Package ‘qgcomp’
August 10, 2023

Title  Quantile G-Computation
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Description  G-computation for a set of time-fixed exposures with quantile-based basis functions, possibly under linearity and homogeneity assumptions. This approach estimates a regression line corresponding to the expected change in the outcome (on the link basis) given a simultaneous increase in the quantile-based category for all exposures. Works with continuous, binary, and right-censored time-to-event outcomes. Reference: Alexander P. Keil, Jessie P. Buckley, Katie M. OBrien, Kelly K. Ferguson, Shanshan Zhao, and Alexandra J. White (2019) A quantile-based g-computation approach to addressing the effects of exposure mixtures; <doi:10.1289/EHP5838>.
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Author  Alexander Keil [aut, cre]
Maintainer  Alexander Keil <alex.keil@nih.gov>
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checknames

checknames

Check for valid model terms in a qgcomp fit

Description

This is an internal function called by \texttt{qgcomp}, \texttt{qgcomp.glm.boot}, and \texttt{qgcomp.glm.noboot}, but is documented here for clarity. Generally, users will not need to call this function directly. This function tries to determine whether there are non-linear terms in the underlying model, which helps infer whether the appropriate function is called, and whether more explicit function calls are needed.

Usage

\begin{verbatim}
checknames(terms)
\end{verbatim}

Arguments

terms model terms from \texttt{attr(terms(modelfunction, data), "term.labels")}

\begin{verbatim}
coxmsm_fit
\end{verbatim}

Marginal structural Cox model (MSM) fitting within quantile g-computation

Description

This is an internal function called by \texttt{qgcomp.cox.noboot}, \texttt{qgcomp.cox.boot}, and \texttt{qgcomp.cox.noboot}, but is documented here for clarity. Generally, users will not need to call this function directly.

Usage

\begin{verbatim}
coxmsm_fit(
  f,
  qdata,
  intvals,
  expnms,
  main = TRUE,
  degree = 1,
  id = NULL,
  weights,
  cluster = NULL,
  MCsize = 10000,
  ...
)
\end{verbatim}
Arguments

- **f**: an R formula representing the conditional model for the outcome, given all exposures and covariates. Interaction terms that include exposure variables should be represented via the `AsIs` function. Offset terms can be included via `Surv(time,event) ~ exposure + offset(z)`
- **qdata**: a data frame with quantized exposures (as well as outcome and other covariates)
- **intvals**: sequence, the sequence of integer values that the joint exposure is ‘set’ to for estimating the msm. For quantile g-computation, this is just 0:(q-1), where q is the number of quantiles of exposure.
- **expnms**: a character vector with the names of the columns in qdata that represent the exposures of interest (main terms only!)
- **main**: logical, internal use: produce estimates of exposure effect (psi) and expected outcomes under g-computation and the MSM
- **degree**: polynomial bases for marginal model (e.g. degree = 2 allows that the relationship between the whole exposure mixture and the outcome is quadratic. Default=1)
- **id**: (optional) NULL, or variable name indexing individual units of observation (only needed if analyzing data with multiple observations per id/cluster)
- **weights**: "case weights" - passed to the "weight" argument of `coxph`
- **cluster**: not yet implemented
- **MCsize**: integer: sample size for simulation to approximate marginal hazards ratios
- **...**: arguments to `coxph` (e.g. ties)

Details

This function first computes expected outcomes under hypothetical interventions to simultaneously set all exposures to a specific quantile. These predictions are based on g-computation, where the exposures are ‘quantized’, meaning that they take on ordered integer values according to their ranks, and the integer values are determined by the number of quantile cutpoints used. The function then takes these expected outcomes and fits an additional model (a marginal structural model) with the expected outcomes as the outcome and the intervention value of the exposures (the quantile integer) as the exposure. Under causal identification assumptions and correct model specification, the MSM yields a causal exposure-response representing the incremental change in the expected outcome given a joint intervention on all exposures.

See Also

- `qgcomp.cox.boot`, and `qgcomp.cox.noboot`

Examples

```r
set.seed(50)
dat <- data.frame(time=(tmg <- pmin(.1,rweibull(50, 10, 0.1))), d=1.0*(tmg<0.1),
                  x1=runif(50), x2=runif(50), z=runif(50))
expnms=paste0("x", 1:2)
qdata = quantize(dat, expnms)$data
```
f = survival::Surv(time, d)~x1 + x2
fit <- survival::coxph(f, data = qdata, y=TRUE, x=TRUE)
rl = qdata[, , drop=FALSE]
times = survival::survfit(fit, newdata=rl, se.fit=FALSE)$time
(obj <- coxmsm_fit(f, qdata, intvals=c(0,1,2,3), expnms, main=TRUE, degree=1,
id=NULL, MCsize=100))
#dat2 <- data.frame(psi=seq(1,4, by=0.1))
#summary(predict(obj))
#summary(predict(obj, newdata=dat2))

---

**glance.qgcompfit**  
*Glance at a qgcompfit object*

**Description**

Glance accepts a model object and returns a tibble::tibble() with exactly one row of model summaries. The summaries are typically goodness of fit measures, p-values for hypothesis tests on residuals, or model convergence information.

Glance never returns information from the original call to the modeling function. This includes the name of the modeling function or any arguments passed to the modeling function.

Glance does not calculate summary measures. Rather, it farms out these computations to appropriate methods and gathers the results together. Sometimes a goodness of fit measure will be undefined. In these cases the measure will be reported as NA. (Description taken from broom::glance help file.)

**Usage**

```r
## S3 method for class 'qgcompfit'
glance(x, ...)
```

**Arguments**

- `x`  
  a qgcompfit object

- `...`  
  Not used

---

**homogeneity_test**  
*Hypothesis testing about joint effect of exposures on a multinomial outcome*

**Description**

Hypothesis testing about joint effect of exposures on a multinomial outcome

**Usage**

```r
homogeneity_test(x, ...)
```
Arguments

- `x` : Result from fit.
- `...` : Unused

---

### homogeneity_test.qgcompmultfit

_Hypothesis testing about joint effect of exposures on a multinomial outcome_

---

**Description**

Tests the null hypothesis that the joint effect of the mixture components is identical across all referent outcome types (homogeneity test for linear effect of the mixture on a quantized basis)

**Usage**

```r
## S3 method for class 'qgcompmultfit'
homogeneity_test(x, ...)
```

**Arguments**

- `x` : Result from qgcomp multinomial fit (qgcompmultfit object).
- `...` : Unused

**Value**

qgcompmulttest object (list) with results of a chi-squared test

---

### hurdlemsm_fit

_Secondary prediction method for the (hurdle) qgcomp MSM._

---

**Description**

This is an internal function called by qgcomp.hurdle.boot, but is documented here for clarity. Generally, users will not need to call this function directly.
Usage

hurdlemsm_fit(f, qdata, intvals, expnms, main = TRUE, degree = 1, id = NULL, weights, MCsize = 10000, containmix = list(count = TRUE, zero = TRUE), bayes = FALSE, x = FALSE, msmcontrol = hurdlemsm_fit.control(), ...)

Arguments

f an r formula representing the conditional model for the outcome, given all exposures and covariates. Interaction terms that include exposure variables should be represented via the AsIs function

qdata a data frame with quantized exposures (as well as outcome and other covariates)

intvals sequence, the sequence of integer values that the joint exposure is 'set' to for estimating the msm. For quantile g-computation, this is just 0:(q-1), where q is the number of quantiles of exposure.

expnms a character vector with the names of the columns in qdata that represent the exposures of interest (main terms only!)

main logical, internal use: produce estimates of exposure effect (psi) and expected outcomes under g-computation and the MSM

degree polynomial bases for marginal model (e.g. degree = 2 allows that the relationship between the whole exposure mixture and the outcome is quadratic. Default=1)

id (optional) NULL, or variable name indexing individual units of observation (only needed if analyzing data with multiple observations per id/cluster)

weights not yet implemented

MCsize integer: sample size for simulation to approximate marginal hazards ratios

containmix named list of logical scalars with names "count" and "zero"

bayes not used

x keep design matrix? (logical)

msmcontrol named list from hurdlemsm_fit.control

... arguments to hurdle (e.g. dist)
Details

This function first computes expected outcomes under hypothetical interventions to simultaneously set all exposures to a specific quantile. These predictions are based on g-computation, where the exposures are ‘quantized’, meaning that they take on ordered integer values according to their ranks, and the integer values are determined by the number of quantile cutpoints used. The function then takes these expected outcomes and fits an additional model (a marginal structural model) with the expected outcomes as the outcome and the intervention value of the exposures (the quantile integer) as the exposure. Under causal identification assumptions and correct model specification, the MSM yields a causal exposure-response representing the incremental change in the expected outcome given a joint intervention on all exposures.

See Also

qgcomp.cox.boot, and qgcomp.cox.noboot

Examples

set.seed(50)
n=100
## Not run:
dat <- data.frame(y=rbinom(n, 1, 0.5)*rpois(n, 1.2), x1=runif(n), x2=runif(n), z=runif(n))
expnms = c("x1", "x2")
q = 4
qdata = quantize(dat, q=q, expnms=expnms)$data
f = y ~ x1 + x2 + z | 1
msmfit <- hurdlemsm_fit(f, qdata, intvals=(1:q)-1, expnms, main=TRUE,
        degree=1, id=NULL, MCsize=10000, containmix=list(count=TRUE, zero=FALSE),
        x=FALSE)
msmfit$msmfit
## End(Not run)
joint_test

Arguments

predmethod character in c("components", "catprobs"). "components" simulates from the model parameters directly while "catprobs" simulates outcomes from the category specific probabilities, which is output from predict.hurdle. The former is slightly more flexible and stable, but the latter is preferred in zero inflated negative binomial models.

Details

Provides fine control over zero inflated MSM fitting

---

### joint_test

Hypothesis testing about joint effect of exposures on a multinomial outcome

---

Description

Hypothesis testing about joint effect of exposures on a multinomial outcome

Usage

joint_test(x, ...)

Arguments

- x Result from fit.
- ... Unused

---

### joint_test.qgcompmultfit

Hypothesis testing about joint effect of exposures on a multinomial outcome

---

Description

Tests the null hypothesis that the joint effect of the mixture components is null across all referent outcome types (Test of global null effect of the mixture on a quantized basis)

Usage

```r
## S3 method for class 'qgcompmultfit'
joint_test(x, ...)
```
Arguments

x Result from qgcomp multinomial fit (qgcompmultfit object).

Value

qgcompmulttest object (list) with results of a chi-squared test

Description

Simulated well water measurements in North Carolina: 16 metals, 6 water chemistry measures, and 2 health outcomes (y = continuous; disease_state = binary/time-to-event in combination with disease_time)

A dataset containing well water measurements and health outcomes for 253 individuals. All continuous variables are standardized to have mean 0, standard deviation 1.

Usage

data(metals)

Format

A data frame with 253 rows and 24 variables:

y continuous birth outcome
disease_state binary outcome
disease_time time-to-disease_state: survival outcome censored at approximately the median
arsenic metal
barium metal
cadmium metal
calcium metal
chloride metal
chromium metal
copper metal
iron metal
lead metal
magnesium metal
manganese metal
mercury metal
mice.impute.leftcenslognorm

Imputation for limits of detection problems

Description
This function integrates with mice to impute values below the LOD using a left censored log-normal distribution. Note that “tobit” is an alias that uses a familiar term for this model.

Usage
mice.impute.leftcenslognorm(
  y,
  ry,
  x,
  wy = NULL,
  lod = NULL,
  debug = FALSE,
  ...
)
mice.impute.tobit(y, ry, x, wy = NULL, lod = NULL, debug = FALSE, ...)

Arguments

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>y</td>
<td>Vector to be imputed</td>
</tr>
<tr>
<td>ry</td>
<td>Logical vector of length length(y) indicating the subset of elements in y to which the imputation model is fitted. The ry generally distinguishes the observed (TRUE) and missing values (FALSE) in y.</td>
</tr>
<tr>
<td>x</td>
<td>Numeric design matrix with length(y) rows with predictors for y. Matrix x may have no missing values.</td>
</tr>
</tbody>
</table>
wy Logical vector of length length(y). A TRUE value indicates locations in y for which imputations are created.

lod numeric vector of limits of detection (must correspond to index in original data) OR list in which each element corresponds to observation level limits of detection for each variable (list index must correspond to index in original data)

debug logical, print extra info

Details

While this function has utility far beyond qgcomp, it is included in the qgcomp package because it will be useful for a variety of settings in which qgcomp is useful. Note that LOD problems where the LOD is small, and the q parameter from qgcomp.glm.noboot or qgcomp.glm.boot is not large, the LOD may be below the lowest quantile cutpoint which will yield identical datasets from the MICE procedure in terms of quantized exposure data. If only exposures are missing, and they have low LODs, then there will be no benefit in qgcomp from using MICE rather than imputing some small value below the LOD.

Value

Vector with imputed data, same type as y, and of length sum(wy)

Examples

N = 100
set.seed(123)
dat <- data.frame(y=runif(N), x1=runif(N), x2=runif(N), z=runif(N))
true = qgcomp.glm.noboot(f=y ~ z + x1 + x2, expnms = c('x1', 'x2'),
                        data=dat, q=2, family=gaussian())
mdat <- dat
mdat$x1 = ifelse(mdat$x1>0.5, mdat$x1, NA)
mdat$x2 = ifelse(mdat$x2>0.75, mdat$x2, NA)
cc <- qgcomp.glm.noboot(f=y ~ z + x1 + x2, expnms = c('x1', 'x2'),
                         data=mdat[complete.cases(mdat),], q=2, family=gaussian())

## Not run:
# note the following example imputes from the wrong parametric model and is expected to be biased # as a result (but it demonstrates how to use qgcomp and mice together)
library("mice")
library("survival")
set.seed(1231)
impdat = mice(data = mdat,
              method = c(""", "leftcenslognorm", "leftcenslognorm", ""),
              lod=c(NA, 0.5, 0.75, NA), debug=FALSE, m=10)
qc.fit.imp <- list(
                  call = call("qgcomp.glm.noboot(y ~ ., expnms = c('x1', 'x2'), family=gaussian())"),
                  call1 = impdat$call,
                  nmis = impdat$nmis,
                  analyses = lapply(1:10, function(x) qgcomp.glm.noboot(y ~ ., expnms = c("x1", "x2"),
                                                            data=complete(impdat, x), family=gaussian(), bayes=TRUE)))
# alternative way to specify limits of detection (useful if not all observations have same limit)

```r
lodlist = list(rep(NA, N), rep(0.5, N), rep(0.75, N), rep(NA, N))
# also works
set.seed(1231)
impdat_alt = mice(data = mdat,
  method = c('', 'leftcenslognorm', 'leftcenslognorm', ''),
  lod=lodlist, debug=FALSE, m=10)
```

```r
qc.fit.imp_alt <- list(
  call = call("qgcomp.glm.noboot(y~., expnms = c("x1", "x2"), family=gaussian())"),
  call1 = impdat_alt$call,
  nmis = impdat_alt$nmis,
  analyses = lapply(1:10, function(x) qgcomp.glm.noboot(y~., expnms = c("x1", "x2"),
    data=complete(impdat_alt, x), family=gaussian(), bayes=TRUE))
)
```

```r
obj = pool(as.mira(qc.fit.imp))
obj_alt = pool(as.mira(qc.fit.imp_alt))
# true values
true
# complete case analysis
cc
# MI based analysis (identical answers for different ways to specify limits of detection)
summary(obj)
summary(obj_alt)
```

```r
# summarizing weights (note that the weights should *not* be pooled
# because they mean different things depending on their direction)
expnms = c("x1", "x2")
wts = as.data.frame(t(sapply(qc.fit.imp$analyses,
  function(x) c(-x$neg.weights, x$pos.weights[expnms]))))
eachwt = do.call(c, wts)
expwts = data.frame(Exposure = rep(expnms, each=nrow(wts)), Weight=eachwt)
library(ggplot2)
```

```r
ggplot(data=expwts)+ theme_classic() +
  geom_point(aes(x=Exposure, y=Weight)) +
  geom_hline(aes(yintercept=0))
```

```r
# this function can be used to impute from an intercept only model
# but you need to "trick" mice to bypass checks for collinearity by including
# a variable that does not need to have values imputed (here, y).
# The internal collinearity checks by the mice package remove collinear variables
# and then throws an error if no predictor variables are retained. Here, the
# trick is to use the "predictorMatrix" parameter to "impute" the non-missing
# variable y using x1 (which does nothing), and remove all predictors from the model for x1.
# This function only imputes x1 from a log normal distribution.
impdat2 = mice(data = mdat[,c("y","x1")],
  method = c('', "tobit"), remove.collinear=FALSE,
  lod=c(NA, 0.5), debug=FALSE, m=1,
  maxit=1, # maxit=1 because there is only 1 variable to impute
  predictorMatrix = as.matrix(rbind(c(0,1), c(0,0))))
plot(density(complete(impdat2, 1)$x1))
# now with survival data (very similar)
impdat = mice(data = mdat,
    method = c("", "tobit", "tobit", ""),
    lod=c(NA, 0.5, 0.75, NA), debug=FALSE)
qc.fit.imp <- list(
    call = call("qgcomp.cox.noboot(Surv(y)~., expnms = c("x1", "x2"))"),
    call1 = impdat$call,
    nmis = impdat$nmis,
    analyses = lapply(1:5, function(x) qgcomp.cox.noboot(Surv(y)~., expnms = c("x1", "x2"),
        data=complete(impdat, x)))
)
obj = pool(as.mira(qc.fit.imp))
# MI based analysis
summary(obj)

## End(Not run)

---

**modelbound.boot**

*Estimating qgcomp regression line confidence bounds*

**Description**

Calculates: expected outcome (on the link scale), and upper and lower confidence intervals (both pointwise and simultaneous)

**Usage**

```r
modelbound.boot(x, alpha = 0.05, pwonly = FALSE)
```

**Arguments**

- `x`: "qgcompfit" object from `qgcomp.glm.boot`,
- `alpha`: alpha level for confidence intervals
- `pwonly`: logical: return only pointwise estimates (suppress simultaneous estimates)

**Details**

This method leverages the bootstrap distribution of qgcomp model coefficients to estimate pointwise regression line confidence bounds. These are defined as the bounds that, for each value of the independent variable X (here, X is the joint exposure quantiles) the 95% bounds (for example) for the model estimate of the regression line E(Y|X) are expected to include the true value of E(Y|X) in 95% of studies. The "simultaneous" bounds are also calculated, and the 95% simultaneous bounds contain the true value of E(Y|X) for all values of X in 95% of studies. The latter are more conservative and account for the multiple testing implied by the former. Pointwise bounds are calculated via the standard error for the estimates of E(Y|X), while the simultaneous bounds are estimated using the bootstrap method of Cheng (reference below). All bounds are large sample bounds that assume normality and thus will be underconservative in small samples. These bounds...
may also include illogical values (e.g., values less than 0 for a dichotomous outcome) and should be interpreted cautiously in small samples.

Reference:

Value
A data frame containing

**linpred**: The linear predictor from the marginal structural model

**r/o/m**: The canonical measure (risk/odds/mean) for the marginal structural model link

**se...**: the standard error of linpred

**ul.../ll...**: Confidence bounds for the effect measure, and bounds centered at the canonical measure (for plotting purposes)

The confidence bounds are either "pointwise" (pw) and "simultaneous" (simul) confidence intervals at each each quantized value of all exposures.

See Also
qgcomp.glm.boot

Examples
```r
set.seed(12)
## Not run:
dat <- data.frame(x1=(x1 <- runif(50)), x2=runif(50), x3=runif(50), z=runif(50), y=runif(50)+x1+x1^2)
ft <- qgcomp.glm.boot(y ~ z + x1 + x2 + x3, expnms=c("x1","x2","x3"), data=dat, q=5)
modelbound.boot(ft, 0.05)
## End(Not run)
```

### msm.predict

**Secondary prediction method for the (non-survival) qgcomp MSM.**

Description
this is an internal function called by qgcomp.glm.boot, but is documented here for clarity. Generally, users will not need to call this function directly.

Get predicted values from a qgcompfit object from qgcomp.glm.boot.

Usage
```r
msm.predict(object, newdata = NULL)
```
Arguments

object    "qgcompfit" object from qgcomp.glm.boot function
newdata   (optional) new set of data (data frame) with a variable called psi representing
the joint exposure level of all exposures under consideration

Details

(Not usually called by user) Makes predictions from the MSM (rather than the conditional g-
computation fit) from a "qgcompfit" object. Generally, this should not be used in favor of the default
predict.qgcompfit function. This function can only be used following the qgcomp.glm.boot
function. For the qgcomp.glm.noboot function, predict.qgcompfit gives identical inference to
predicting from an MSM.

Examples

set.seed(50)
dat <- data.frame(y=runif(50), x1=runif(50), x2=runif(50), z=runif(50))
obj <- qgcomp.glm.boot(y ~ z + x1 + x2 + I(z*x1), expnms = c('x1', 'x2'),
  data=dat, q=4, B=10, seed=125)
dat2 <- data.frame(psi=seq(1,4, by=0.1))
summary(msm.predict(obj))
summary(msm.predict(obj, newdata=dat2))

Description

This is an internal function called by qgcomp, qgcomp.glm.boot, and qgcomp.glm.noboot, but is
documented here for clarity. Generally, users will not need to call this function directly.

Usage

msm_fit(
  f,
  qdata,
  intvals,
  expnms,
  rr = TRUE,
  main = TRUE,
  degree = 1,
  id = NULL,
  weights,
  bayes = FALSE,
  MCsize = nrow(qdata),
  hasintercept = TRUE,
  ...
)
Arguments

- **f**: an r formula representing the conditional model for the outcome, given all exposures and covariates. Interaction terms that include exposure variables should be represented via the AsIs function.
- **qdata**: a data frame with quantized exposures.
- **intvals**: sequence, the sequence of integer values that the joint exposure is 'set' to for estimating the msm. For quantile g-computation, this is just 0:(q-1), where q is the number of quantiles of exposure.
- **expnms**: a character vector with the names of the columns in qdata that represent the exposures of interest (main terms only!).
- **rr**: logical, estimate log(risk ratio) (family='binomial' only).
- **main**: logical, internal use: produce estimates of exposure effect (psi) and expected outcomes under g-computation and the MSM.
- **degree**: polynomial bases for marginal model (e.g. degree = 2 allows that the relationship between the whole exposure mixture and the outcome is quadratic. Default=1).
- **id**: (optional) NULL, or variable name indexing individual units of observation (only needed if analyzing data with multiple observations per id/cluster).
- **weights**: "case weights" - passed to the "weight" argument of glm or bayesglm.
- **bayes**: use underlying Bayesian model (arm package defaults). Results in penalized parameter estimation that can help with very highly correlated exposures. Note: this does not lead to fully Bayesian inference in general, so results should be interpreted as frequentist.
- **MCsize**: integer: sample size for simulation to approximate marginal zero inflated model parameters. This can be left small for testing, but should be as large as needed to reduce simulation error to an acceptable magnitude (can compare psi coefficients for linear fits with qgcomp.zi.noboot to gain some intuition for the level of expected simulation error at a given value of MCsize).
- **hasintercept**: (logical) does the model have an intercept?
- **...**: arguments to glm (e.g. family).

Details

This function first computes expected outcomes under hypothetical interventions to simultaneously set all exposures to a specific quantile. These predictions are based on g-computation, where the exposures are 'quantized', meaning that they take on ordered integer values according to their ranks, and the integer values are determined by the number of quantile cutpoints used. The function then takes these expected outcomes and fits an additional model (a marginal structural model) with the expected outcomes as the outcome and the intervention value of the exposures (the quantile integer) as the exposure. Under causal identification assumptions and correct model specification, the MSM yields a causal exposure-response representing the incremental change in the expected outcome given a joint intervention on all exposures.

See Also

qgcomp glm.boot, and qgcomp
Examples

```r
set.seed(50)
dat <- data.frame(y=runif(200), x1=runif(200), x2=runif(200), z=runif(200))
X <- c('x1', 'x2')
qdat <- quantize(dat, X, q=4)$data
mod <- msm_fit(f=y ~ z + x1 + x2 + I(x1*x2),
                   expnms = c('x1', 'x2'), qdata=qdat, intvals=1:4, bayes=FALSE)
summary(mod$fit) # outcome regression model
summary(mod$msmfit) # msm fit (variance not valid - must be obtained via bootstrap)
```

**Description**

This is an internal function called by `qgcomp.multinomial.boot`, but is documented here for clarity. Generally, users will not need to call this function directly.

**Usage**

```r
msm_multinomial_fit(
  f, qdata, intvals, expnms, main = TRUE, degree = 1, id = NULL, weights, bayes = FALSE, MCsize = nrow(qdata), hasintercept = TRUE, ...
)
```

**Arguments**

- `f`: an r formula representing the conditional model for the outcome, given all exposures and covariates. Interaction terms that include exposure variables should be represented via the `AsIs` function.
- `qdata`: a data frame with quantized exposures.
- `intvals`: sequence, the sequence of integer values that the joint exposure is ‘set’ to for estimating the msm. For quantile g-computation, this is just 0:(q-1), where q is the number of quantiles of exposure.
- `expnms`: a character vector with the names of the columns in qdata that represent the exposures of interest (main terms only!).
msm_multinomial_fit

main: logical, internal use: produce estimates of exposure effect (psi) and expected outcomes under g-computation and the MSM

degree: polynomial bases for marginal model (e.g. degree = 2 allows that the relationship between the whole exposure mixture and the outcome is quadratic. Default=1)

id: (optional) NULL, or variable name indexing individual units of observation (only needed if analyzing data with multiple observations per id/cluster)

weights: "case weights" - passed to the "weight" argument of glm or bayesglm

bayes: use underlying Bayesian model (arm package defaults). Results in penalized parameter estimation that can help with very highly correlated exposures. Note: this does not lead to fully Bayesian inference in general, so results should be interpreted as frequentist.

MCsize: integer: sample size for simulation to approximate marginal zero inflated model parameters. This can be left small for testing, but should be as large as needed to reduce simulation error to an acceptable magnitude (can compare psi coefficients for linear fits with qgcomp.zi.noboot to gain some intuition for the level of expected simulation error at a given value of MCsize)

hasintercept: (logical) does the model have an intercept?

Arguments to glm (e.g. family)

Details

This function first computes expected outcomes under hypothetical interventions to simultaneously set all exposures to a specific quantile. These predictions are based on g-computation, where the exposures are 'quantized', meaning that they take on ordered integer values according to their ranks, and the integer values are determined by the number of quantile cutpoints used. The function then takes these expected outcomes and fits an additional model (a marginal structural model) with the expected outcomes as the outcome and the intervention value of the exposures (the quantile integer) as the exposure. Under causal identification assumptions and correct model specification, the MSM yields a causal exposure-response representing the incremental change in the expected outcome given a joint intervention on all exposures.

See Also

qgcomp glm.boot, and qgcomp

Examples

data("metals") # from qgcomp package
# create categorical outcome from the existing continuous outcome (usually, one will already exist)
metals$ycat = factor(quantize(metals, "y", q=4)$data$y, levels=c("0", "1", "2", "3"),
labels=c("cct", "ccg", "aat", "aag"))
# restrict to smaller dataset for simplicity
smallmetals = metals[,c("ycat", "arsenic", "lead", "cadmium", "mage35")]

### 1: Define mixture and underlying model ###
mixture = c("arsenic", "lead", "cadmium")
f0 = ycat ~ arsenic + lead + cadmium # the multinomial model
# (be sure that factor variables are properly coded ahead of time in the dataset)
qdat <- quantize(smallmetals, mixture, q=4)$data
mod <- msm_multinomial_fit(f0, expnms = mixture, qdata=qdat, intvals=1:4, bayes=FALSE)
summary(mod$fit) # outcome regression model
summary(mod$msmfit) # msm fit (variance not valid - must be obtained via bootstrap)

plot.qgcompfit  Default plotting method for a qgcompfit object

Description

Plot a quantile g-computation object. For qgcomp.glm.noboot, this function will create a butterfly plot of weights. For qgcomp.glm.boot, this function will create a box plot with smoothed line overlaying that represents a non-parametric fit of a model to the expected outcomes in the population at each quantile of the joint exposures (e.g. '1' represents 'at the first quantile for every exposure')

Usage

## S3 method for class 'qgcompfit'
plot(
x,
suppressprint = FALSE,
pointwisebars = TRUE,
modelfitline = TRUE,
modelband = TRUE,
flexfit = TRUE,
pointwiseref = ceiling(x$q/2),
...
)

## S3 method for class 'qgcompmultfit'
plot(
x,
suppressprint = FALSE,
pointwisebars = TRUE,
modelfitline = TRUE,
modelband = TRUE,
flexfit = TRUE,
pointwiseref = ceiling(x$q/2),
...
)

Arguments

x "qgcompfit" object from qgcomp.glm.noboot, qgcomp.glm.boot, qgcomp.cox.noboot, qgcomp.cox.boot, qgcomp.zi.noboot or qgcomp.zi.boot functions
suppressprint If TRUE, suppresses the plot, rather than printing it by default (it can be saved as a ggplot2 object (or list of ggplot2 objects if x is from a zero-inflated model) and used programmatically) (default = FALSE)

pointwisebars (boot.gcomp only) If TRUE, adds 95% error bars for pointwise comparisons of \( E(Y|\text{joint exposure}) \) to the smooth regression line plot

modelfitline (boot.gcomp only) If TRUE, adds fitted (MSM) regression line of \( E(Y|\text{joint exposure}) \) to the smooth regression line plot

modelband If TRUE, adds 95% prediction bands for \( E(Y|\text{joint exposure}) \) (the MSM fit)

flexfit (boot.gcomp only) If TRUE, adds flexible interpolation of predictions from underlying (conditional) model

pointwiseref (boot.gcomp only) integer: which category of exposure (from 1 to q) should serve as the referent category for pointwise comparisons? (default=1)

... unused

Functions

- plot(qgcompmultfit): Plot method for qgcomp multinomial fits

See Also

qgcomp.glm.noboot, qgcomp.glm.boot, and qgcomp

Examples

```r
set.seed(12)
dat <- data.frame(x1=(x1 <- runif(100)), x2=runif(100), x3=runif(100), z=runif(100), y=runif(100)+x1+x1^2)
ft <- qgcomp.glm.noboot(y ~ z + x1 + x2 + x3, expnms=c('x1','x2','x3'), data=dat, q=4)
ft
# display weights
plot(ft)
# examining fit
plot(ft$fit, which=1) # residual vs. fitted is not straight line!
## Not run:
# using non-linear outcome model
ft2 <- qgcomp.glm.boot(y ~ z + x1 + x2 + x3 + I(x1*x1), expnms=c('x1','x2','x3'),
data=dat, q=4, B=10)
ft2
plot(ft2$fit, which=1) # much better looking fit diagnostics suggests it is better to include interaction term for x
plot(ft2) # the msm predictions don't match up with a smooth estimate of the expected outcome, so we should consider a non-linear MSM

# using non-linear marginal structural model
ft3 <- qgcomp.glm.boot(y ~ z + x1 + x2 + x3 + I(x1^2), expnms=c('x1','x2','x3'),
data=dat, q=4, B=10, degree=2)
# plot(ft3$fit, which=1) - not run - this is identical to ft2 fit
plot(ft3) # the MSM estimates look much closer to the smoothed estimates
```
# suggesting the non-linear MSM fits the data better and should be used
# for inference about the effect of the exposure

# binary outcomes, logistic model with or without a log-binomial marginal
# structural model
dat <- data.frame(y=rbinom(100,1,0.5), x1=runif(100), x2=runif(100), z=runif(100))
fit1 <- qgcomp.glm.boot(y ~ z + x1 + x2, family="binomial", expnms = c('x1', 'x2'),
data = dat, q=9, B=100, rr=FALSE)
fit2 <- qgcomp.glm.boot(y ~ z + x1 + x2, family="binomial", expnms = c('x1', 'x2'),
data = dat, q=9, B=100, rr=TRUE)
plot(fit1)
plot(fit2)

# Using survival data ()
set.seed(50)
N=200
dat <- data.frame(time=(tmg <- pmin(.1,rweibull(N, 10, 0.1))),
d=1.0*(tmg<0.1), x1=runif(N), x2=runif(N), z=runif(N))
expnms=paste0("x", 1:2)
f = survival::Surv(time, d)-x1 + x2
(fit1 <- survival::coxph(f, data = dat))
# non-bootstrap method to get a plot of weights
(obj <- qgcomp.cox.noboot(f, expnms = expnms, data = dat))
plot(obj)

# bootstrap method to get a survival curve
# this plots the expected survival curve for the underlying (conditional) model
# as well as the expected survival curve for the MSM under the following scenarios:
# 1) highest joint exposure category
# 2) lowest joint exposure category
# 3) average across all exposure categories
# differences between the MSM and conditional fit suggest that the MSM is not flexible
# enough to accommodate non-linearities in the underlying fit (or they may simply signal that
# MCSize should be higher). Note that if linearity
# is assumed in the conditional model, the MSM will typically also appear linear and
# will certainly appear linear if no non-exposure covariates are included in the model
# not run (slow when using boot version to proper precision)
(obj2 <- qgcomp.cox.boot(f, expnms = expnms, data = dat, B=10, MCsize=2000))
plot(obj2)

## End(Not run)
Usage

```
pointwisebound.boot(x, pointwiseref = 1, alpha = 0.05)
```

Arguments

- **x**: "qgcompfit" object from `qgcomp.glm.boot`
- **pointwiseref**: referent quantile (e.g. 1 uses the lowest joint-exposure category as the referent category for calculating all mean differences/standard deviations)
- **alpha**: alpha level for confidence intervals

Details

The comparison of interest following a qgcomp fit is often comparisons of model predictions at various values of the joint-exposures (e.g. expected outcome at all exposures at the 1st quartile vs. the 3rd quartile). The expected outcome at a given joint exposure, and marginalized over non-exposure covariates (W), is given as $E(Y|S) = \sum_w E_w(Y|S,W)Pr(W) = \sum_i E(Y_i|S)$ where $Pr(W)$ is the empirical distribution of W and S takes on integer values 0 to q-1. Thus, comparisons are of the type $E_w(Y|S=s) - E_w(Y|S=s2)$ where s and s2 are two different values of the joint exposures (e.g. 0 and 2). This function yields $E_w(Y|S)$ as well as $E_w(Y|S=s) - E_w(Y|S=p)$ where s is any value of S and p is the value chosen via "pointwise ref" - e.g. for binomial variables this will equal the risk/prevalence difference at all values of S, with the referent category S=p-1. The standard error of $E(Y|S=s) - E(Y|S=p)$ is calculated from the bootstrap covariance matrix of $E_w(Y|S)$, such that the standard error for $E_w(Y|S=s) - E_w(Y|S=p)$ is given by

$$\text{Var}(E_w(Y|S=s)) + \text{Var}(E_w(Y|S=p)) - 2\text{Cov}(E_w(Y|S=p), - E_w(Y|S=s))$$

This is used to create pointwise confidence intervals. Note that this differs slightly from the `pointwisebound.noboot` function, which estimates the variance of the conditional regression line given by $E(Y|S,W=w)$, where w is a vector of medians of W (i.e. predictions are made at the median value of all covariates).

Value

A data frame containing

- **linpred**: The linear predictor from the marginal structural model
- **rr/or/mean.diff**: The canonical effect measure (risk ratio/odds ratio/mean difference) for the marginal structural model link
- **se....**: the standard error of the effect measure
- **ul.../ll....**: Confidence bounds for the effect measure, and bounds centered at the linear predictor (for plotting purposes)

See Also

- `qgcomp.glm.boot`
- `pointwisebound.noboot`
Examples

```r
set.seed(12)
## Not run:
n=100
# non-linear model for continuous outcome
dat <- data.frame(x1=(x1 <- runif(100)), x2=runif(100), x3=runif(100), z=runif(100),
                  y=runif(100)+x1+x1^2)
ft <- qgcomp.glm.boot(y ~ z + x1 + x2 + x3, expnms=c('x1','x2','x3'), data=dat, q=10)
pointwisebound.boot(ft, alpha=0.05, pointwiseref=3)
## End(Not run)
```

pointwisebound.noboot  

Estimating pointwise comparisons for qgcomp.glm.noboot objects

Description

Calculates: expected outcome (on the link scale), mean difference (link scale) and the standard error of the mean difference (link scale) for pointwise comparisons.

Usage

```r
pointwisebound.noboot(x, alpha = 0.05, pointwiseref = 1)
```

Arguments

- `x`: "qgcompfit" object from `qgcomp.glm.noboot`
- `alpha`: alpha level for confidence intervals
- `pointwiseref`: referent quantile (e.g. 1 uses the lowest joint-exposure category as the referent category for calculating all mean differences/standard deviations)

Details

The comparison of interest following a qgcomp fit is often comparisons of model predictions at various values of the joint-exposures (e.g. expected outcome at all exposures at the 1st quartile vs. the 3rd quartile). The expected outcome at a given joint exposure and at a given level of non-exposure covariates (W=w) is given as E(Y|S,W=w), where S takes on integer values 0 to q-1. Thus, comparisons are of the type E(Y|S=s,W=w) - E(Y|S=s2,W=w) where s and s2 are two different values of the joint exposures (e.g. 0 and 2). This function yields E(Y|S,W=w) as well as E(Y|S=s,W=w) - E(Y|S=p,W=w) where s is any value of S and p is the value chosen via "pointwiseref" - e.g. for binomial variables this will equal the risk/prevalence difference at all values of S, with the referent category S=p-1. For the non-bootstrapped version of quantile g-computation (under a linear model). Note that w is taken to be the referent level of covariates so that if meaningful values of E(Y|S,W=w) and E(Y|S=s,W=w) - E(Y|S=p,W=w) are desired, then it is advisable to set the referent levels of W to meaningful values. This can be done by, e.g. centering continuous age so that the predictions are made at the population mean age, rather than age 0.
Note that function only works with standard "qgcompfit" objects from qgcomp glm noboot (so it doesn’t work with zero inflated, hurdle, or Cox models).

Variance for the overall effect estimate is given by: \( \text{transpose}(G) \text{Cov}(\beta)G \)

Where the "gradient vector" \( G \) is given by

\[
G = [\partial(f(\beta))/\partial \beta_1 = 1, \ldots, \partial(f(\beta))/\partial \beta_k = 1]
\]

\( f(\beta) = \sum\beta_i \), and \( \partial y / \partial x \) denotes the partial derivative/gradient. The vector \( G \) takes on values that equal the difference in quantiles of \( S \) for each pointwise comparison (e.g. for a comparison of the 3rd vs the 5th category, \( G \) is a vector of 2s).

This variance is used to create pointwise confidence intervals via a normal approximation: (e.g. upper 95% CI = \( \psi \) + variance*1.96)

Value

A data frame containing

- **hx**: The "partial" linear predictor \( \beta_0 + \psi \sum_j X_j w_j \), or the effect of the mixture + intercept after conditioning out any confounders. This is similar to the \( h(x) \) function in bkmr. This is not a full prediction of the outcome, but only the partial outcome due to the intercept and the confounders.

- **rr/or/mean.diff**: The canonical effect measure (risk ratio/odds ratio/mean difference) for the marginal structural model link

- **se/...**: The standard error of the effect measure

- **ul/ll/...**: Confidence bounds for the effect measure

See Also

- qgcomp glm noboot, pointwisebound.boot

Examples

```r
set.seed(12)
## Not run:
n = 100
data.frame(x1=(x1 <- runif(n)), x2=(x2 <- runif(n)),
            x3=(x3 <- runif(n)), z=(z <- runif(n)),
y=rnorm(n)+x1 + x2 - x3 +z)

# linear model for continuous outcome
ft <- qgcomp glm noboot(y ~ z + x1 + x2 + x3,
                         expnms=c('x1','x2','x3'), data=dat, q=10)
ft2 <- qgcomp glm boot(y ~ z + x1 + x2 + x3,
                        expnms=c('x1','x2','x3'), data=dat, q=10)
pointwisebound noboot(ft, alpha=0.05, pointwiseref=3)
pointwisebound.boot(ft2, alpha=0.05, pointwiseref=3)

dat <- data.frame(x1=(x1 <- runif(n)), x2=(x2 <- runif(n)),
                  x3=(x3 <- runif(n)), z=(z <- runif(n)),
y=rbinom(n, 1, 1/(1+exp(-(x1 + x2 - x3 +z)))))

# glms for binary outcome, centering covariate to a potentially more meaningful value
dat$zcen = dat$z - mean(dat$z)
```
predict.qgcompfit

Default prediction method for a qgcompfit object (non-survival outcomes only)

Description

get predicted values from a qgcompfit object, or make predictions in a new set of data based on the qgcompfit object. Note that when making predictions from an object from qgcomp.glm.boot, the predictions are made from the (conditional) g-computation model rather than the marginal structural model. Predictions from the marginal structural model can be obtained via msm.predict. Note that this function accepts non-quantized exposures in "newdata" and automatically quantizes them according to the quantile cutpoints in the original fit.

Usage

## S3 method for class 'qgcompfit'
predict(object, expnms = NULL, newdata = NULL, type = "response", ...)

Arguments

object "qgcompfit" object from qgcomp.glm.noboot, qgcomp.glm.boot, qgcomp.zi.noboot, or qgcomp.zi.bootfunctions

expnms character vector of exposures of interest

newdata (optional) new set of data with all predictors from "qgcompfit" object

type (from predict.glm) the type of prediction required. The default is on the scale of the linear predictors; the alternative "response" is on the scale of the response variable. Thus for a default binomial model the default predictions are of logits (probabilities on logit scale) and type = "response" gives the predicted probabilities. The "terms" option returns a matrix giving the fitted values of each term in the model formula on the linear predictor scale.

... arguments to predict.glm
Examples

```r
set.seed(50)
dat <- data.frame(y=runif(50), x1=runif(50), x2=runif(50), z=runif(50))
obj1 <- qgcomp.glm.noboot(y ~ z + x1 + x2, expnms = c('x1', 'x2'), data=dat, q=2)
obj2 <- qgcomp.glm.boot(y ~ z + x1 + x2, expnms = c('x1', 'x2'), data=dat, q=2, B=10, seed=125)
set.seed(52)
dat2 <- data.frame(y=runif(50), x1=runif(50), x2=runif(50), z=runif(50))
summary(predict(obj1, expnms = c('x1', 'x2'), newdata=dat2))
summary(predict(obj2, expnms = c('x1', 'x2'), newdata=dat2))
```

print.qgcompfit

Default printing method for a qgcompfit object

Description

Gives variable output depending on whether `qgcomp.glm.noboot` or `qgcomp.glm.boot` is called. For `qgcomp.glm.noboot` will output final estimate of joint exposure effect (similar to the 'index' effect in weighted quantile sums), as well as estimates of the 'weights' (standardized coefficients). For `qgcomp.glm.boot`, the marginal effect is given, but no weights are reported since this approach generally incorporates non-linear models with interaction terms among exposures, which preclude weights with any useful interpretation.

Usage

```r
## S3 method for class 'qgcompfit'
print(x, showweights = TRUE, ...)
```

Arguments

- `x`: "qgcompfit" object from `qgcomp`, `qgcomp.glm.noboot` or `qgcomp.glm.boot` function
- `showweights`: logical: should weights be printed, if estimated?
- `...`: unused

See Also

`qgcomp.glm.noboot`, `qgcomp.glm.boot`, and `qgcomp`

Examples

```r
set.seed(50)
dat <- data.frame(y=runif(50), x1=runif(50), x2=runif(50), z=runif(50))
obj1 <- qgcomp.glm.noboot(y ~ z + x1 + x2, expnms = c('x1', 'x2'), data=dat, q=2)
obj2 <- qgcomp.glm.boot(y ~ z + x1 + x2, expnms = c('x1', 'x2'), data=dat, q=2, B=10, seed=125)
# does not need to be explicitly called, but included here for clarity
print(obj1)
print(obj2)
```
Description

This function automatically selects between qgcomp.glm.noboot, qgcomp.glm.boot, qgcomp.cox.noboot, and qgcomp.cox.boot for the most efficient approach to estimate the average expected change in the (log) outcome per quantile increase in the joint exposure to all exposures in expnms’, given the underlying model. For example, if the underlying model (specified by the formula f) is a linear model with all linear terms for exposure, then qgcomp.glm.noboot will be called to fit the model. Non-linear terms or requesting the risk ratio for binomial outcomes will result in the qgcomp.glm.boot function being called. For a given linear model, boot and noboot versions will give identical inference, though when using survival outcomes, the ‘boot’ version uses simulation based inference, which can vary from the ‘noboot’ version due to simulation error (which can be minimized via setting the MCsize parameter very large - see qgcomp.cox.boot for details).

Usage

qgcomp(f, data = data, family = gaussian(), rr = TRUE, ...)

Arguments

f R style formula (may include survival outcome via Surv)
data data framefamily gaussian(), binomial(), cox(), poisson() (works as argument to ‘family’ parameter in glm or ‘dist’ parameter in zeroinfl)rr logical: if using binary outcome and rr=TRUE, qgcomp.glm.boot will estimate risk ratio rather than odds ratio. Note, to get population average effect estimates for a binary outcome, set rr=TRUE (default: ORs are generally not of interest as population average effects, so if rr=FALSE then a conditional OR will be estimated, which cannot be interpreted as a population average effect... arguments to qgcomp.glm.noboot or qgcomp.glm.boot (e.g. q) or glm

Value

a qgcompfit object, which contains information about the effect measure of interest (psi) and associated variance (var.psi), as well as information on the model fit (fit) and possibly information on the marginal structural model (mmsfit) used to estimate the final effect estimates (qgcomp.glm.boot, qgcomp.cox.boot only). If appropriate, weights are also reported, which represent the proportion of a directional (positive/negative) effect that is accounted for by each exposure.

See Also

qgcomp.glm.noboot, qgcomp.glm.boot, qgcomp.cox.noboot, qgcomp.cox.boot qgcomp.zi.noboot and qgcomp.zi.boot (qgcomp is just a wrapper for these functions)
Examples

```r
set.seed(50)
dat <- data.frame(y=runif(50), x1=runif(50), x2=runif(50), z=runif(50))
qgcomp.glm.noboot(y ~ z + x1 + x2, expnms = c('x1', 'x2'), data=dat, q=2)
qgcomp.glm.boot(y ~ z + x1 + x2, expnms = c('x1', 'x2'), data=dat, q=2, B=10, seed=125)
# automatically selects appropriate method
qgcomp(y ~ z + x1 + x2, expnms = c('x1', 'x2'), data=dat, q=2)
# note for binary outcome this will choose the risk ratio (and bootstrap methods) by default
dat <- data.frame(y=rbinom(100, 1, 0.5), x1=runif(100), x2=runif(100), z=runif(100))
## Not run:
qgcomp.glm.noboot(y ~ z + x1 + x2, expnms = c('x1', 'x2'), data=dat, q=2, family=binomial())
set.seed(1231)
qgcomp.glm.boot(y ~ z + x1 + x2, expnms = c('x1', 'x2'), data=dat, q=2, family=binomial())
set.seed(1231)
qgcomp(y ~ z + x1 + x2, expnms = c('x1', 'x2'), data=dat, q=2, family=binomial())

# automatically selects appropriate method when specifying rr or degree explicitly
qgcomp(y ~ z + x1 + x2, expnms = c('x1', 'x2'), data=dat, q=2, family=binomial(), rr=FALSE)
qgcomp(y ~ z + x1 + x2, expnms = c('x1', 'x2'), data=dat, q=2, family=binomial(), rr=TRUE)
qgcomp(y ~ z + factor(x1) + factor(x2), degree=2, expnms = c('x1', 'x2'), data=dat, q=4, family=binomial())

# survival objects
set.seed(50)
N=200
dat <- data.frame(time=(tmg <- pmin(.1,rweibull(N, 10, 0.1))),
d=1.0*(tmg<0.1), x1=runif(N), x2=runif(N), z=runif(N))
expnms=paste0("x", 1:2)
f = survival::Surv(time, d)~x1 + x2
qgcomp(f, expnms = expnms, data = dat)
# note if B or MCsize are set but the model is linear, an error will result
try(qgcomp(f, expnms = expnms, data = dat, B=1, MCsize))
# note that in the survival models, MCsize should be set to a large number
# such that results are repeatable (within an error tolerance such as 2 significant digits)
# if you run them under different seed values
f = survival::Surv(time, d)~x1 + x2 + x1:x2
qgcomp(f, expnms = expnms, data = dat, B=10, MCsize=100)
```

## Description

This function performs quantile g-computation in a survival setting. The approach estimates the covariate-conditional hazard ratio for a joint change of 1 quantile in each exposure variable specified in expnms parameter.
Usage

```r
qgcomp.cch.noboot(
  f,
  data,
  subcoh = NULL,
  id = NULL,
  cohort.size = NULL,
  expnms = NULL,
  q = 4,
  breaks = NULL,
  weights,
  cluster = NULL,
  alpha = 0.05,
  ...
)
```

Arguments

- **f**: R style survival formula, which includes `Surv` in the outcome definition. E.g. `Surv(time,event) ~ exposure`. Offset terms can be included via `Surv(time,event) ~ exposure + offset(z)`
- **data**: data frame
- **subcoh**: (From `cch` help) Vector of indicators for subjects sampled as part of the sub-cohort. Code 1 or TRUE for members of the sub-cohort, 0 or FALSE for others. If `data` is a data frame then `subcoh` may be a one-sided formula.
- **id**: (From `cch` help) Vector of unique identifiers, or formula specifying such a vector.
- **cohort.size**: (From `cch` help) Vector with size of each stratum original cohort from which subcohort was sampled
- **expnms**: character vector of exposures of interest
- **q**: NULL or number of quantiles used to create quantile indicator variables representing the exposure variables. If NULL, gcomp proceeds with un-transformed version of exposures in the input datasets (useful if data are already transformed, or for performing standard g-computation)
- **breaks**: (optional) NULL, or a list of (equal length) numeric vectors that characterize the minimum value of each category for which to break up the variables named in `expnms`. This is an alternative to using ‘q’ to define cutpoints.
- **weights**: Not used here
- **cluster**: not yet implemented
- **alpha**: alpha level for confidence limit calculation
- **...**: arguments to glm (e.g. family)

Details

For survival outcomes (as specified using methods from the survival package), this yields a conditional log hazard ratio representing a change in the expected conditional hazard (conditional on
covariates) from increasing every exposure by 1 quantile. In general, this quantity is not equivalent to g-computation estimates. Hypothesis test statistics and 95% confidence intervals are based on using the delta estimate variance of a linear combination of random variables.

Value

A qgcompfit object, which contains information about the effect measure of interest (psi) and associated variance (var.psi), as well as information on the model fit (fit) and information on the weights/standardized coefficients in the positive (pos.weights) and negative (neg.weights) directions.

See Also

Other qgcomp_methods: qgcomp.cox.boot(), qgcomp.cox.noboot(), qgcomp.glm.boot(), qgcomp.glm.noboot(), qgcomp.hurdle.boot(), qgcomp.hurdle.noboot(), qgcomp.multinomial.boot(), qgcomp.multinomial.noboot(), qgcomp.partials(), qgcomp.zi.boot(), qgcomp.zi.noboot()

Examples

set.seed(50)
N=200
dat <- data.frame(time=(tmg <- pmin(.1,rweibull(N, 10, .1))),
d=1.0*(tmg<0.1), x1=runif(N), x2=runif(N), z=runif(N))
expnms=paste0("x", 1:2)
f = survival::Surv(time, d)-x1 + x2
(fit1 <- survival::coxph(f, data = dat))
(obj <- qgcomp.cox.noboot(f, expnms = expnms, data = dat))

## Not run:
# weighted analysis
dat$w = runif(N)
qudata = quantize(dat, expnms=expnms)
(obj2 <- qgcomp.cox.noboot(f, expnms = expnms, data = dat, weight=w))
obj2$fit

survival::coxph(f, data = qdata$data, weight=w)

# not run: bootstrapped version is much slower
(obj2 <- qgcomp.cox.boot(f, expnms = expnms, data = dat, B=2000, MCsize=20000))

## End(Not run)
Usage

```r
qgcomp.cox.boot(
  f,
  data,
  expnms = NULL,
  q = 4,
  breaks = NULL,
  id = NULL,
  weights,
  cluster = NULL,
  alpha = 0.05,
  B = 200,
  MCsize = 10000,
  degree = 1,
  seed = NULL,
  parallel = FALSE,
  parplan = FALSE,
  ...
)
```

Arguments

- **f**: R style survival formula, which includes `Surv` in the outcome definition. E.g. `Surv(time,event) ~ exposure`. Offset terms can be included via `Surv(time,event) ~ exposure + offset(z)`.
- **data**: data frame
- **expnms**: character vector of exposures of interest
- **q**: NULL or number of quantiles used to create quantile indicator variables representing the exposure variables. If NULL, then gcomp proceeds with untransformed version of exposures in the input datasets (useful if data are already transformed, or for performing standard g-computation).
- **breaks**: (optional) NULL, or a list of (equal length) numeric vectors that characterize the minimum value of each category for which to break up the variables named in `expnms`. This is an alternative to using 'q' to define cutpoints.
- **id**: (optional) NULL, or variable name indexing individual units of observation (only needed if analyzing data with multiple observations per id/cluster). Note that `qgcomp glm noboot` will not produce cluster-appropriate standard errors. `qgcomp glm boot` can be used for this, which will use bootstrap sampling of clusters/individuals to estimate cluster-appropriate standard errors via bootstrapping.
- **weights**: "case weights" - passed to the "weight" argument of `coxph`
- **cluster**: not yet implemented
- **alpha**: alpha level for confidence limit calculation
- **B**: integer: number of bootstrap iterations (this should typically be >=200, though it is set lower in examples to improve run-time).
qgcomp.cox.boot

MCsize integer: sample size for simulation to approximate marginal hazards ratios (if < sample size, then set to sample size). Note that large values will slow down the fitting, but will result in higher accuracy - if you run the function multiple times you will see that results vary due to simulation error. Ideally, MCsize would be set such that simulation error is negligible in the precision reported (e.g. if you report results to 2 decimal places, then MCsize should be set high enough that you consistently get answers that are the same to 2 decimal places).

degree polynomial bases for marginal model (e.g. degree = 2 allows that the relationship between the whole exposure mixture and the outcome is quadratic.

seed integer or NULL: random number seed for replicable bootstrap results

parallel logical (default FALSE): use future package to speed up bootstrapping

parplan (logical, default=FALSE) automatically set future::plan to plan(multisession) (and set to existing plan, if any, after bootstrapping)

... arguments to glm (e.g. family)

Details

qgcomp.cox.boot estimates the log(hazard ratio) per quantile increase in the joint exposure to all exposures in expnms'. This function uses g-computation to estimate the parameters of a marginal structural model for the population average effect of increasing all exposures in 'expnms' by a single quantile. This approach involves specifying an underlying conditional outcome model, given all exposures of interest (possibly with non-linear basis function representations such as splines or product terms) and confounders or covariates of interest. This model is fit first, which is used to generate expected outcomes at each quantile of all exposures, which is then used in a second model to estimate a population average dose-response curve that is linear or follows a simple polynomial function. See section on MCSize below

Test statistics and confidence intervals are based on a non-parametric bootstrap, using the standard deviation of the bootstrap estimates to estimate the standard error. The bootstrap standard error is then used to estimate Wald-type confidence intervals. Note that no bootstrapping is done on estimated quantiles of exposure, so these are treated as fixed quantities

MCSize is crucial to get accurate point estimates. In order to get marginal estimates of the population hazard under different values of the joint exposure at a given quantile for all exposures in expnms, qgcomp.cox.boot uses Monte Carlo simulation to generate outcomes implied by the underlying conditional model and then fit a separate (marginal structural) model to those outcomes. In order to get accurate results that don’t vary much from run-to-run of this approach, MCSize must be set large enough so that results are stable across runs according to a pre-determined precision (e.g. 2 significant digits).

Value

a qgcompfit object, which contains information about the effect measure of interest (psi) and associated variance (var.psi), as well as information on the model fit (fit) and information on the marginal structural model (msmfit) used to estimate the final effect estimates.

See Also

Other qgcomp_methods: qgcomp.cch.noboot(), qgcomp.cox.noboot(), qgcomp.glm.boot(), qgcomp.glm.noboot(), qgcomp.hurdle.boot(), qgcomp.hurdle.noboot(), qgcomp.multinomial.boot(),
Examples

```r
set.seed(50)
N=200
dat <- data.frame(time=(tmg <- pmin(.1,rweibull(N, 10, 0.1))),
                  d=1.0*(tmg<0.1), x1=runif(N), x2=runif(N), z=runif(N))
expnms=paste0("x", 1:2)
f = survival::Surv(time, d)~x1 + x2
(fit1 <- survival::coxph(f, data = dat))
(obj <- qgcomp.cox.noboot(f, expnms = expnms, data = dat))
## Not run:
# not run (slow when using boot version to proper precision)
(obj2 <- qgcomp.cox.boot(f, expnms = expnms, data = dat, B=10, MCsize=20000))
# weighted analysis
# using future package, marginalizing over confounder z
(obj3 <- qgcomp.cox.boot(survival::Surv(time, d)~x1 + x2 + z, expnms = expnms, data = dat,
                         B=1000, MCsize=20000, parallel=TRUE, parplan=TRUE))
# non-constant hazard ratio, non-linear terms
(obj4 <- qgcomp.cox.boot(survival::Surv(time, d)~factor(x1) + splines::bs(x2) + z,
                         expnms = expnms, data = dat,
                         B=1000, MCsize=20000, parallel=FALSE, degree=1))
# weighted analysis
dat$w = runif(N)
(objw1 <- qgcomp.cox.noboot(f, expnms = expnms, data = dat, weights=w))
(objw2 <- qgcomp.cox.boot(f, expnms = expnms, data = dat, weights=w, B=5, MCsize=20000))
## End(Not run)
```

---

**qgcomp.cox.noboot**

Quantile g-computation for survival outcomes under linearity/additivity

**Description**

This function performs quantile \(g\)-computation in a survival setting. The approach estimates the covariate-conditional hazard ratio for a joint change of 1 quantile in each exposure variable specified in `expnms` parameter.

**Usage**

```r
qgcomp.cox.noboot(
  f,
  data,
  expnms = NULL,
  q = 4,
  ...)
```
breaks = NULL,
id = NULL,
weights,
cluster = NULL,
alpha = 0.05,
...
)

Arguments

f R style survival formula, which includes Surv in the outcome definition. E.g. Surv(time, event) ~ exposure. Offset terms can be included via Surv(time, event) ~ exposure + offset(z)

data data frame
expnms character vector of exposures of interest
q NULL or number of quantiles used to create quantile indicator variables representing the exposure variables. If NULL, then gcomp proceeds with untransformed version of exposures in the input datasets (useful if data are already transformed, or for performing standard g-computation)
breaks (optional) NULL, or a list of (equal length) numeric vectors that characterize the minimum value of each category for which to break up the variables named in expnms. This is an alternative to using 'q' to define cutpoints.
id (optional) NULL, or variable name indexing individual units of observation (only needed if analyzing data with multiple observations per id/cluster)
weights "case weights" - passed to the "weight" argument of coxph
cluster not yet implemented
alpha alpha level for confidence limit calculation
...
arguments to glm (e.g. family)

Details

For survival outcomes (as specified using methods from the survival package), this yields a conditional log hazard ratio representing a change in the expected conditional hazard (conditional on covariates) from increasing every exposure by 1 quantile. In general, this quantity quantity is not equivalent to g-computation estimates. Hypothesis test statistics and 95% confidence intervals are based on using the delta estimate variance of a linear combination of random variables.

Value

a qgcompfit object, which contains information about the effect measure of interest (psi) and associated variance (var.psi), as well as information on the model fit (fit) and information on the weights/standardized coefficients in the positive (pos.weights) and negative (neg.weights) directions.
Quantile g-computation for continuous and binary outcomes

Description

This function estimates a dose-response parameter representing a one quantile increase in a set of exposures of interest. This model estimates the parameters of a marginal structural model (MSM) based on g-computation with quantized exposures. Note: this function allows non-linear and non-additive effects of individual components of the exposure, as well as non-linear joint effects of the mixture via polynomial basis functions, which increase the computational burden due to the need for non-parametric bootstrapping. qgcomp.boot is an equivalent function (slated for deprecation).

Usage

qgcomp.glm.boot(
  f,
  data,
)
qgcomp.boot(  
  f,  
  data,  
  expnms = NULL,  
  q = 4,  
  breaks = NULL,  
  id = NULL,  
  weights,  
  alpha = 0.05,  
  B = 200,  
  rr = TRUE,  
  degree = 1,  
  seed = NULL,  
  bayes = FALSE,  
  MCsize = nrow(data),  
  parallel = FALSE,  
  parplan = FALSE,  
  ...  
)

Arguments

f R style formula
data data frame
expnms character vector of exposures of interest
q NULL or number of quantiles used to create quantile indicator variables representing the exposure variables. If NULL, then gcomp proceeds with untransformed version of exposures in the input datasets (useful if data are already transformed, or for performing standard g-computation)
breaks (optional) NULL, or a list of (equal length) numeric vectors that characterize the minimum value of each category for which to break up the variables named in
expnms. This is an alternative to using 'q' to define cutpoints.

id (optional) NULL, or variable name indexing individual units of observation (only needed if analyzing data with multiple observations per id/cluster). Note that qgcomp.glm.noboot will not produce cluster-appropriate standard errors. qgcomp.glm.boot can be used for this, which will use bootstrap sampling of clusters/individuals to estimate cluster-appropriate standard errors via bootstrapping.

weights "case weights" - passed to the "weight" argument of glm or bayesglm

alpha alpha level for confidence limit calculation

B integer: number of bootstrap iterations (this should typically be >=200, though it is set lower in examples to improve run-time).

rr logical: if using binary outcome and rr=TRUE, qgcomp.glm.boot will estimate risk ratio rather than odds ratio

degree polynomial bases for marginal model (e.g. degree = 2 allows that the relationship between the whole exposure mixture and the outcome is quadratic (default = 1).

seed integer or NULL: random number seed for replicable bootstrap results

bayes use underlying Bayesian model (arm package defaults). Results in penalized parameter estimation that can help with very highly correlated exposures. Note: this does not lead to fully Bayesian inference in general, so results should be interpreted as frequentist.

MCsize integer: sample size for simulation to approximate marginal zero inflated model parameters. This can be left small for testing, but should be as large as needed to reduce simulation error to an acceptable magnitude (can compare psi coefficients for linear fits with qgcomp.glm.noboot to gain some intuition for the level of expected simulation error at a given value of MCsize). This likely won’t matter much in linear models, but may be important with binary or count outcomes.

parallel use (safe) parallel processing from the future and future.apply packages

parplan (logical, default=FALSE) automatically set future::plan to plan(multisession) (and set to existing plan, if any, after bootstrapping)

... arguments to glm (e.g. family)

Details

Estimates correspond to the average expected change in the (log) outcome per quantile increase in the joint exposure to all exposures in ‘expnms’. Test statistics and confidence intervals are based on a non-parametric bootstrap, using the standard deviation of the bootstrap estimates to estimate the standard error. The bootstrap standard error is then used to estimate Wald-type confidence intervals. Note that no bootstrapping is done on estimated quantiles of exposure, so these are treated as fixed quantities.

Value

a qgcompfit object, which contains information about the effect measure of interest (psi) and associated variance (var.psi), as well as information on the model fit (fit) and information on the marginal structural model (msmfit) used to estimate the final effect estimates.
See Also

Other qgcomp_methods: qgcomp.cch.noboot(), qgcomp.cox.boot(), qgcomp.cox.noboot(), qgcomp.glm.noboot(), qgcomp.hurdle.boot(), qgcomp.hurdle.noboot(), qgcomp.multinomial.boot(), qgcomp.multinomial.noboot(), qgcomp.partials(), qgcomp.zi.boot(), qgcomp.zi.noboot()

Examples

set.seed(30)
# continuous outcome
dat <- data.frame(y=rnorm(100), x1=runif(100), x2=runif(100), z=runif(100))
# Conditional linear slope
qgcomp.glm.noboot(y ~ z + x1 + x2, expnms = c('x1', 'x2'), data=dat, q=4, family=gaussian())
# Marginal linear slope (population average slope, for a purely linear, # additive model this will equal the conditional)
## Not run:
qgcomp.glm.boot(f=y ~ z + x1 + x2, expnms = c('x1', 'x2'), data=dat, q=4, 
family=gaussian(), B=200) # B should be at least 200 in actual examples
# no intercept model
qgcomp.glm.boot(f=y ~ -1+z + x1 + x2, expnms = c('x1', 'x2'), data=dat, q=4, 
family=gaussian(), B=200) # B should be at least 200 in actual examples

# Note that these give different answers! In the first, the estimate is conditional on Z, # but in the second, Z is marginalized over via standardization. The estimates # can be made approximately the same by centering Z (for linear models), but # the conditional estimate will typically have lower standard errors.
dat$z = dat$z - mean(dat$z)
# Conditional linear slope
qgcomp.glm.noboot(y ~ z + x1 + x2, expnms = c('x1', 'x2'), data=dat, q=4, family=gaussian())
# Marginal linear slope (population average slope, for a purely linear, # additive model this will equal the conditional)
qgcomp.glm.boot(f=y ~ z + x1 + x2, expnms = c('x1', 'x2'), data=dat, q=4, 
family=gaussian(), B=200) # B should be at least 200 in actual examples

# Population average mixture slope which accounts for non-linearity and interactions qgcomp.glm.boot(y ~ z + x1 + x2 + I(x1^2) + I(x2*x1), family="gaussian", 
expnms = c('x1', 'x2'), data=dat, q=4, B=200)
# generally non-linear/non-additive underlying models lead to non-linear mixture slopes qgcomp.glm.boot(y ~ z + x1 + x2 + I(x1^2) + I(x2*x1), family="gaussian", 
expnms = c('x1', 'x2'), data=dat, q=4, B=200, deg=2)
# binary outcome
dat <- data.frame(y=rbinom(50,1,0.5), x1=runif(50), x2=runif(50), z=runif(50))
# Conditional mixture OR
qgcomp.glm.noboot(y ~ z + x1 + x2, family="binomial", expnms = c('x1', 'x2'), 
data=dat, q=2)
#Marginal mixture OR (population average OR - in general, this will not equal the # conditional mixture OR due to non-collapsibility of the OR)
qgcomp.glm.boot(y ~ z + x1 + x2, family="binomial", expnms = c('x1', 'x2'), data=dat, q=2, B=3, rr=FALSE)

# Population average mixture RR
qgcomp.glm.boot(y ~ z + x1 + x2, family="binomial", expnms = c('x1', 'x2'), data=dat, q=2, rr=TRUE, B=3)

# Population average mixture RR, indicator variable representation of x2
# note that I(x==...) operates on the quantile-based category of x,
# rather than the raw value
res = qgcomp.glm.boot(y ~ z + I(x2==1) + I(x2==2) + I(x2==3),
family="binomial", expnms = c('x1', 'x2'), data=dat, q=4, rr=TRUE, B=200)
res$fit
plot(res)

# now add in a non-linear MSM
res2 = qgcomp.glm.boot(y ~ z + x1 + I(x2==1) + I(x2==2) + I(x2==3),
family="binomial", expnms = c('x1', 'x2'), data=dat, q=4, rr=TRUE, B=200,
degree=2)
res2$fit
res2$msmfit # correct point estimates, incorrect standard errors
res2 # correct point estimates, correct standard errors
plot(res2)

# Log risk ratio per one IQR change in all exposures (not on quantile basis)
dat$x1iqr <- dat$x1/with(dat, diff(quantile(x1, c(.25, .75))))
dat$x2iqr <- dat$x2/with(dat, diff(quantile(x2, c(.25, .75))))
# note that I(x>...) now operates on the untransformed value of x,
# rather than the quantized value
res2 = qgcomp.glm.boot(y ~ z + x1iqr + I(x2iqr>0.1) + I(x2>0.4) + I(x2>0.9),
family="binomial", expnms = c('x1iqr', 'x2iqr'), data=dat, q=NULL, rr=TRUE, B=200,
degree=2)
res2
# using parallel processing
qgcomp.glm.boot(y ~ z + x1iqr + I(x2iqr>0.1) + I(x2>0.4) + I(x2>0.9),
family="binomial", expnms = c('x1iqr', 'x2iqr'), data=dat, q=NULL, rr=TRUE, B=200,
degree=2, parallel=TRUE, parplan=TRUE)

# weighted model
N=5000
dat4 <- data.frame(id=seq_len(N), x1=runif(N), x2=runif(N), z=runif(N))
dat4$y <- with(dat4, rnorm(N, x1*z + z, 1))
dat4$w=runif(N) + dat4$z*5
qdata = quantize(dat4, expnms = c("x1", "x2"), q=4)$data
# first equivalent models with no covariates
qgcomp.glm.noboot(f=y ~ x1 + x2, expnms = c('x1', 'x2'), data=dat4, q=4, family=gaussian())
qgcomp.glm.noboot(f=y ~ x1 + x2, expnms = c('x1', 'x2'), data=dat4, q=4, family=gaussian(),
weights=w)
set.seed(13)
qgcomp.glm.boot(f=y ~ x1 + x2, expnms = c('x1', 'x2'), data=dat4, q=4, family=gaussian(),
weights=w)
```r
# using the correct model
set.seed(13)
qgcomp.glm.boot(f=y ~ x1*z + x2, expnms = c('x1', 'x2'), data=dat4, q=4, family=gaussian(),
weights=w, id="id")
(qgcfit <- qgcomp.glm.boot(f=y ~ z + x1 + x2, expnms = c('x1', 'x2'), data=dat4, q=4,
family=gaussian(), weights=w))
qgcfit$fit
summary(glm(y ~ z + x1 + x2, data = qdata, weights=w))

## End(Not run)
```

---

**qgcomp.glm.noboot**

Quantile g-computation for continuous, binary, and count outcomes under linearity/additivity

### Description

This function estimates a linear dose-response parameter representing a one quantile increase in a set of exposures of interest. This function is limited to linear and additive effects of individual components of the exposure. This model estimates the parameters of a marginal structural model (MSM) based on g-computation with quantized exposures. Note: this function is valid only under linear and additive effects of individual components of the exposure, but when these hold the model can be fit with very little computational burden. qgcomp.noboot is an equivalent function (slated for deprecation)

### Usage

```r
qgcomp.glm.noboot(
  f,
  data,
  expnms = NULL,
  q = 4,
  breaks = NULL,
  id = NULL,
  weights,
  alpha = 0.05,
  bayes = FALSE,
  ...)
```

```r
qgcomp.noboot(
  f,
  data,
  expnms = NULL,
  q = 4,
  breaks = NULL,
  id = NULL,
  weights,
  ...)
```
alpha = 0.05,
bayes = FALSE,
...
)

Arguments

f
R style formula
data
data frame
expnms
character vector of exposures of interest
q
NULL or number of quantiles used to create quantile indicator variables representing the exposure variables. If NULL, then gcomp proceeds with untransformed version of exposures in the input datasets (useful if data are already transformed, or for performing standard g-computation)
breaks
(optional) NULL, or a list of (equal length) numeric vectors that characterize the minimum value of each category for which to break up the variables named in expnms. This is an alternative to using 'q' to define cutpoints.
id
(optional) NULL, or variable name indexing individual units of observation (only needed if analyzing data with multiple observations per id/cluster). Note that qgcomp.glm.noboot will not produce cluster-appropriate standard errors (this parameter is essentially ignored in qgcomp.glm.noboot). qgcomp.glm.boot can be used for this, which will use bootstrap sampling of clusters/individuals to estimate cluster-appropriate standard errors via bootstrapping.
weights
"case weights" - passed to the "weight" argument of glm or bayesglm
alpha
alpha level for confidence limit calculation
bayes
use underlying Bayesian model (arm package defaults). Results in penalized parameter estimation that can help with very highly correlated exposures. Note: this does not lead to fully Bayesian inference in general, so results should be interpreted as frequentist.
...
arguments to glm (e.g. family)

Details

For continuous outcomes, under a linear model with no interaction terms, this is equivalent to g-computation of the effect of increasing every exposure by 1 quantile. For binary/count outcomes outcomes, this yields a conditional log odds/rate ratio(s) representing the change in the expected conditional odds/rate (conditional on covariates) from increasing every exposure by 1 quantile. In general, the latter quantity is not equivalent to g-computation estimates. Hypothesis test statistics and confidence intervals are based on using the delta estimate variance of a linear combination of random variables.

Value

a qgcompfit object, which contains information about the effect measure of interest (psi) and associated variance (var.psi), as well as information on the model fit (fit) and information on the weights/standardized coefficients in the positive (pos.weights) and negative (neg.weights) directions.
See Also

Other qgcomp_methods: qgcomp.cch.noboot(), qgcomp.cox.boot(), qgcomp.cox.noboot(), qgcomp.glm.boot(), qgcomp.hurdle.boot(), qgcomp.hurdle.noboot(), qgcomp.multinomial.boot(), qgcomp.multinomial.noboot(), qgcomp.partials(), qgcomp.zi.boot(), qgcomp.zi.noboot()

Examples

set.seed(50)
# linear model
dat <- data.frame(y=runif(50,-1,1), x1=runif(50), x2=runif(50), z=runif(50))
qgcomp.glm.noboot(f=y ~ z + x1 + x2, expnms = c('x1', 'x2'), data=dat, q=2, family=gaussian())
# not intercept model
qgcomp.glm.noboot(f=y ~-1 + z + x1 + x2, expnms = c('x1', 'x2'), data=dat, q=2, family=gaussian())
# logistic model
dat2 <- data.frame(y=rbinom(50, 1,0.5), x1=runif(50), x2=runif(50), z=runif(50))
qgcomp.glm.noboot(f=y ~ z + x1 + x2, expnms = c('x1', 'x2'), data=dat2, q=2, family=binomial())
# poisson model
dat3 <- data.frame(y=rpois(50, .5), x1=runif(50), x2=runif(50), z=runif(50))
qgcomp.glm.noboot(f=y ~ z + x1 + x2, expnms = c('x1', 'x2'), data=dat3, q=2, family=poisson())
# weighted model
N=5000
dat4 <- data.frame(y=runif(N), x1=runif(N), x2=runif(N), z=runif(N))
dat4$w=runif(N)*2
qdata = quantize(dat4, expnms = c("x1", "x2"))$data
(qgcfit <- qgcomp.glm.noboot(f=y ~ z + x1 + x2, expnms = c('x1', 'x2'), data=dat4, q=4,
family=gaussian(), weights=w))
qgcfit$fit
glm(y ~ z + x1 + x2, data = qdata, weights=w)

qgcomp.hurdle.boot     Quantile g-computation for hurdle count outcomes

Description

This function estimates a linear dose-response parameter representing a one quantile increase in a set of exposures of interest for hurdle count outcomes. This function is limited to linear and additive effects of individual components of the exposure. This model estimates the parameters of a marginal structural hurdle count model (MSM) based on g-computation with quantized exposures. Note: this function allows linear and non-additive effects of individual components of the exposure, as well as non-linear joint effects of the mixture via polynomial basis functions, which increase the computational computational burden due to the need for non-parametric bootstrapping.

Usage

qgcomp.hurdle.boot(
  f,
  data,
  expnms = NULL,
q = 4,
breaks = NULL,
id = NULL,
weights,
alpha = 0.05,
B = 200,
degree = 1,
seed = NULL,
bayes = FALSE,
parallel = FALSE,
MCsize = 10000,
msmcontrol = hurdle msm_fit.control(),
parplan = FALSE,
...
)

Arguments

f                  R style formula

data               data frame
expnms             character vector of exposures of interest
q                   NULL or number of quantiles used to create quantile indicator variables representing the exposure variables. If NULL, then gcomp proceeds with untransformed version of exposures in the input datasets (useful if data are already transformed, or for performing standard g-computation)
breaks             (optional) NULL, or a list of (equal length) numeric vectors that characterize the minimum value of each category for which to break up the variables named in expnms. This is an alternative to using 'q' to define cutpoints.
id                 (optional) NULL, or variable name indexing individual units of observation (only needed if analyzing data with multiple observations per id/cluster)
weights            "case weights" - passed to the "weight" argument of hurdle. NOTE - this does not work with parallel=TRUE!
alpha              alpha level for confidence limit calculation
B                  integer: number of bootstrap iterations (this should typically be >=200, though it is set lower in examples to improve run-time).
degree             polynomial basis function for marginal model (e.g. degree = 2 allows that the relationship between the whole exposure mixture and the outcome is quadratic.
seed               integer or NULL: random number seed for replicable bootstrap results
bayes              not currently implemented.
parallel           use (safe) parallel processing from the future and future.apply packages
MCsize             integer: sample size for simulation to approximate marginal zero inflated model parameters. This can be left small for testing, but should be as large as needed to reduce simulation error to an acceptable magnitude (can compare psi coefficients for linear fits with qgcomp.hurdle.noboot to gain some intuition for the level of expected simulation error at a given value of MCsize)
Details

Hurdle count models allow excess zeros in standard count outcome (e.g. Poisson distributed outcomes). Such models have two components: 1) the probability of arising from a degenerate distribution at zero (versus arising from a count distribution) and 2) the rate parameter of a (possibly truncated > 0) count distribution. Thus, one has the option of allowing exposure and covariate effects on the zero distribution, the count distribution, or both. The zero distribution parameters correspond to log-odds ratios for the probability of arising from the zero distribution. Count distribution parameters correspond to log-rate-ratio parameters. Test statistics and confidence intervals are based on a non-parametric bootstrap, using the standard deviation of the bootstrap estimates to estimate the standard error. The bootstrap standard error is then used to estimate Wald-type confidence intervals. Note that no bootstrapping is done on estimated quantiles of exposure, so these are treated as fixed quantities.

Of note, this function yields marginal estimates of the expected outcome under values of the joint exposure quantiles (e.g. the expected outcome if all exposures are below the 1st quartile). These outcomes can be used to derive estimates of the effect on the marginal expectation of the outcome, irrespective of zero/count portions of the statistical model.

Estimates correspond to the average expected change in the (log) outcome per quantile increase in the joint exposure to all exposures in ‘expnms’. Test statistics and confidence intervals are based on a non-parametric bootstrap, using the standard deviation of the bootstrap estimates to estimate the standard error. The bootstrap standard error is then used to estimate Wald-type confidence intervals. Note that no bootstrapping is done on estimated quantiles of exposure, so these are treated as fixed quantities.

Value

A qgcompfit object, which contains information about the effect measure of interest (psi) and associated variance (var.psi), as well as information on the model fit (fit) and information on the marginal structural model (msmfit) used to estimate the final effect estimates.

See Also

Other qgcomp methods: qgcomp.cch.noboot(), qgcomp.cox.boot(), qgcomp.cox.noboot(), qgcomp.glm.boot(), qgcomp.glm.noboot(), qgcomp.hurdle.noboot(), qgcomp.multinomial.boot(), qgcomp.multinomial.noboot(), qgcomp.partials(), qgcomp.zi.boot(), qgcomp.zi.noboot()

Examples

set.seed(50)
n=500
dat <- data.frame(y=rbinom(n, 1, 0.5)*rpois(n, 1.2), x1=runif(n), x2=runif(n), z=runif(n))
# poisson count model, mixture in both portions
## Not run:
# warning: the examples below can take a long time to run
res = qgcomp.hurdle.boot(f=y ~ x1 + x2 | x1 + x2, expnms = c('x1', 'x2'),
    data=dat, q=4, dist="poisson", B=1000, MCsize=10000, parallel=TRUE, parplan=TRUE)
qgcomp.hurdle.noboot(f=y ~ x1 + x2 | x1 + x2, expnms = c('x1', 'x2'),
    data=dat, q=4, dist="poisson")
res

# accuracy for small MCsize is suspect (compare coefficients between boot/noboot versions),
# so re-check with MCsize set to larger value (this takes a long time to run)
res2 = qgcomp.hurdle.boot(f=y ~ x1 + x2 | x1 + x2, expnms = c('x1', 'x2'),
    data=dat, q=4, dist="poisson", B=1000, MCsize=50000, parallel=TRUE, parplan=TRUE)
res2
plot(density(res2$bootsamps[4,:]))

# negative binomial count model, mixture and covariate in both portions
qgcomp.hurdle.boot(f=y ~ z + x1 + x2 | z + x1 + x2, expnms = c('x1', 'x2'),
    data=dat, q=4, dist="negbin", B=10, MCsize=10000)

# weighted analysis (NOTE THIS DOES NOT WORK WITH parallel=TRUE!)
dat$w = runif(n)*5
qgcomp.hurdle.noboot(f=y ~ z + x1 + x2 | x1 + x2, expnms = c('x1', 'x2'),
    data=dat, q=4, dist="poisson", weights=w)
# You may see this:
# Warning message:
# In eval(family$initialize) : non-integer #successes in a binomial glm!
qgcomp.hurdle.boot(f=y ~ x1 + x2 | x1 + x2, expnms = c('x1', 'x2'),
    data=dat, q=4, dist="poisson", B=5, MCsize=50000, parallel=FALSE, weights=w)
# Log rr per one IQR change in all exposures (not on quantile basis)
dat$x1iqr <- dat$x1/with(dat, diff(quantile(x1, c(.25, .75))))
dat$x2iqr <- dat$x2/with(dat, diff(quantile(x2, c(.25, .75))))
# note that I(x>...) now operates on the untransformed value of x,
# rather than the quantized value
res2 = qgcomp.hurdle.boot(f=y ~ z + x1iqr + x2iqr + I(x2iqr>0.1) +
    I(x2iqr>0.4) + I(x2iqr>0.9) | x1iqr + x2iqr,
    expnms = c('x1iqr', 'x2iqr'),
    data=dat, q=NULL, B=2, dist="poisson")
res2

## End(Not run)

---

**qgcomp.hurdle.noboot**

Quantile g-computation for hurdle count outcomes under linearity/additivity

**Description**

This function estimates a linear dose-response parameter representing a one quantile increase in a set of exposures of interest for hurdle count outcomes. This function is limited to linear and additive effects of individual components of the exposure. This model estimates the parameters of a marginal structural hurdle model (MSM) based on g-computation with quantized exposures. Note: this function is valid only under linear and additive effects of individual components of the exposure, but when these hold the model can be fit with very little computational burden.
Usage

qgcomp.hurdle.noboot(
  f,
  data,
  expnms = NULL,
  q = 4,
  breaks = NULL,
  id = NULL,
  weights,
  alpha = 0.05,
  bayes = FALSE,
  ...
)

Arguments

f           R style formula using syntax from 'pscl' package: depvar ~ indvars_count | indvars_zero
data         data frame
expnms       character vector of exposures of interest
q            NULL or number of quantiles used to create quantile indicator variables representing the exposure variables. If NULL, then gcomp proceeds with untransformed version of exposures in the input datasets (useful if data are already transformed, or for performing standard g-computation)
breaks       (optional) NULL, or a list of (equal length) numeric vectors that characterize the minimum value of each category for which to break up the variables named in expnms. This is an alternative to using 'q' to define cutpoints.
id           (optional) NULL, or variable name indexing individual units of observation (only needed if analyzing data with multiple observations per id/cluster)
weights      "case weights" - passed to the "weight" argument of hurdle.
alpha        alpha level for confidence limit calculation
bayes        not yet implemented
...           arguments to hurdle (e.g. dist)

Details

A hurdle version of quantile g-computation based on the implementation in the 'pscl' package. A hurdle distribution is a mixture distribution in which one of the distributions is a point mass at zero (with probability given by a logistic model), and the other distribution is a discrete or continuous distribution. This estimates the effect of a joint increase in all exposures on 1) the odds of belonging to the "zero" vs. "count" portions of the distribution and/or 2) the rate parameter for the "count" portion of the distribution.
Value

A `qgcompfit` object, which contains information about the effect measure of interest (psi) and associated variance (var.psi), as well as information on the model fit (fit) and information on the weights/standardized coefficients in the positive (pos.weights) and negative (neg.weights) directions.

See Also

`qgcomp.hurdle.boot`, `qgcompglm.noboot`, `qgcompcox.noboot`, and `hurdle`

Other `qgcomp` methods: `qgcomp.cch.noboot()`, `qgcomp.cox.boot()`, `qgcomp.cox.noboot()`, `qgcomp.glm.boot()`, `qgcomp.glm.noboot()`, `qgcomp.hurdle.boot()`, `qgcomp.multinomial.boot()`, `qgcomp.multinomial.noboot()`, `qgcomp.partials()`, `qgcomp.zi.boot()`, `qgcomp.zi.noboot()`

Examples

```r
set.seed(50)
n=100
dat <- data.frame(y=rbinom(n, 1, 0.5)*rpois(n, 1.2), x1=runif(n), x2=runif(n), z=runif(n))

# poisson count model, mixture in both portions
qgcomp.hurdle.noboot(f=y ~ z + x1 + x2 | x1 + x2, expnms = c('x1', 'x2'),
                      data=dat, q=2, dist="poisson")

# negative binomial count model, mixture and covariate in both portions
qgcomp.hurdle.noboot(f=y ~ z + x1 + x2 | z + x1 + x2, expnms=c('x1', 'x2'),
                      data=dat, q=2, dist="negbin")
qgcomp.hurdle.noboot(f=y ~ z + x1 + x2, expnms=c('x1', 'x2'),
                      data=dat, q=2, dist="negbin") # equivalent

# negative binomial count model, mixture only in the 'count' portion of the model
qgcomp.hurdle.noboot(f=y ~ z + x1 + x2 | z, expnms=c('x1', 'x2'), data=dat, q=2, dist="negbin")

# weighted analysis
dat$w <- runif(n)*5
qgcomp.hurdle.noboot(f=y ~ z + x1 + x2 | x1 + x2, expnms = c('x1', 'x2'),
                      data=dat, q=2, dist="poisson", weights=w)
# Expect this:
# Warning message:
# In eval(family$initialize) : non-integer #successes in a binomial glm!
```

---

`qgcomp.multinomial.boot`

Quantile g-computation for multinomial outcomes
Description

This function estimates a dose-response parameter representing a one quantile increase in a set of exposures of interest. This model estimates the parameters of a marginal structural model (MSM) based on g-computation with quantized exposures. Note: this function allows linear and non-additive effects of individual components of the exposure, as well as non-linear joint effects of the mixture via polynomial basis functions, which increase the computational burden due to the need for non-parametric bootstrapping.

Usage

```r
qgcomp.multinomial.boot(
  f,
  data,
  expnms = NULL,
  q = 4,
  breaks = NULL,
  id = NULL,
  weights,
  alpha = 0.05,
  B = 200,
  rr = TRUE,
  degree = 1,
  seed = NULL,
  bayes = FALSE,
  MCsize = nrow(data),
  parallel = FALSE,
  parplan = FALSE,
  ...
)
```

Arguments

- `f` R style formula
- `data` data frame
- `expnms` character vector of exposures of interest
- `q` NULL or number of quantiles used to create quantile indicator variables representing the exposure variables. If NULL, then gcomp proceeds with untransformed version of exposures in the input datasets (useful if data are already transformed, or for performing standard g-computation)
- `breaks` (optional) NULL, or a list of (equal length) numeric vectors that characterize the minimum value of each category for which to break up the variables named in expnms. This is an alternative to using ‘q’ to define cutpoints.
- `id` (optional) NULL, or variable name indexing individual units of observation (only needed if analyzing data with multiple observations per id/cluster). Note that qgcomp.glm.noboot will not produce cluster-appropriate standard errors. qgcomp.glm.boot can be used for this, which will use bootstrap sampling of
clusters/individuals to estimate cluster-appropriate standard errors via bootstrapping.

weights
"case weights" - passed to the "weight" argument of glm or bayesglm

alpha
alpha level for confidence limit calculation

B
integer: number of bootstrap iterations (this should typically be >=200, though it is set lower in examples to improve run-time).

rr
logical: if using binary outcome and rr=TRUE, qgcomp.glm.boot will estimate risk ratio rather than odds ratio

degree
polynomial bases for marginal model (e.g. degree = 2 allows that the relationship between the whole exposure mixture and the outcome is quadratic (default = 1).

seed
integer or NULL: random number seed for replicable bootstrap results

bayes
use underlying Bayesian model (arm package defaults). Results in penalized parameter estimation that can help with very highly correlated exposures. Note: this does not lead to fully Bayesian inference in general, so results should be interpreted as frequentist.

MCsize
integer: sample size for simulation to approximate marginal zero inflated model parameters. This can be left small for testing, but should be as large as needed to reduce simulation error to an acceptable magnitude (can compare psi coefficients for linear fits with qgcomp.glm.noboot to gain some intuition for the level of expected simulation error at a given value of MCsize). This likely won’t matter much in linear models, but may be important with binary or count outcomes.

parallel
use (safe) parallel processing from the future and future.apply packages

parplan
logical, default=FALSE) automatically set future::plan to plan(multisession) (and set to existing plan, if any, after bootstrapping)

... arguments to glm (e.g. family)

Details

Estimates correspond to the average expected change in the probability of an outcome type per quantile increase in the joint exposure to all exposures in ’expnms’. Test statistics and confidence intervals are based on a non-parametric bootstrap, using the standard deviation of the bootstrap estimates to estimate the standard error. The bootstrap standard error is then used to estimate Wald-type confidence intervals. Note that no bootstrapping is done on estimated quantiles of exposure, so these are treated as fixed quantities

Value

a qgcompfit object, which contains information about the effect measure of interest (psi) and associated variance (var.psi), as well as information on the model fit (fit) and information on the marginal structural model (msmfit) used to estimate the final effect estimates.

See Also

Other qgcomp_methods: qgcomp.cch.noboot(), qgcomp.cox.boot(), qgcomp.cox.noboot(), qgcomp.glm.boot(), qgcomp.glm.noboot(), qgcomp.hurdle.boot(), qgcomp.hurdle.noboot(), qgcomp.multinomial.noboot(), qgcomp.partials(), qgcomp.zi.boot(), qgcomp.zi.noboot()
**Examples**

```r
data("metals") # from qgcomp package
# create categorical outcome from the existing continuous outcome (usually, one will already exist)
metals$ycat = factor(quantize(metals, "y", q=4)$data$y, levels=c("0", "1", "2", "3"),
    labels=c("cct", "ccg", "aat", "aag"))
# restrict to smaller dataset for simplicity
smallmetals = metals[,c("ycat", "arsenic", "lead", "cadmium", "mage35")]

### 1: Define mixture and underlying model ####
mixture = c("arsenic", "lead", "cadmium")
f0 = ycat ~ arsenic + lead + cadmium # the multinomial model
# (be sure that factor variables are properly coded ahead of time in the dataset)
rr = qgcomp.multinomial.boot(
    f0,
    expnms = mixture,
    q=4,
    data = smallmetals,
    B = 5, # set to higher values in real examples
    MCsize = 100, # set to higher values in small samples
)

rr2 = qgcomp.multinomial.noboot(
    f0,
    expnms = mixture,
    q=4,
    data = smallmetals
)

### 5: Create summary qgcomp object for nice printing ####

summary(rr, tests=c("H")) # include homogeneity test

# 95% confidence intervals
#confint(rr, level=0.95)
#rr$breaks # quantile cutpoints for exposures
# homogeneity_test(rr)
#joint_test(rr)

qdat = simdata_quantized(
    outcometype="multinomial",
    n=10000, corr=c(-.9), coef=cbind(c(.2,-.2,0,0), c(.1,.1,.1,.1)),
    q = 4
)

rr_sim = qgcomp.multinomial.noboot(
    y~x1+x2+x3+x4,
    expnms = c("x1", "x2", "x3", "x4"),
    q=4,
    data = qdat
)

rr_sim2 = qgcomp.multinomial.boot(
```

```r
```
y~x1+x2+x3+x4,
expnms = c("x1", "x2", "x3", "x4"),
q=4,
data = qdat,
B=1
)

qgcomp.multinomial.noboot

Quantile g-computation for multinomial outcomes

Description
Quantile g-computation for multinomial outcomes

Usage
qgcomp.multinomial.noboot(
  f,
data,
  expnms = NULL,
  q = 4,
breaks = NULL,
id = NULL,
weights,
alpha = 0.05,
bayes = FALSE,
...
)

Arguments

- **f**: R style formula
- **data**: data frame
- **expnms**: character vector of exposures of interest
- **q**: NULL or number of quantiles used to create quantile indicator variables representing the exposure variables. If NULL, then gcomp proceeds with untransformed version of exposures in the input datasets (useful if data are already transformed, or for performing standard g-computation)
- **breaks**: (optional) NULL, or a list of (equal length) numeric vectors that characterize the minimum value of each category for which to break up the variables named in expnms. This is an alternative to using `q` to define cutpoints.
- **id**: (optional) NULL, or variable name indexing individual units of observation (only needed if analyzing data with multiple observations per id/cluster). Note that qgcomp.glm.noboot will not produce cluster-appropriate standard errors
weights    "case weights" - passed to the "weight" argument of \texttt{multinom}
alpha      \texttt{alpha} level for confidence limit calculation
bayes      Logical, Not yet implemented (gives an error if set to TRUE)
...         arguments to \texttt{nnet::multinom}

\textbf{Value}

a \texttt{qgcompmultfit} object, which contains information about the effect measure of interest (psi) and associated variance (var.psi), as well as information on the model fit (fit) and information on the weights/standardized coefficients in the positive and negative directions (weights).

\textbf{See Also}

\texttt{qgcomp.glm.noboot}, \texttt{multinom}

Other \texttt{qgcomp} methods: \texttt{qgcomp.cch.noboot()}, \texttt{qgcomp.cox.boot()}, \texttt{qgcomp.cox.noboot()}, \texttt{qgcomp.glm.boot()}, \texttt{qgcomp.glm.noboot()}, \texttt{qgcomp.hurdle.boot()}, \texttt{qgcomp.hurdle.noboot()}, \texttt{qgcomp.multinomial.boot()}, \texttt{qgcomp.partials()}, \texttt{qgcomp.zi.boot()}, \texttt{qgcomp.zi.noboot()}

\textbf{Examples}

data("metals") # from qgcomp package
# create categorical outcome from the existing continuous outcome (usually, one will already exist)
metals$ycat = factor(quantize(metals, "y", q=4)$data$y, levels=c("0", "1", "2", "3"),
        labels=c("cct", "ccg", "aat", "aag"))
# restrict to smaller dataset for simplicity
smallmetals = metals[,c("ycat", "arsenic", "lead", "cadmium", "mage35")]

### 1: Define mixture and underlying model ###
mixture = c("arsenic", "lead", "cadmium")
f0 = ycat ~ arsenic + lead + cadmium # the multinomial model
# (be sure that factor variables are properly coded ahead of time in the dataset)
rr = qgcomp.multinomial.noboot(
    f0,
    expnms = mixture,
    q=4,
    data = smallmetals,
)

### 5: Create summary qgcomp object for nice printing ###

summary(rr, tests=c("H")) # include homogeneity test

# 95% confidence intervals
confint(rr, level=0.95)
rr$breaks # quantile cutpoints for exposures
# homogeneity_test(rr)
joint_test(rr)

**qgcomp.partials**  
*Partial effect sizes, confidence intervals, hypothesis tests*

**Description**

Obtain effect estimates for "partial positive" and "partial negative" effects using quantile g-computation. This approach uses sample splitting to evaluate the overall impact of a set of variables with effects in a single direction, where, using training data, all variables with effects in the same direction are grouped.

**Usage**

```r
gcomp.partials(
  fun = c("qgcomp.glm.noboot", "qgcomp.cox.noboot", "qgcomp.zi.noboot"),
  traindata = NULL,
  validdata = NULL,
  expnms = NULL,
  .fixbreaks = TRUE,
  .globalbreaks = FALSE,
  ...
)
```

**Arguments**

- `fun` character variable in the set "qgcomp.glm.noboot" (binary, count, continuous outcomes), "qgcomp.cox.noboot" (survival outcomes), "qgcomp.zi.noboot" (zero inflated outcomes). This describes which qgcomp package function is used to fit the model. (default = "qgcomp.glm.noboot")
- `traindata` Data frame with training data
- `validdata` Data frame with validation data
- `expnms` Exposure mixture of interest
- `.fixbreaks` (logical, overridden by .globalbreaks) Use the same quantile cutpoints in the training and validation data (selected in the training data). As of version 2.8.11, the default is TRUE, whereas it was implicitly FALSE in prior versions. Setting to TRUE increases variance but greatly decreases bias in smaller samples.
- `.globalbreaks` (logical, if TRUE, overrides .fixbreaks) Use the same quantile cutpoints in the training and validation data (selected in combined training and validation data). As of version 2.8.11, the default is TRUE, whereas it was implicitly FALSE in prior versions. Setting to TRUE increases variance but greatly decreases bias in smaller samples.
- `...` Arguments to qgcomp.glm.noboot, qgcomp.cox.noboot, or qgcomp.zi.noboot
Details

In the basic (non bootstrapped) qgcomp functions, the positive and negative "sums of coefficients" or "partial effect sizes" are given, which equal the sum of the negative and positive coefficients in the underlying model. Unfortunately, these partial effects don’t constitute variables for which we can derive confidence intervals or hypothesis tests, so they are mainly for exploratory purposes. By employing sample splitting, however, we can obtain better estimates of these partial effects.

Sample splitting proceeds by partitioning the data into two samples (40/60 training/validation split seems acceptable in many circumstances). The "overall mixture effect" is then estimated in the training data, and the mixture variables with positive and negative coefficients are split into separate groups. These two different groups are then used as "the mixture of interest" in two additional qgcomp fits, where the mixture of interest is adjusted for the other exposure variables. For example, if the "positive partial effect" is of interest, then this effect is equal to the sum of the coefficients in the qgcomp model fit to the validation data, with the mixture of interest selected by the original fit to the training data (note that some of these coefficients may be negative in the fit to the validation data - this is expected and necessary for valid hypothesis tests).

The positive/negative partial effects are necessarily exploratory, but sample splitting preserves the statistical properties at the expense of wider confidence intervals and larger variances. The two resulting mixture groups groups should be inspected for

Value

A ‘qgcompmultifit’ object, which inherits from list, which contains

posmix character vector of variable names with positive coefficients in the qgcomp model fit to the training data

negmix character vector of variable names with negative coefficients in the qgcomp model fit to the training data

pos.fit a qgcompfit object fit to the validation data, in which the exposures of interest are contained in ‘posmix’

neg.fit a qgcompfit object fit to the validation data, in which the exposures of interest are contained in ‘negmix’

See Also

Other qgcomp_methods: qgcomp.cch.noboot(), qgcomp.cox.boot(), qgcomp.cox.noboot(), qgcomp.glm.boot(), qgcomp.glm.noboot(), qgcomp.hurdle.boot(), qgcomp.hurdle.noboot(), qgcomp.multinomial.boot(), qgcomp.multinomial.noboot(), qgcomp.zi.boot(), qgcomp.zi.noboot()

Examples

set.seed(123223)
dat = qgcomp::simdata_quantized(n=1000, outcomtype="continuous", cor=c(.75, 0),
  b0=0, coef=c(.25,-.25,0,0), q=4)
cor(dat)
# overall fit (more or less null due to counteracting exposures)
(overall <- qgcomp.glm.noboot(f=y~., q=NULL, expnms=c("x1", "x2", "x3", "x4"), data=dat))
# partial effects using 40% training/60% validation split
trainidx <- sample(1:nrow(dat), round(nrow(dat)*0.4))
valididx <- setdiff(1:nrow(dat),trainidx)
traindata = dat[trainidx,]
validdata = dat[valididx,]
splitres <- qgcomp.partials(fun="qgcomp.glm.noboot", f=y~., q=NULL,
traindata=traindata,validdata=validdata, expnms=c("x1", "x2", "x3", "x4"))
splitres
## Not run:
# under the null, both should give null results
set.seed(123223)

# 40% training/60% validation
trainidx2 <- sample(1:nrow(dat), round(nrow(dat)*0.4))
valididx2 <- setdiff(1:nrow(dat),trainidx2)
traindata2 <- dat[trainidx2,]
validdata2 <- dat[valididx2,]
splitres2 <- qgcomp.partials(fun="qgcomp.glm.noboot", f=y~.,
q=NULL, traindata=traindata2,validdata=validdata2, expnms=c("x1", "x2", "x3", "x4"))
splitres2

# 60% training/40% validation
trainidx3 <- sample(1:nrow(dat), round(nrow(dat)*0.6))
valididx3 <- setdiff(1:nrow(dat),trainidx3)
traindata3 <- dat[trainidx3,]
validdata3 <- dat[valididx3,]
splitres3 <- qgcomp.partials(fun="qgcomp.glm.noboot", f=y~., q=NULL,
traindata=traindata3,validdata=validdata3, expnms=c("x1", "x2", "x3", "x4"))
splitres3

# survival outcome
set.seed(50)
N=1000

# zero inflated count outcome
set.seed(50)
n=1000

x4=runif(n), z=runif(n))
# poisson count model, mixture in both portions, but note that the qgcomp.partials
# function defines the "positive" variables only by the count portion of the model
overall5 <- qgcomp.zi.noboot(f=y ~ z + x1 + x2 + x3 + x4 | x1 + x2 + x3 + x4 + z,
                           expnms = c("x1", "x2", "x3", "x4"),
                           data=dat, q=4, dist="poisson")

trainidx5 <- sample(1:nrow(dat), round(nrow(dat)*0.6))
valididx5 <- setdiff(1:nrow(dat), trainidx5)
traindata5 <- dat[trainidx5,]
validdata5 <- dat[valididx5,]
splitres5 <- qgcomp.partials(fun="qgcomp.zi.noboot",
                           f=y ~ x1 + x2 + x3 + x4 + z | x1 + x2 + x3 + x4 + z, q=4,
                           traindata=traindata5, validdata=validdata5,
                           expnms=c("x1", "x2", "x3", "x4"))

## End(Not run)

qgcomp.survcurve.boot

Survival curve data from a qgcomp survival fit

Description

It is often of interest to examine survival curves from qgcomp.cox.boot models. They can be useful for checking assumptions about how well the marginal structural model conforms to the underlying conditional model, such that the overall fit approximates the non-linearity in the underlying model. This function will yield survival curves, but no measures of uncertainty.

Usage

qgcomp.survcurve.boot(x, ...)

Arguments

x               a qgcompfit object from qgcomp.cox.boot
...

Value

a list of data.frames: 

- 'mdfpop': Average Survival curve (survival, time) based on marginal structural model, averaged over the population at every quantile of exposure
- 'cdfpop': Population average survival curve (survival, time) based on the underlying conditional model
- 'mdfq': Survival curves (survival, time) for each quantile based on marginal structural model
- 'cdfq': Survival curves (survival, time) for each quantile based on underlying conditional model
Examples

```r
set.seed(50)
N=200
dat <- data.frame(time=(tmg <- pmin(.1,rweibull(N, 10, 0.1))),
    d=1.0*(tmg<0.1), x1=runif(N), x2=runif(N), z=runif(N))
expnms=paste0("x", 1:2)
f = survival::Surv(time, d)-x1+x2
(fit1 <- survival::coxph(f, data = dat))
(obj <- qgcomp.cox.noboot(f, expnms = expnms, data = dat))
## Not run:
## Not run:

(obj2 <- qgcomp.cox.boot(f, expnms = expnms, data = dat, B=10, MCsize=20000))
curves = cox.survcurve.boot(obj2)
rbind(head(curves$mdfq),tail(curves$mdfq))
## End(Not run)
```

qgcomp.zi.boot  

Quantile g-computation for zero-inflated count outcomes

Description

This function estimates a linear dose-response parameter representing a one quantile increase in a set of exposures of interest for zero-inflated count outcomes. This function is limited to linear and additive effects of individual components of the exposure. This model estimates the parameters of a marginal structural zero-inflated count model (MSM) based on g-computation with quantized exposures. Note: this function allows linear and non-additive effects of individual components of the exposure, as well as non-linear joint effects of the mixture via polynomial basis functions, which increase the computational computational burden due to the need for non-parametric bootstrapping.

Usage

```r
qgcomp.zi.boot(
    f,
    data,
    expnms = NULL,
    q = 4,
    breaks = NULL,
    id = NULL,
    weights,
    alpha = 0.05,
    B = 200,
    degree = 1,
    seed = NULL,
    bayes = FALSE,
    parallel = FALSE,
```
```
MCsize = 10000,
msmcontrol = zimsm_fit.control(),
parplan = FALSE,
...)
```

### Arguments

- **f**
  - R style formula

- **data**
  - data frame

- **expnms**
  - character vector of exposures of interest

- **q**
  - NULL or number of quantiles used to create quantile indicator variables representing the exposure variables. If NULL, then gcomp proceeds with untransformed version of exposures in the input datasets (useful if data are already transformed, or for performing standard g-computation)

- **breaks**
  - (optional) NULL, or a list of (equal length) numeric vectors that characterize the minimum value of each category for which to break up the variables named in expnms. This is an alternative to using 'q' to define cutpoints.

- **id**
  - (optional) NULL, or variable name indexing individual units of observation (only needed if analyzing data with multiple observations per id/cluster)

- **weights**
  - "case weights" - passed to the "weight" argument of `zeroinfl`. NOTE - this does not work with parallel=TRUE!

- **alpha**
  - alpha level for confidence limit calculation

- **B**
  - integer: number of bootstrap iterations (this should typically be >=200, though it is set lower in examples to improve run-time).

- **degree**
  - polynomial basis function for marginal model (e.g. degree = 2 allows that the relationship between the whole exposure mixture and the outcome is quadratic.)

- **seed**
  - integer or NULL: random number seed for replicable bootstrap results

- **bayes**
  - not currently implemented.

- **parallel**
  - use (safe) parallel processing from the future and future.apply packages

- **MCsize**
  - integer: sample size for simulation to approximate marginal zero inflated model parameters. This can be left small for testing, but should be as large as needed to reduce simulation error to an acceptable magnitude (can compare psi coefficients for linear fits with qgcomp.zi.noboot to gain some intuition for the level of expected simulation error at a given value of MCsize)

- **msmcontrol**
  - named list from `zimsm_fit.control`

- **parplan**
  - (logical, default=FALSE) automatically set future::plan to plan(multisession) (and set to existing plan, if any, after bootstrapping)

... arguments to glm (e.g. family)
Details

Zero-inflated count models allow excess zeros in standard count outcome (e.g. Poisson distributed outcomes). Such models have two components: 1) the probability of arising from a degenerate distribution at zero (versus arising from a count distribution) and 2) the rate parameter of a count distribution. Thus, one has the option of allowing exposure and covariate effects on the zero distribution, the count distribution, or both. The zero distribution parameters correspond to log-odds ratios for the probability of arising from the zero distribution. Count distribution parameters correspond to log-rate-ratio parameters. Test statistics and confidence intervals are based on a non-parametric bootstrap, using the standard deviation of the bootstrap estimates to estimate the standard error. The bootstrap standard error is then used to estimate Wald-type confidence intervals. Note that no bootstrapping is done on estimated quantiles of exposure, so these are treated as fixed quantities.

Of note, this function yields marginal estimates of the expected outcome under values of the joint exposure quantiles (e.g. the expected outcome if all exposures are below the 1st quartile). These outcomes can be used to derive estimates of the effect on the marginal expectation of the outcome, irrespective of zero-inflated/count portions of the statistical model.

Estimates correspond to the average expected change in the (log) outcome per quantile increase in the joint exposure to all exposures in ‘expnms’. Test statistics and confidence intervals are based on a non-parametric bootstrap, using the standard deviation of the bootstrap estimates to estimate the standard error. The bootstrap standard error is then used to estimate Wald-type confidence intervals. Note that no bootstrapping is done on estimated quantiles of exposure, so these are treated as fixed quantities.

Value

a qgcompfit object, which contains information about the effect measure of interest (psi) and associated variance (var.psi), as well as information on the model fit (fit) and information on the marginal structural model (msmfit) used to estimate the final effect estimates.

See Also

Other qgcomp methods: qgcomp.cch.noboot(), qgcomp.cox.boot(), qgcomp.cox.noboot(), qgcomp.glm.boot(), qgcomp.glm.noboot(), qgcomp.hurdle.boot(), qgcomp.hurdle.noboot(), qgcomp.multinomial.boot(), qgcomp.multinomial.noboot(), qgcomp.partials(), qgcomp.zi.noboot()

Examples

set.seed(50)
n=100
dat <- data.frame(y=rbinom(n, 1, 0.5)*rpois(n, 1.2), x1=runif(n), x2=runif(n), z=runif(n))
# poisson count model, mixture in both portions
## Not run:
# warning: the examples below can take a long time to run
res = qgcomp.zi.boot(f=y ~ x1 + x2 | x1 + x2, expnms = c('x1', 'x2'),
  data=dat, q=4, dist="poisson", B=1000, MCsize=10000, parallel=TRUE, parplan=TRUE)
qucomp.zi.noboot(f=y ~ x1 + x2 | x1 + x2, expnms = c('x1', 'x2'),
  data=dat, q=4, dist="poisson")
res
accuracy for small MCsize is suspect (compare coefficients between boot/noboot versions),
so re-check with MCsize set to larger value (this takes a long time to run)
res2 = qgcomp.zi.boot(f=y ~ x1 + x2 | x1 + x2, expnms = c('x1', 'x2'),
data=dat, q=4, dist="poisson", B=1000, MCsize=50000, parallel=TRUE, parplan=TRUE)
res2
plot(density(res2$bootsamps[4,]))

# negative binomial count model, mixture and covariate in both portions
qgcomp.zi.boot(f=y ~ z + x1 + x2 | z + x1 + x2, expnms = c('x1', 'x2'),
data=dat, q=4, dist="negbin", B=10, MCsize=10000)

# weighted analysis (NOTE THIS DOES NOT WORK WITH parallel=TRUE!)
dat$w = runif(n)*5
qgcomp.zi.noboot(f=y ~ z + x1 + x2 | x1 + x2, expnms = c('x1', 'x2'),
data=dat, q=4, dist="poisson", weights=w)

# Expect this:
# Warning message:
# In eval(family$initialize) : non-integer #successes in a binomial glm!
qgcomp.zi.boot(f=y ~ x1 + x2 | x1 + x2, expnms = c('x1', 'x2'),
data=dat, q=4, dist="poisson", B=5, MCsize=50000, parallel=FALSE, weights=w)

# Log rr per one IQR change in all exposures (not on quantile basis)
dat$x1iqr <- dat$x1/with(dat, diff(quantile(x1, c(.25, .75))))
dat$x2iqr <- dat$x2/with(dat, diff(quantile(x2, c(.25, .75))))

# note that I(x>...) now operates on the untransformed value of x,
# rather than the quantized value
res2 = qgcomp.zi.boot(y ~ z + x1iqr + x2iqr + I(x2iqr>0.1) + I(x2>0.4) + I(x2>0.9) | x1iqr + x2iqr,
family="binomial", expnms = c('x1iqr', 'x2iqr'), data=dat, q=NULL, B=2,
degree=2, MCsize=200, dist="poisson")
res2

## End(Not run)

---

qgcomp.zi.noboot

Quantile g-computation for zero-inflated count outcomes under linearity/additivity

### Description

This function estimates a linear dose-response parameter representing a one quantile increase in a set of exposures of interest for zero-inflated count outcomes. This function is limited to linear and additive effects of individual components of the exposure. This model estimates the parameters of a marginal structural zero-inflated model (MSM) based on g-computation with quantized exposures. Note: this function is valid only under linear and additive effects of individual components of the exposure, but when these hold the model can be fit with very little computational burden.

### Usage

```r
qgcomp.zi.noboot(
  f,
```
Arguments

- **f**: R style formula using syntax from ‘pscl’ package: `depvar ~ indvars_count | indvars_zero`
- **data**: data frame
- **expnms**: character vector of exposures of interest
- **q**: NULL or number of quantiles used to create quantile indicator variables representing the exposure variables. If NULL, then gcomp proceeds with untransformed version of exposures in the input datasets (useful if data are already transformed, or for performing standard g-computation)
- **breaks**: (optional) NULL, or a list of (equal length) numeric vectors that characterize the minimum value of each category for which to break up the variables named in expnms. This is an alternative to using ‘q’ to define cutpoints.
- **id**: (optional) NULL, or variable name indexing individual units of observation (only needed if analyzing data with multiple observations per id/cluster)
- **weights**: "case weights" - passed to the "weight" argument of `zeroinfl`
- **alpha**: alpha level for confidence limit calculation
- **bayes**: not yet implemented
- ... arguments to `zeroinfl` (e.g. `dist`)

Details

A zero-inflated version of quantile g-computation based on the implementation in the ‘pscl’ package. A zero-inflated distribution is a mixture distribution in which one of the distributions is a point mass at zero (with probability given by a logistic model), and the other distribution is a discrete or continuous distribution. This estimates the effect of a joint increase in all exposures on 1) the odds of belonging to the "zero" vs. "count" portions of the distribution and/or 2) the rate parameter for the "count" portion of the distribution.

Value

a `qgcompfit` object, which contains information about the effect measure of interest (psi) and associated variance (var.psi), as well as information on the model fit (fit) and information on the weights/standardized coefficients in the positive (pos.weights) and negative (neg.weights) directions.
quantize

Quantizing exposure data

Description

Create variables representing indicator functions with cutpoints defined by quantiles. Output a list that includes: 1) a dataset that is a copy of data, except that the variables whose names are included in the `expnms` variable are transformed to their quantized version and 2) an unnamed list of the quantile cutpoints that are used for each of the variables that were quantized.

Usage

```r
quantize(data, expnms, q = 4, breaks = NULL)
```

See Also

Other `qgcomp` methods: `qgcomp.ch.noboot()`, `qgcomp.cox.boot()`, `qgcomp.cox.noboot()`, `qgcomp.glm.boot()`, `qgcomp.glm.noboot()`, `qgcomp.hurdle.boot()`, `qgcomp.hurdle.noboot()`, `qgcomp.multinomial.boot()`, `qgcomp.multinomial.noboot()`, `qgcomp.partials()`, `qgcomp.zi.boot()`
Arguments

data  a data frame
expnms  a character vector with the names of the columns to be quantized
q  integer, number of quantiles used in creating quantized variables
breaks  (optional) list of (equal length) numeric vectors that characterize the minimum value of each category for which to break up the variables named in expnms. This is an alternative to using 'q' to define cutpoints.

Details

This function creates categorical variables in place of the exposure variables named in 'expnms.' For example, a continuous exposure 'x1' will be replaced in the output data by another 'x1' that takes on values 0:(q-1), where, for example, the value 1 indicates that the original x1 value falls between the first and the second quantile.

Value

A list containing the following fields

data  a quantized version of the original dataframe
breaks  a list of the quantile cutpoints used to create the quantized variables which includes a very small number for the minimum and a very large number for the maximum to avoid causing issues when using these breaks to quantize new data.

Examples

set.seed(1232)
dat = data.frame(y=runif(100), x1=runif(100), x2=runif(100), z=runif(100))
qdata = quantize(data=dat, expnms=c("x1", "x2"), q=4)
table(qdata$data$x1)
table(qdata$data$x2)
summary(dat[c("y", "z")]);summary(qdata$data[c("y", "z")])  # not touched
dat = data.frame(y=runif(100), x1=runif(100), x2=runif(100), z=runif(100))
# using 'breaks' requires specifying min and max (the qth quantile)
# example with theoretical quartiles (could be other relevant values)
qdata2 = quantize(data=dat, expnms=c("x1", "x2"),
    breaks=list(c(-1e64, .25, .5, .75, 1e64),
      c(-1e64, .25, .5, .75, 1e64))
)
table(qdata2$data$x1)
table(qdata2$data$x2)
Calculate standard error of weighted linear combination of random variables

Description

This function uses the Delta method to calculate standard errors of linear functions of variables (similar to `lincom` in Stata). Generally, users will not need to call this function directly.

Usage

```r
se_comb(expnms, covmat, grad = NULL)
```

Arguments

- `expnms`: a character vector with the names of the columns to be of interest in the covariance matrix for which a standard error will be calculated (e.g. same as `expnms` in `qgcomp` fit)
- `covmat`: covariance matrix for parameters, e.g. from a model or bootstrap procedure
- `grad`: the "weight" vector for calculating the contribution of each variable in `expnms` to the final standard error. For a linear combination, this is equal to a vector of ones (and is set automatically). Or can be calculated via the `grad.poly` procedure, in the case of coming up with proper weights when the combination of `expnms` derives from a polynomial function (as in `qgcomp.glm.boot` with `degree>1`).

Details

This function takes inputs of a set of exposure names (character vector) and a covariance matrix (with colnames/rownames that contain the full set of exposure names), as well as a possible `grad` parameter to calculate the variance of a weighted combination of the exposures in `expnms`, where the weights are based off of `grad` (which defaults to 1, so that this function yields the variance of a sum of all variables in `expnms`)

Here is a simple version of the delta method for a linear combination of three model coefficients:

- \( f(\beta) = \beta_1 + \beta_2 + \beta_3 \) given gradient vector
- \( G = [d(f(\beta))/d\beta_1 = 1, d(f(\beta))/d\beta_2 = 1, d(f(\beta))/d\beta_3 = 1] \)

\[ t(G) Cov(\beta) G = \text{delta method variance} \]

\[ \text{where } t() \text{ is the transpose operator} \]

Examples

```r
cov = rbind(c(1.2, .9), c(.9, 2.0))
colnames(cov) <- rownames(cov) <- expnms <- c("x1", "x2")
se_comb(expnms, cov, c(1, 0))^2 # returns the given variance
se_comb(expnms, cov, c(1, 1)) # default linear MSM fit: all exposures
# have equal weight
se_comb(expnms, cov, c(.3, .1)) # used when one exposure contributes
# to the overall fit more than others = d(msmefect)/dx
```
**simdata_quantized**  
Simulate quantized exposures for testing methods

**Description**

Simulate quantized exposures for testing methods

**Usage**

```r
simdata_quantized(
  outcometype = c("continuous", "logistic", "survival", "multinomial"),
  n = 100,
  corr = NULL,
  b0 = 0,
  coef = c(1, 0, 0, 0),
  q = 4,
  yscale = 1,
  shape0 = 3,
  scale0 = 5,
  censtime = 4,
  ncheck = TRUE,
  ...
)
```

**Arguments**

- **outcometype**: Character variable that is one of c("continuous", "logistic", "survival"). Selects what type of outcome should be simulated (or how). continuous = normal, continuous outcome, logistic= binary outcome from logistic model, survival = right censored survival outcome from Weibull model.
- **n**: Sample size
- **corr**: NULL, or vector of correlations between the first exposure and subsequent exposures (if length(corr) < (length(coef)-1), then this will be backfilled with zeros)
- **b0**: (continuous, binary outcomes) model intercept
- **coef**: Vector of coefficients for the outcome (i.e. model coefficients for exposures). The length of this determines the number of exposures.
- **q**: Number of levels or "quanta" of each exposure
- **yscale**: (continuous outcomes) error scale (residual error) for normally distributed outcomes
- **shape0**: (survival outcomes) baseline shape of weibull distribution `rweibull`
- **scale0**: (survival outcomes) baseline scale of weibull distribution `rweibull`
- **censtime**: (survival outcomes) administrative censoring time
- **ncheck**: (logical, default=TRUE) adjust sample size if needed so that exposures are exactly evenly distributed (so that qgcomp::quantize(exposure) = exposure)
- **...**: unused
**Details**

Simulate continuous (normally distributed errors), binary (logistic function), or event-time outcomes as a linear function

**Value**

a data frame

**See Also**

`qgcomp.glm.boot` and `qgcomp.glm.noboot`

**Examples**

```r
set.seed(50)
qdat = simdata_quantized(
  outcome type="continuous",
  n=10000, corr=c(.9,.3), coef=c(1, 1, 0, 0),
  q = 8
)
cor(qdat)
qdat = simdata_quantized(
  outcome type="continuous",
  n=10000, corr=c(-.9,.3), coef=c(1, 2, 0, 0),
  q = 4
)
cor(qdat)
table(qdat$x1)
qgcomp.glm.noboot(y~., data=qdat)

qdat = simdata_quantized(
  outcome type="multinomial",
  n=10000, corr=c(-.9), coef=cbind(c(1, -1, 0, 0), c(1, .2, 0, 0)),
  q = 4
)
```

---

**split_data**  
*Perform sample splitting*

**Description**

This is a convenience function to split the input data into two independent sets, possibly accounting for single level clustering. These two sets can be used with `qgcomp.partials` to get "partial" positive/negative effect estimates from the original data, where sample splitting is necessary to get valid confidence intervals and p-values. Sample splitting is also useful for any sort of exploratory model selection, where the training data can be used to select the model and the validation model used to generate the final estimates (this process should not be iterative - e.g. no "checking" the results in the validation data and then re-fitting, as this invalidates inference in the validation set.)
E.g. you could use the training data to select non-linear terms for the model and then re-fit in validation data to get unbiased estimates.

Usage

```r
split_data(data, cluster = NULL, prop.train = 0.4)
```

Arguments

- `data`: A data.frame for use in qgcomp fitting
- `cluster`: NULL (default) or character value naming a cluster identifier in the data. This is to prevent observations from a single cluster being in both the training and validation data, which reduces the effectiveness of sample splitting.
- `prop.train`: proportion of the original dataset (or proportion of the clusters identified via the `cluster` parameter) that are used in the training data (default=0.4)

Value

A list of the following type: list(trainidx = trainidx, valididx = valididx, traindata = traindata, validdata = validdata)

e.g. if you call `spl = split_data(dat)`, then `spl$traindata` will contain a 40% sample from the original data, `spl$validdata` will contain the other 60% and `spl$trainidx, spl$valididx` will contain integer indexes that track the row numbers (from the original data `dat`) that have the training and validation samples.

Examples

```r
data(metals)
set.seed(1231124)
spl = split_data(metals)
Xnm <- c(
  'arsenic', 'barium', 'cadmium', 'calcium', 'chromium', 'copper',
  'iron', 'lead', 'magnesium', 'manganese', 'mercury', 'selenium', 'silver',
  'sodium', 'zinc'
)
dim(spl$traindata) # 181 observations = 40% of total
dim(spl$validdata) # 271 observations = 60% of total
splitres <- qgcomp.partials(fun="qgcomp.glm.noboot", f=y~, q=4,
  traindata=spl$traindata,validdata=spl$validdata, expnms=Xnm)
splitres

# also used to compare linear vs. non-linear fits (useful if you have enough data)
set.seed(1231)
spl = split_data(metals, prop.train=.5)
lin = qgcomp.glm.boot(f=y~, q=4, expnms=Xnm, B=5, data=spl$traindata)
nlin1 = qgcomp.glm.boot(f=y~. + I(manganese^2) + I(calcium^2), expnms=Xnm, deg=2,
  q=4, B=5, data=spl$traindata)
nlin2 = qgcomp.glm.boot(f=y~. + I(arsenic^2) + I(cadmium^2), expnms=Xnm, deg=2,
  q=4, B=5, data=spl$traindata)
AIC(lin);AIC(nlin1);AIC(nlin2)
```
# linear has lowest training AIC, so base final fit off that (and bootstrap not needed)
qgcomp.glm.noboot(f=y~, q=4, expnms=Xnm, data=spl$validdata)

summary.qgcompmultfit  Summarize qgcompmultfit object

Description
Summary printing to include coefficients, standard errors, hypothesis tests, weights

Usage
## S3 method for class 'qgcompmultfit'
summary(object, ..., tests = NULL)

Arguments

object  Result from qgcomp multinomial fit (qgcompmultfit object).
...
Unused
tests  Character vector (e.g. c("global", "homogeneity")) that determine the types of hypothesis tests that are printed

Value
qgcompmulttest object (list) with results of a chi-squared test

tidy.qgcompfit  Tidy method for qgcompfit object

Description
Tidy summarizes information about the components of a model. A model component might be a single term in a regression, a single hypothesis, a cluster, or a class. Exactly what tidy considers to be a model component varies cross models but is usually self-evident. If a model has several distinct types of components, you will need to specify which components to return. (Description taken from tidyr::tidy help file.)

Usage
## S3 method for class 'qgcompfit'
tidy(x, conf.level = 1 - x$alpha, exponentiate = FALSE, quick = FALSE, ...)
vc_comb

Calculate covariance matrix between one random variable and a linear combination of random variables

Description

This function uses the Delta method to calculate a covariance matrix of linear functions of variables and is used internally in qgcomp. Generally, users will not need to call this function directly.

Usage

vc_comb(aname = "(Intercept)", expnms, covmat, grad = NULL)

Arguments

aname character scalar with the name of the first column of interest (e.g. variable A in the examples given in the details section)
expnms a character vector with the names of the columns to be of interest in the covariance matrix for which a standard error will be calculated (e.g. same as expnms in qgcomp fit)
covmat covariance matrix for parameters, e.g. from a model or bootstrap procedure
grad not yet used
Details

This function takes inputs of a name of random variable (character), as set of exposure names (character vector) and a covariance matrix (with colnames/rownames that contain the independent variable and the full set of exposure names). See se_comb for details on variances of sums of random variables. Briefly, for variables A, B and C with covariance matrix Cov(A,B,C), we can calculate the covariance Cov(A,B+C) with the formula Cov(A,B) + Cov(A,C), and Cov(A,B+C+D) = Cov(A,B) + Cov(A,C) + Cov(A,D), and so on.

Value

A covariance matrix

Examples

```r
vcov = rbind(c(0.010051348, -0.0039332248, -0.0036965571),
c(-0.003933225, 0.0051807876, 0.0007706792),
c(-0.003696557, 0.0007706792, 0.0050996587))
colnames(vcov) <- rownames(vcov) <- c("(Intercept)", "x1", "x2")
expnms <- rownames(vcov)[2:3]
aname = rownames(vcov)[1]
vc_comb(aname, expnms, vcov) # returns the given covariance matrix
```

Description

this is an internal function called by qgcomp.zi.boot, but is documented here for clarity. Generally, users will not need to call this function directly.

Usage

```r
zimsm_fit(f, qdata, intvals, expnms, main = TRUE, degree = 1, id = NULL, weights, MCsize = 10000, containmix = list(count = TRUE, zero = TRUE), bayes = FALSE, x = FALSE, msmcontrol = zimsm_fit.control(), ...)
```
Arguments

f  an r formula representing the conditional model for the outcome, given all exposures and covariates. Interaction terms that include exposure variables should be represented via the \texttt{AsIs} function

data  a data frame with quantized exposures (as well as outcome and other covariates)

intvals  sequence, the sequence of integer values that the joint exposure is 'set' to for estimating the msm. For quantile g-computation, this is just 0:(q-1), where q is the number of quantiles of exposure.

expnms  a character vector with the names of the columns in \texttt{qdata} that represent the exposures of interest (main terms only!)

main  logical, internal use: produce estimates of exposure effect (psi) and expected outcomes under g-computation and the MSM

degree  polynomial bases for marginal model (e.g. degree = 2 allows that the relationship between the whole exposure mixture and the outcome is quadratic. Default=1)

id  (optional) NULL, or variable name indexing individual units of observation (only needed if analyzing data with multiple observations per id/cluster)

weights  not yet implemented

MCsize  integer: sample size for simulation to approximate marginal hazards ratios

containmix  named list of logical scalars with names "count" and "zero"

bayes  not used

x  keep design matrix? (logical)

msmcontrol  named list from \texttt{zimsm_fit.control}

...  arguments to \texttt{zeroinfl} (e.g. dist)

Details

This function first computes expected outcomes under hypothetical interventions to simultaneously set all exposures to a specific quantile. These predictions are based on g-computation, where the exposures are 'quantized', meaning that they take on ordered integer values according to their ranks, and the integer values are determined by the number of quantile cutpoints used. The function then takes these expected outcomes and fits an additional model (a marginal structural model) with the expected outcomes as the outcome and the intervention value of the exposures (the quantile integer) as the exposure. Under causal identification assumptions and correct model specification, the MSM yields a causal exposure-response representing the incremental change in the expected outcome given a joint intervention on all exposures.

See Also

\texttt{qgcomp.cox.boot}, and \texttt{qgcomp.cox.noboot}
Examples

```r
set.seed(50)
n=100
## Not run:
dat <- data.frame(y=rbinom(n, 1, 0.5)*rpois(n, 1.2), x1=runif(n), x2=runif(n), z=runif(n))
expnms = c("x1", "x2")
q = 4
qdata = quantize(dat, q=q, expnms=expnms)$data
f = y ~ x1 + x2 + z | 1
msmfit <- zimsm_fit(f, qdata, intvals=(1:q)-1, expnms, main=TRUE,
              degree=1, id=NULL, MCsize=10000, containmix=list(count=TRUE, zero=FALSE),
              x=FALSE)
msmfit$msmfit
## End(Not run)
```

zimsm_fit.control: Control of fitting parameters for zero inflated MSMs

Description

This is an internal function called by `qgcomp.zi.boot`, but is documented here for clarity. Generally, users will not need to call this function directly.

Usage

```r
zimsm_fit.control(predmethod = c("components", "catprobs"))
```

Arguments

- `predmethod` character in c("components", "catprobs"). "components" simulates from the model parameters directly while "catprobs" simulates outcomes from the category specific probabilities, which is output from `predict.zeroinfl`. The former is slightly more flexible and stable, but the latter is preferred in zero inflated negative binomial models.

Details

Provides fine control over zero inflated MSM fitting
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