dhaz	rate for death hazard if it is extended to time-range of first event
haz2	rate of second cause if it is extended to time-range of first event
dependence	0:independence; 1:all share same random effect with variance var.z; 2:random effect exp(normal) with correlation structure from cor.mat; 3:additive gamma distributed random effects, z1= (z11+ z12)/2 such that mean is 1 , z2= (z11^cor.mat(1,2)+ z13)/2, z3= (z12^(cor.mat(2,3)+z13^cor.mat(1,3))/2, with z11 z12 z13 are gamma with mean and variance 1 , first random effect is z1 and for N1 second random effect is z2 and for N2 third random effect is for death
var.z	variance of random effects
cor.mat	correlation matrix for var.z variance of random effects
cens	rate of censoring exponential distribution
...	Additional arguments to lower level funtions

Details

Must give hazard of death and two recurrent events. Possible with two event types and their dependence can be specified but the two recurrent events need to share random effect. Based on drawing the from cumhaz and cumhaz2 and taking the first event rather the cumulative and then distributing it out. Key advantage of this is that there is more flexibility wrt random effects

Author(s)

Thomas Scheike

Examples

```
######################################
## getting some rates to mimick
######################################

data(base1cumhaz)
data(base4cumhaz)
data(drcumhaz)
dr <- drcumhaz
base1 <- base1cumhaz
base4 <- base4cumhaz

cor.mat <- corM <- rbind(c(1.0, 0.6, 0.9), c(0.6, 1.0, 0.5), c(0.9, 0.5, 1.0))

######################################################################
### simulating simple model that mimicks data
######################################################################
rr <- simRecurrent(5,base1,death.cumhaz=dr)
dlist(rr,.~id,n=0)
```

```
rr <- simRecurrent(100,base1,death.cumhaz=dr)
par(mfrow=c(1,3))
showfitsim(causes=1,rr,dr,base1,base1)
#########################################################################
### simulating simple model
### random effect for all causes (Z shared for death and recurrent)
#########################################################################
rr <- simRecurrent(100,base1,death.cumhaz=dr,dependence=1,var.gamma=0.4)

#########################################################################
### simulating simple model that mimicks data
### now with two event types and second type has same rate as death rate
#########################################################################
set.seed(100)
rr <- simRecurrentII(100,base1,base4,death.cumhaz=dr)
dtable(rr,~death+status)
par(mfrow=c(2,2))
showfitsim(causes=2,rr,dr,base1,base4)
```

`simRecurrentTS` *Simulation of recurrent events data based on cumulative hazards: Two-stage model*

Description

Simulation of recurrent events data based on cumulative hazards

Usage

```
simRecurrentTS(
  n,
  cumhaz,
  cumhaz2,
  death.cumhaz = NULL,
  nu = rep(1, 3),
  share1 = 0.3,
  vargamD = 2,
  vargam12 = 0.5,
  gap.time = FALSE,
  max.recurrent = 100,
  cens = NULL,
  ...
)
```

Arguments

n	number of id's

cumhaz	cumulative hazard of recurrent events
cumhaz2	cumulative hazard of recurrent events of type 2
death.cumhaz	cumulative hazard of death
nu	powers of random effects where nu > -1/shape
share1	how random effect for death splits into two parts
vargamD	variance of random effect for death
vargam12	shared random effect for N1 and N2
gap.time	if true simulates gap-times with specified cumulative hazard
max.recurrent	limits number recurrent events to 100
cens	rate of censoring exponential distribution
...	Additional arguments to lower level funtions

Details

Model is constructed such that marginals are on specified form by linear approximations of cumulative hazards that are on a specific form to make them equivalent to marginals after integrating out over survivors. Therefore E(dN_1 | D>t) = cumhaz, E(dN_2 | D>t) = cumhaz2, and hazard of death is death.cumhazard

Must give hazard of death and two recurrent events. Hazard of death is death.cumhazard two event types and their dependence can be specified but the two recurrent events need to share random effect.

Random effect for death Z.death=(Zd1+Zd2), Z1=(Zd1^nu1) Z12, Z2=(Zd2^nu2) Z12^nu3

$$Z.death = Zd1 + Zd2$$

gamma distributions

$$Zdj$$

gamma distribution with mean parameters (sharej), vargamD, share2=1-share1

$$Z12$$

gamma distribution with mean 1 and variance vargam12

Author(s)

Thomas Scheike

Examples

```
########################################
## getting some rates to mimick
########################################

data(base1cumhaz)
data(base4cumhaz)
data(drcumhaz)
dr <- drcumhaz
```

```
base1 <- base1cumhaz
base4 <- base4cumhaz

rr <- simRecurrentTS(1000,base1,base4,death.cumhaz=dr)
dtable(rr,~death+status)
showfitsim(causes=2,rr,dr,base1,base4)
```

---

summary.cor *Summary for dependence models for competing risks*

Description

Computes concordance and casewise concordance for dependence models for competing risks models of the type cor.cif, rr.cif or or.cif for the given cumulative incidences and the different dependence measures in the object.

Usage

```
## S3 method for class 'cor'
summary(object, marg.cif = NULL, marg.cif2 = NULL, digits = 3, ...)
```

Arguments

object	object from cor.cif rr.cif or or.cif for dependence between competing risks data for two causes.
marg.cif	a number that gives the cumulative incidence in one time point for which concordance and casewise concordance are computed.
marg.cif2	the cumulative incidence for cause 2 for concordance and casewise concordance are computed. Default is that it is the same as marg.cif.
digits	digits in output.
...	Additional arguments.

Value

prints summary for dependence model.

casewise	gives casewise concordance that is, probability of cause 2 (related to cif2) given that cause 1 (related to cif1) has occured.
concordance	gives concordance that is, probability of cause 2 (related to cif2) and cause 1 (related to cif1).
cif1	cumulative incidence for cause1.
cif2	cumulative incidence for cause1.

Author(s)

Thomas Scheike

References

Cross odds ratio Modelling of dependence for Multivariate Competing Risks Data, Scheike and Sun (2012), Biostatistics.

A Semiparametric Random Effects Model for Multivariate Competing Risks Data, Scheike, Zhang, Sun, Jensen (2010), Biometrika.

Examples

```
## library("timereg")
## data("multcif",package="mets") # simulated data
## multcif$cause[multcif$cause==0] <- 2
##
## times=seq(0.1,3,by=0.1) # to speed up computations use only these time-points
## add <- timereg::comp.risk(Event(time,cause)~+1+cluster(id),
##                           data=multcif,n.sim=0,times=times,cause=1)
###
## out1<-cor.cif(add,data=multcif,cause1=1,cause2=1,theta=log(2+1))
## summary(out1)
##
## pad <- predict(add,X=1,se=0,uniform=0)
## summary(out1,marg.cif=pad)
```

---

summaryGLM *Reporting OR (exp(coef)) from glm with binomial link and glm predictions*

Description

Reporting OR from glm with binomial link and glm predictions

Usage

```
summaryGLM(object, id = NULL, fun = NULL, ...)
```

Arguments

object	glm output
id	possible id for cluster corrected standard errors
fun	possible function for non-standard predictions based on object
...	arguments of estimate of lava for example level=0.95

Author(s)

Thomas Scheike

Examples

```
data(sTRACE)
sTRACE$id <- sample(1:100,nrow(sTRACE),replace=TRUE)

model <- glm(I(status==9)~sex+factor(diabetes)+age,data=sTRACE,family=binomial)
summaryGLM(model)
summaryGLM(model,id=sTRACE$id)

nd <- data.frame(sex=c(0,1),age=67,diabetes=1)
predictGLM(model,nd)
```

`survival.twostage` *Twostage survival model for multivariate survival data*

Description

Fits Clayton-Oakes or bivariate Plackett models for bivariate survival data using marginals that are on Cox form. The dependence can be modelled via

1. Regression design on dependence parameter.
2. Random effects, additive gamma model.

If clusters contain more than two subjects, we use a composite likelihood based on the pairwise bivariate models, for full MLE see twostageMLE.

The two-stage model is constructed such that given the gamma distributed random effects it is assumed that the survival functions are indpendent, and that the marginal survival functions are on Cox form (or additive form)

$$P(T > t|x) = S(t|x) = exp(-exp(x^T\beta)A_0(t))$$

One possibility is to model the variance within clusters via a regression design, and then one can specify a regression structure for the independent gamma distributed random effect for each cluster, such that the variance is given by

$$\theta = h(z_j^T\alpha)$$

where z is specified by theta.des, and a possible link function var.link=1 will will use the exponential link $h(x) = exp(x)$, and var.link=0 the identity link $h(x) = x$. The reported standard errors are based on the estimated information from the likelihood assuming that the marginals are known (unlike the twostageMLE and for the additive gamma model below).

Can also fit a structured additive gamma random effects model, such as the ACE, ADE model for survival data. In this case the random.design specificies the random effects for each subject within a cluster. This is a matrix of 1's and 0's with dimension n x d. With d random effects. For a cluster with two subjects, we let the random.design rows be v_1 and v_2. Such that the random effects for subject 1 is

$$v_1^T(Z_1, ..., Z_d)$$

, for d random effects. Each random effect has an associated parameter $(\lambda_1, ..., \lambda_d)$. By construction subjects 1's random effect are Gamma distributed with mean $\lambda_j/v_1^T\lambda$ and variance $\lambda_j/(v_1^T\lambda)^2$.

Note that the random effect $v_1^T(Z_1, ..., Z_d)$ has mean 1 and variance $1/(v_1^T\lambda)$. It is here asssumed that $lamtot = v_1^T\lambda$ is fixed within clusters as it would be for the ACE model below.

Based on these parameters the relative contribution (the heritability, h) is equivalent to the expected values of the random effects: $\lambda_j/v_1^T\lambda$

The DEFAULT parametrization (var.par=1) uses the variances of the random effecs

$$\theta_j = \lambda_j/(v_1^T\lambda)^2$$

For alternative parametrizations one can specify how the parameters relate to λ_j with the argument var.par=0.

For both types of models the basic model assumptions are that given the random effects of the clusters the survival distributions within a cluster are independent and ' on the form

$$P(T > t|x, z) = exp(-Z \cdot Laplace^{-1}(lamtot, lamtot, S(t|x)))$$

with the inverse laplace of the gamma distribution with mean 1 and variance 1/lamtot.

The parameters $(\lambda_1, ..., \lambda_d)$ are related to the parameters of the model by a regression construction $pard$ (d x k), that links the d λ parameters with the (k) underlying θ parameters

$$\lambda = theta.des\theta$$

here using theta.des to specify these low-dimension association. Default is a diagonal matrix. This can be used to make structural assumptions about the variances of the random-effects as is needed for the ACE model for example.

The case.control option that can be used with the pair specification of the pairwise parts of the estimating equations. Here it is assumed that the second subject of each pair is the proband.

Usage

```
survival.twostage(
  margsurv,
  data = parent.frame(),
  method = "nr",
  detail = 0,
  clusters = NULL,
  silent = 1,
  weights = NULL,
  theta = NULL,
  theta.des = NULL,
  var.link = 1,
  baseline.iid = 1,
  model = "clayton.oakes",
  marginal.trunc = NULL,
  marginal.survival = NULL,
  strata = NULL,
  se.clusters = NULL,
  numDeriv = 1,
  random.design = NULL,
```

```
  pairs = NULL,
  dim.theta = NULL,
  numDeriv.method = "simple",
  additive.gamma.sum = NULL,
  var.par = 1,
  no.opt = FALSE,
  ...
)
```

Arguments

margsurv	Marginal model
data	data frame
method	Scoring method "nr", for lava NR optimizer
detail	Detail
clusters	Cluster variable
silent	Debug information
weights	Weights
theta	Starting values for variance components
theta.des	design for dependence parameters, when pairs are given the indeces of the theta-design for this pair, is given in pairs as column 5
var.link	Link function for variance: exp-link.
baseline.iid	to adjust for baseline estimation, using phreg function on same data.
model	model
marginal.trunc	marginal left truncation probabilities
marginal.survival	optional vector of marginal survival probabilities
strata	strata for fitting, see example
se.clusters	for clusters for se calculation with iid
numDeriv	to get numDeriv version of second derivative, otherwise uses sum of squared scores for each pair
random.design	random effect design for additive gamma model, when pairs are given the indeces of the pairs random.design rows are given as columns 3:4
pairs	matrix with rows of indeces (two-columns) for the pairs considered in the pairwise composite score, useful for case-control sampling when marginal is known.
dim.theta	dimension of the theta parameter for pairs situation.
numDeriv.method	uses simple to speed up things and second derivative not so important.
additive.gamma.sum	for two.stage=0, this is specification of the lamtot in the models via a matrix that is multiplied onto the parameters theta (dimensions=(number random effects x number of theta parameters), when null then sums all parameters.

var.par	is 1 for the default parametrization with the variances of the random effects, var.par=0 specifies that the λ_j's are used as parameters.
no.opt	for not optimizng
...	Additional arguments to maximizer NR of lava. and ascertained sampling

Author(s)

Thomas Scheike

References

Twostage estimation of additive gamma frailty models for survival data. Scheike (2019), work in progress

Shih and Louis (1995) Inference on the association parameter in copula models for bivariate survival data, Biometrics, (1995).

Glidden (2000), A Two-Stage estimator of the dependence parameter for the Clayton Oakes model, LIDA, (2000).

Measuring early or late dependence for bivariate twin data Scheike, Holst, Hjelmborg (2015), LIDA

Estimating heritability for cause specific mortality based on twins studies Scheike, Holst, Hjelmborg (2014), LIDA

Additive Gamma frailty models for competing risks data, Biometrics (2015) Eriksson and Scheike (2015),

Examples

```
data(diabetes)

# Marginal Cox model  with treat as covariate
margph <- phreg(Surv(time,status)~treat+cluster(id),data=diabetes)
### Clayton-Oakes, MLE
fitco1<-twostageMLE(margph,data=diabetes,theta=1.0)
summary(fitco1)

### Plackett model
mph <- phreg(Surv(time,status)~treat+cluster(id),data=diabetes)
fitp <- survival.twostage(mph,data=diabetes,theta=3.0,Nit=40,
              clusters=diabetes$id,var.link=1,model="plackett")
summary(fitp)

### Clayton-Oakes
fitco2 <- survival.twostage(mph,data=diabetes,theta=0.0,detail=0,
                clusters=diabetes$id,var.link=1,model="clayton.oakes")
summary(fitco2)
fitco3 <- survival.twostage(margph,data=diabetes,theta=1.0,detail=0,
                clusters=diabetes$id,var.link=0,model="clayton.oakes")
summary(fitco3)

### without covariates but with stratafied
marg <- phreg(Surv(time,status)~+strata(treat)+cluster(id),data=diabetes)
```

```
fitpa <- survival.twostage(marg,data=diabetes,theta=1.0,
                clusters=diabetes$id,model="clayton.oakes")
summary(fitpa)

fitcoa <- survival.twostage(marg,data=diabetes,theta=1.0,clusters=diabetes$id,
                 model="clayton.oakes")
summary(fitcoa)

### Piecewise constant cross hazards ratio modelling
#########################################################

d <- subset(simClaytonOakes(2000,2,0.5,0,stoptime=2,left=0),!truncated)
udp <- piecewise.twostage(c(0,0.5,2),data=d,method="optimize",
                          id="cluster",timevar="time",
                          status="status",model="clayton.oakes",silent=0)
summary(udp)

 ## Reduce Ex.Timings
### Same model using the strata option, a bit slower
#########################################################
## makes the survival pieces for different areas in the plane
##ud1=surv.boxarea(c(0,0),c(0.5,0.5),data=d,id="cluster",timevar="time",status="status")
##ud2=surv.boxarea(c(0,0.5),c(0.5,2),data=d,id="cluster",timevar="time",status="status")
##ud3=surv.boxarea(c(0.5,0),c(2,0.5),data=d,id="cluster",timevar="time",status="status")
##ud4=surv.boxarea(c(0.5,0.5),c(2,2),data=d,id="cluster",timevar="time",status="status")

## everything done in one call
ud <- piecewise.data(c(0,0.5,2),data=d,timevar="time",status="status",id="cluster")
ud$strata <- factor(ud$strata);
ud$intstrata <- factor(ud$intstrata)

## makes strata specific id variable to identify pairs within strata
## se's computed based on the id variable across strata "cluster"
ud$idstrata <- ud$id+(as.numeric(ud$strata)-1)*2000

marg2 <- timereg::aalen(Surv(boxtime,status)~-1+factor(num):factor(intstrata),
               data=ud,n.sim=0,robust=0)
tdes <- model.matrix(~-1+factor(strata),data=ud)
fitp2 <- survival.twostage(marg2,data=ud,se.clusters=ud$cluster,clusters=ud$idstrata,
                 model="clayton.oakes",theta.des=tdes,step=0.5)
summary(fitp2)

### now fitting the model with symmetry, i.e. strata 2 and 3 same effect
ud$stratas <- ud$strata;
ud$stratas[ud$strata=="0.5-2,0-0.5"] <- "0-0.5,0.5-2"
tdes2 <- model.matrix(~-1+factor(stratas),data=ud)
fitp3 <- survival.twostage(marg2,data=ud,clusters=ud$idstrata,se.cluster=ud$cluster,
                 model="clayton.oakes",theta.des=tdes2,step=0.5)
summary(fitp3)

### same model using strata option, a bit slower
fitp4 <- survival.twostage(marg2,data=ud,clusters=ud$cluster,se.cluster=ud$cluster,
                 model="clayton.oakes",theta.des=tdes2,step=0.5,strata=ud$strata)
```

```
summary(fitp4)


 ## Reduce Ex.Timings
### structured random effects model additive gamma ACE
### simulate structured two-stage additive gamma ACE model
data <- simClaytonOakes.twin.ace(4000,2,1,0,3)
out <- twin.polygen.design(data,id="cluster")
pardes <- out$pardes
pardes
des.rv <- out$des.rv
head(des.rv)
aa <- phreg(Surv(time,status)~x+cluster(cluster),data=data,robust=0)
ts <- survival.twostage(aa,data=data,clusters=data$cluster,detail=0,
       theta=c(2,1),var.link=0,step=0.5,
       random.design=des.rv,theta.des=pardes)
summary(ts)
```

---

survivalG *G-estimator for Cox and Fine-Gray model*

Description

Computes G-estimator

$$\hat{S}(t, A = a) = n^{-1} \sum_i \hat{S}(t, A = a, Z_i)$$

for the Cox model based on phreg og the Fine-Gray model based on the cifreg function. Gives influence functions of these risk estimates and SE's are based on these. If first covariate is a factor then all contrast are computed, and if continuous then considered covariate values are given by Avalues.

Usage

```
survivalG(
  x,
  data,
  time = NULL,
  Avalues = c(0, 1),
  varname = NULL,
  same.data = TRUE,
  id = NULL
)
```

Arguments

x	phreg or cifreg object
data	data frame for risk averaging
time	for estimate
Avalues	values to compare for first covariate A
varname	if given then averages for this variable, default is first variable
same.data	assumes that same data is used for fitting of survival model and averaging.
id	might be given to link to data to iid decomposition of survival data, must be coded as 1,2,..,

Author(s)

Thomas Scheike

Examples

```
data(bmt); bmt$time <- bmt$time+runif(408)*0.001
bmt$event <- (bmt$cause!=0)*1
dfactor(bmt) <- tcell.f~tcell

fg1 <- cifreg(Event(time,cause)~tcell.f+platelet+age,bmt,cause=1,
              cox.prep=TRUE,propodds=NULL)
summary(survivalG(fg1,bmt,50))

ss <- phreg(Surv(time,event)~tcell.f+platelet+age,bmt)
summary(survivalG(ss,bmt,50))
```

---

test.conc *Concordance test Compares two concordance estimates*

Description

.. content for description (no empty lines) ..

Usage

```
test.conc(conc1, conc2, same.cluster = FALSE)
```

Arguments

conc1	Concordance estimate of group 1
conc2	Concordance estimate of group 2
same.cluster	if FALSE then groups are independent, otherwise estimates are based on same data.

Author(s)

Thomas Scheike

`tetrachoric` *Estimate parameters from odds-ratio*

Description

Calculate tetrachoric correlation of probabilities from odds-ratio

Usage

```
tetrachoric(P, OR, approx = 0, ...)
```

Arguments

`P`	Joint probabilities or marginals (if OR is given)
`OR`	Odds-ratio
`approx`	If TRUE an approximation of the tetrachoric correlation is used
`...`	Additional arguments

Examples

```
tetrachoric(0.3,1.25) # Marginal p1=p2=0.3, OR=2
P <- matrix(c(0.1,0.2,0.2,0.5),2)
prod(diag(P))/prod(lava::revdiag(P))
##mets:::assoc(P)
tetrachoric(P)
or2prob(2,0.1)
or2prob(2,c(0.1,0.2))
```

`TRACE` *The TRACE study group of myocardial infarction*

Description

The TRACE data frame contains 1877 patients and is a subset of a data set consisting of approximately 6000 patients. It contains data relating survival of patients after myocardial infarction to various risk factors.

Format

This data frame contains the following columns:

id a numeric vector. Patient code.

status a numeric vector code. Survival status. 9: dead from myocardial infarction, 0: alive, 7: dead from other causes.

time a numeric vector. Survival time in years.

chf a numeric vector code. Clinical heart pump failure, 1: present, 0: absent.

diabetes a numeric vector code. Diabetes, 1: present, 0: absent.

vf a numeric vector code. Ventricular fibrillation, 1: present, 0: absent.

wmi a numeric vector. Measure of heart pumping effect based on ultrasound measurements where 2 is normal and 0 is worst.

sex a numeric vector code. 1: female, 0: male.

age a numeric vector code. Age of patient.

Details

sTRACE is a subsample consisting of 300 patients.

tTRACE is a subsample consisting of 1000 patients.

Source

The TRACE study group.

Jensen, G.V., Torp-Pedersen, C., Hildebrandt, P., Kober, L., F. E. Nielsen, Melchior, T., Joen, T. and P. K. Andersen (1997), Does in-hospital ventricular fibrillation affect prognosis after myocardial infarction?, European Heart Journal 18, 919–924.

Examples

```
data(TRACE)
names(TRACE)
```

---

ttpd *ttpd discrete survival data on interval form*

Description

ttpd discrete survival data on interval form

Source

Simulated data

`twin.clustertrunc` *Estimation of twostage model with cluster truncation in bivariate situation*

Description

Estimation of twostage model with cluster truncation in bivariate situation

Usage

```
twin.clustertrunc(
  survformula,
  data = parent.frame(),
  theta.des = NULL,
  clusters = NULL,
  var.link = 1,
  Nit = 10,
  final.fitting = FALSE,
  ...
)
```

Arguments

`survformula`	Formula with survival model aalen or cox.aalen, some limitiation on model specification due to call of fast.reshape (so for example interactions and * and : do not work here, expand prior to call)
`data`	Data frame
`theta.des`	design for dependence parameters in two-stage model
`clusters`	clustering variable for twins
`var.link`	exp link for theta
`Nit`	number of iteration
`final.fitting`	TRUE to do final estimation with SE and ... arguments for marginal models
`...`	Additional arguments to lower level functions

Author(s)

Thomas Scheike

Examples

```
library("timereg")
data(diabetes)
v <- diabetes$time*runif(nrow(diabetes))*rbinom(nrow(diabetes),1,0.5)
diabetes$v <- v

aout <- twin.clustertrunc(Surv(v,time,status)~1+treat+adult,
```

```
 data=diabetes,clusters="id")
aout$two        ## twostage output
par(mfrow=c(2,2))
plot(aout$marg) ## marginal model output

out <- twin.clustertrunc(Surv(v,time,status)~1+prop(treat)+prop(adult),
 data=diabetes,clusters="id")
out$two        ## twostage output
plot(out$marg) ## marginal model output
```

`twinbmi` *BMI data set*

Description

BMI data set

Format

Self-reported BMI-values on 11,411 subjects

tvparnr: twin id bmi: BMI (m/kg^2) age: Age gender: (male/female) zyg: zygosity, MZ:=mz, DZ(same sex):=dz, DZ(opposite sex):=os

---

`twinlm` *Classic twin model for quantitative traits*

Description

Fits a classical twin model for quantitative traits.

Usage

```
twinlm(
  formula,
  data,
  id,
  zyg,
  DZ,
  group = NULL,
  group.equal = FALSE,
  strata = NULL,
  weights = NULL,
  type = c("ace"),
  twinnum = "twinnum",
  binary = FALSE,
  ordinal = 0,
```

```
  keep = weights,
  estimator = NULL,
  constrain = TRUE,
  control = list(),
  messages = 1,
  ...
)
```

Arguments

formula	Formula specifying effects of covariates on the response
data	data.frame with one observation pr row. In addition a column with the zygosity (DZ or MZ given as a factor) of each individual much be specified as well as a twin id variable giving a unique pair of numbers/factors to each twin pair
id	The name of the column in the dataset containing the twin-id variable.
zyg	The name of the column in the dataset containing the zygosity variable
DZ	Character defining the level in the zyg variable corresponding to the dyzogitic twins. If this argument is missing, the reference level (i.e. the first level) will be interpreted as the dyzogitic twins
group	Optional. Variable name defining group for interaction analysis (e.g., gender)
group.equal	If TRUE marginals of groups are asummed to be the same
strata	Strata variable name
weights	Weights matrix if needed by the chosen estimator. For use with Inverse Probability Weights
type	Character defining the type of analysis to be performed. Can be a subset of "aced" (additive genetic factors, common environmental factors, unique environmental factors, dominant genetic factors). Other choices are: • "0" (or "sat"): Saturated model where twin 1 and twin 2 within each twin pair may have a different marginal distribution. • "1" (or "flex","zyg"): Within twin pairs the marginal distribution is the same, but the marginal distribution may differ between MZ and DZ twins. A free correlation structure within MZ and DZ twins. • "2" (or "u", "eqmarg"): All individuals have the same marginals but a free correlation structure within MZ and DZ twins. The default value is an additive polygenic model type="ace".
twinnum	The name of the column in the dataset numbering the twins (1,2). If it does not exist in data it will automatically be created.
binary	If TRUE a liability model is fitted. Note that if the right-hand-side of the formula is a factor, character vector, og logical variable, then the liability model is automatically chosen (wrapper of the bptwin function).
ordinal	If non-zero (number of bins) a liability model is fitted.
keep	Vector of variables from data that are not specified in formula, to be added to data.frame of the SEM
estimator	Choice of estimator/model

constrain	Development argument
control	Control argument parsed on to the optimization routine
messages	Control amount of messages shown
...	Additional arguments parsed on to lower-level functions

Value

Returns an object of class twinlm.

Author(s)

Klaus K. Holst

See Also

bptwin, twinlm.time, twinlm.strata, twinsim

Examples

```
## Simulate data
set.seed(1)
d <- twinsim(1000,b1=c(1,-1),b2=c(),acde=c(1,1,0,1))
## E(y|z1,z2) = z1 - z2. var(A) = var(C) = var(E) = 1

## E.g to fit the data to an ACE-model without any confounders we simply write
ace <- twinlm(y ~ 1, data=d, DZ="DZ", zyg="zyg", id="id")
ace
## An AE-model could be fitted as
ae <- twinlm(y ~ 1, data=d, DZ="DZ", zyg="zyg", id="id", type="ae")
## LRT:
lava::compare(ae,ace)
## AIC
AIC(ae)-AIC(ace)
## To adjust for the covariates we simply alter the formula statement
ace2 <- twinlm(y ~ x1+x2, data=d, DZ="DZ", zyg="zyg", id="id", type="ace")
## Summary/GOF
summary(ace2)
 ## Reduce Ex.Timings
## An interaction could be analyzed as:
ace3 <- twinlm(y ~ x1+x2 + x1:I(x2<0), data=d, DZ="DZ", zyg="zyg", id="id", type="ace")
ace3
## Categorical variables are also supported
d2 <- transform(d,x2cat=cut(x2,3,labels=c("Low","Med","High")))
ace4 <- twinlm(y ~ x1+x2cat, data=d2, DZ="DZ", zyg="zyg", id="id", type="ace")
```

`twinsim` *Simulate twin data*

Description

Simulate twin data from a linear normal ACE/ADE/AE model.

Usage

```
twinsim(
  nMZ = 100,
  nDZ = nMZ,
  b1 = c(),
  b2 = c(),
  mu = 0,
  acde = c(1, 1, 0, 1),
  randomslope = NULL,
  threshold = 0,
  cens = FALSE,
  wide = FALSE,
  ...
)
```

Arguments

`nMZ`	Number of monozygotic twin pairs
`nDZ`	Number of dizygotic twin pairs
`b1`	Effect of covariates (labelled x1,x2,...) of type 1. One distinct covariate value for each twin/individual.
`b2`	Effect of covariates (labelled g1,g2,...) of type 2. One covariate value for each twin pair.
`mu`	Intercept parameter.
`acde`	Variance of random effects (in the order A,C,D,E)
`randomslope`	Logical indicating wether to include random slopes of the variance components w.r.t. x1,x2,...
`threshold`	Treshold used to define binary outcome y0
`cens`	Logical variable indicating whether to censor outcome
`wide`	Logical indicating if wide data format should be returned
`...`	Additional arguments parsed on to lower-level functions

Author(s)

Klaus K. Holst

See Also

twinlm

---

twinstut *Stutter data set*

Description

Based on nation-wide questionnaire answers from 33,317 Danish twins

Format

tvparnr: twin-pair id zyg: zygosity, MZ:=mz, DZ(same sex):=dz, DZ(opposite sex):=os stutter: stutter status (yes/no) age: age nr: number within twin-pair

---

twostageMLE *Twostage survival model fitted by pseudo MLE*

Description

Fits Clayton-Oakes clustered survival data using marginals that are on Cox form in the likelihood for the dependence parameter as in Glidden (2000). The dependence can be modelled via a

1. Regression design on dependence parameter.

We allow a regression structure for the indenpendent gamma distributed random effects and their variances that may depend on cluster covariates. So

$$\theta = h(z_j^T \alpha)$$

where z is specified by theta.des . The link function can be the exp when var.link=1

Usage

```
twostageMLE(
  margsurv,
  data = parent.frame(),
  theta = NULL,
  theta.des = NULL,
  var.link = 0,
  method = "NR",
  no.opt = FALSE,
  weights = NULL,
  se.cluster = NULL,
  ...
)
```

Arguments

margsurv	Marginal model from phreg
data	data frame
theta	Starting values for variance components
theta.des	design for dependence parameters, when pairs are given this is could be a (pairs) x (numer of parameters) x (max number random effects) matrix
var.link	Link function for variance if 1 then uses exp link
method	type of opitmizer, default is Newton-Raphson "NR"
no.opt	to not optimize, for example to get score and iid for specific theta
weights	cluster specific weights, but given with length equivalent to data-set, weights for score equations
se.cluster	specifies how the influence functions are summed before squared when computing the variance. Note that the id from the marginal model is used to construct MLE, and then these scores can be summed with the se.cluster argument.
...	arguments to be passed to optimizer

Author(s)

Thomas Scheike

References

Measuring early or late dependence for bivariate twin data Scheike, Holst, Hjelmborg (2015), LIDA

Twostage modelling of additive gamma frailty models for survival data. Scheike and Holst, working paper

Shih and Louis (1995) Inference on the association parameter in copula models for bivariate survival data, Biometrics, (1995).

Glidden (2000), A Two-Stage estimator of the dependence parameter for the Clayton Oakes model, LIDA, (2000).

Examples

```
data(diabetes)
dd <- phreg(Surv(time,status==1)~treat+cluster(id),diabetes)
oo <- twostageMLE(dd,data=diabetes)
summary(oo)

theta.des <- model.matrix(~-1+factor(adult),diabetes)

oo <-twostageMLE(dd,data=diabetes,theta.des=theta.des)
summary(oo)
```

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