Package 'maczic'

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Type Package

Title Mediation Analysis for Count and Zero-Inflated Count Data

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Depends R (>= 4.0), MASS, pscl, graphics

Imports sandwich, survival, stats, mediation, emplik, BB, mathjaxr

Suggests SuppDists

RdMacros mathjaxr

Description Performs causal mediation analysis for count and zero-inflated count data without or with a post-treatment confounder; calculates power to detect prespecified causal mediation effects, direct effects, and total effects; performs sensitivity analysis when there is a treatment-induced mediator-outcome confounder as described by Cheng, J., Cheng, N.F., Guo, Z., Gregorich, S., Ismail, A.I., Gansky, S.A. (2018) <doi:10.1177/0962280216686131>. Implements Instrumental Variable (IV) method to estimate the controlled (natural) direct and mediation effects, and compute the bootstrap Confidence Intervals as described by Guo, Z., Small, D.S., Gansky, S.A., Cheng, J. (2018) <doi:10.1111/rssc.12233>.

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LazyData true

RoxygenNote 7.1.1

R topics documented:

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maczic	*maczic: Mediation Analysis for Count and Zero-inflated Count Data.*

Description

Performs causal mediation analysis for count and zero-inflated count data; calculates power of causal mediation effects, direct effects, total effects; implements Instrumental Variable (IV) method to estimate the controlled (natural) direct and mediation effect, and the bootstrap CIs; calculates power of controlled (natural) direct and mediation effect using IV method; performs sensitivity analysis when there is a treatment-induced mediator-outcome confounder by varing coefficient of treatment in the confounder model and plots sensitivity graph.

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maczic_power	*Power Calculation for Mediation Analysis with Count and Zero-Inflated Count Data*

Description

'maczic_power' computes powers to detect average causal mediation effects (indirect effect), average direct effects, and total effect. This function uses simulations of 3 optional covariates (binary, normal, and multinomial), mediator (can be binary or continuous), and outcome (can be Normal, Poisson, Negative Binomial, zero-inflated Poisson/Negative Binomial) based on user-specified parameter values.

Usage

```
maczic_power(
  nsim,
  nsp,
  mtype,
  boot = FALSE,
  sims = 1000,
  conf.level = 0.95,
  ydist,
  size = 1,
  ymax,
  lpct0 = 0,
  hpct0 = 100,
  px1,
  am,
  bm,
  e1m,
  e2m,
  e3m,
  ag,
  bg,
  gg,
  e1g,
  e2g,
```

```
    e3g,
    delta = 0,
    ag2 = 0,
    bg2 = 0,
    gg2 = 0,
    e1g2 = 0,
    e2g2 = 0,
    e3g2 = 0,
    delta2 = 0
)
```

Arguments

nsim	Number of simulations.
nsp	Total sample size.
mtype	Type of mediator, either 'binary' or 'continuous'.
boot	A logical value. if 'FALSE' a quasi-Bayesian approximation is used for confidence intervals; if 'TRUE' nonparametric bootstrap will be used. Default is 'FALSE'.
sims	Number of Monte Carlo draws for nonparametric bootstrap or quasi-Bayesian approximation. Default is 1000.
conf.level	Level of the returned two-sided confidence intervals. The default value, 0.95, is to return the 2.5 and 97.5 percentiles of the simulated quantities.
ydist	Outcome distribution. Can be 'poisson', 'negbin', 'zip', 'zinb', or 'normal'.
size	Dispersion parameter for negative binomial outcome distribution. Default is 1. It's ignored for other outcome distribution.
ymax	Maximum value of outcome allowed.
lpct0	Low bound for percent of zeros in outcome. Default is 0.
hpct0	High bound for percent of zeros in outcome. Default is 100.
px1	Probability of the binary covariate being 1.
am	User-specified value for the intercept in the mediator model.
bm	User-specified value for the treatment coefficient in the mediator model.
e1m	User-specified value for the coefficient of the binary covariate variable in the mediator model.
e2m	User-specified value for the coefficient of the continuous covariate variable in the mediator model.
e3m	User-specified value for the coefficient of the multinomial covariate variable in the mediator model.
ag	User-specified value for the intercept in the outcome model or in the count model of zero-inflated Poisson/Negative Binomial outcome.
bg	User-specified value for the treatment coefficient in the outcome model or in the count model of zero-inflated Poisson/Negative Binomial outcome.
gg	User-specified value for the mediator coefficient in the outcome model or in the count model of zero-inflated Poisson/Negative Binomial outcome.
e1g	User-specified value for the coefficient of the binary covariate variable in the outcome model or in the count model of zero-inflated Poisson/Negative Binomial outcome.

e2g	User-specified value for the coefficient of the continuous covariate variable in the outcome model or in the count model of zero-inflated Poisson/Negative Binomial outcome.
e3g	User-specified value for the coefficient of the multinomial covariate variable in the outcome model or in the count model of zero-inflated Poisson/Negative Binomial outcome.
delta	User-specified value for the treatment-by-mediator interaction coefficient in the outcome model or in the count model of zero-inflated Poisson/Negative Binomial outcome model. Default is 0.
ag2	User-specified value for the intercept in the zero-inflation model of zero-inflated Poisson/Negative Binomial outcome. Note that this argument along with the following argument bg2, gg2, e1g2, e2g2, e3g2 and delta2 only apply to zero-inflated Poisson/Negative Binomial outcome. Default is 0.
bg2	User-specified value for the treatment coefficient in the zero-inflation model of zero-inflated Poisson/Negative Binomial outcome. Default is 0.
gg2	User-specified value for the mediator coefficient in the zero-inflation model of zero-inflated Poisson/Negative Binomial outcome. Default is 0.
e1g2	User-specified value for the coefficient of the binary covariate variable in the zero-inflation model of zero-inflated Poisson/Negative Binomial outcome. Default is 0.
e2g2	User-specified value for the coefficient of the continuous covariate variable in the zero-inflation model of zero-inflated Poisson/Negative Binomial outcome. Default is 0.
e3g2	User-specified value for the coefficient of the multinomial covariate variable in the zero-inflation model of zero-inflated Poisson/Negative Binomial outcome. Default is 0.
delta2	User-specified value for the coefficient of treatment-by-mediator interaction in the zero-inflation model of zero-inflated Poisson/Negative Binomial outcome. Default is 0.

Value

maczic_power returns a data frame with the following components and prints them out in a matrix format:

te.d0, te.d1	average true mediation effects under the control and treatment conditions.
te.z0, te.z1	average true direct effects under the control and treatment conditions.
te.tau	average true total effect.
ee.d0.rej, ee.d1.rej	
	power to detect mediation effects under the control and treatment conditions.
ee.z0.rej, ee.z1.rej	
	power to detect direct effects under the control and treatment conditions.
ee.tau.rej	power to detect total effect.
mean.y.z0	mean outcome in control in the simulated data, not available if outcome is normal.
mean.y.z1	mean outcome in treatment in the simulated data, not available if outcome is normal.

mean.y.gt0.z0	mean non-zero outcome in control in the simulated data, not available if outcome is normal.
mean.y.gt0.z1	mean non-zero outcome in treatment in the simulated data, not available if outcome is normal
pct0.y.z0	mean percent zero outcome in control in the simulated data, not available if outcome is normal.
pct0.y.z1	mean percent zero outcome in treatment in the simulated data, not available if outcome is normal.

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References

Cheng, J., Cheng, N.F., Guo, Z., Gregorich, S., Ismail, A.I., Gansky, S.A (2018) Mediation analysis for count and zero-inflated count data. Statistical Methods in Medical Research. 27(9):2756-2774.

Tingley, D., Yamamoto, T., Hirose, K., Imai, K. and Keele, L. (2014). "mediation: R package for Causal Mediation Analysis", Journal of Statistical Software, Vol. 59, No. 5, pp. 1-38.

Imai, K., Keele, L., Tingley, D. and Yamamoto, T. (2011). Unpacking the Black Box of Causality: Learning about Causal Mechanisms from Experimental and Observational Studies, American Political Science Review, Vol. 105, No. 4 (November), pp. 765-789.

Imai, K., Keele, L. and Tingley, D. (2010) A General Approach to Causal Mediation Analysis, Psychological Methods, Vol. 15, No. 4 (December), pp. 309-334.

Imai, K., Keele, L. and Yamamoto, T. (2010) Identification, Inference, and Sensitivity Analysis for Causal Mediation Effects, Statistical Science, Vol. 25, No. 1 (February), pp. 51-71.

Imai, K., Keele, L., Tingley, D. and Yamamoto, T. (2009) "Causal Mediation Analysis Using R" in Advances in Social Science Research Using R, ed. H. D. Vinod New York: Springer.

See Also

mediate_zi

Examples

```
# For illustration purposes a small number of simulations are used
# Example 1: simulate Poisson outcome with sample size 100, binary mediator
# and 2 covariate (binary and normal) variables
posOut <- maczic_power(nsim = 8, nsp = 100,  mtype = 'binary',
                       sims = 40, ydist = "Poisson", ymax = 60,
                       px1 = 0.5, am = 0.2, bm = 0.5,
                       e1m = 0.1, e2m = 0.1, e3m = 0,
                       ag = 0.1, bg = 0.3, gg = 1,
                       e1g = 0.5, e2g = -0.2, e3g = 0, delta = 0.1)

# Example 2: simulate zero-inflated Poisson outcome with sample size 80,
# continuous mediator and 1 normal covariate variable
zipOut <-maczic_power(nsim = 5, nsp = 80, mtype = 'continuous',
                      sims=30, ydist = "zip", ymax = 88, hpct0 = 60,
                      px1 = 0.5, am = 0.1, bm = 1,
                      e1m = 0, e2m = 0.2, e3m = 0,
                      ag = 0.6, bg = 0.6, gg = 0.2, e1g = 0, e2g = -0.2,
```

```
                            e3g = 0, ag2 = -0.7, bg2 = 0.2, gg2 = 0.1,
                            e2g2 = 0.1, delta2 = 0.15)
```

---

mediate_iv   *Mediation Analysis for Count and Zero-Inflated Count Data Using In-*
                               strumental Variable Method

Description

'mediate_iv' is used to estimate controlled or natural direct effect ratio, indirect (mediation) effect
ratio for count and zero-inflated count data using Instrumental Variable (IV) method described in
Guo, Z., Small, D.S., Gansky, S.A., Cheng, J. (2018).

Usage

```
mediate_iv(
  y,
  z,
  m,
  zm.int = FALSE,
  ydist = "poisson",
  mtype = "binary",
  x.IV,
  x.nonIV = NULL,
  tol = 1e-05,
  n.init = 3,
  control = list(),
  conf.level = 0.95,
  sims = 1000
)
```

Arguments

y	Outcome variable.
z	Treatment variable.
m	Mediator variable.
zm.int	A logical value. if 'FALSE' the interaction of treatment by mediator will not be included in the outcome model; if 'TRUE' the interaction will be included in the outcome model. Default is 'FALSE'.
ydist	A character string indicating outcome distribution which will be used to fit for getting the initial parameter estimates. Can only take one of the these three values - 'poisson', 'negbin', or 'neyman type a' Default is 'poisson'. Use 'neyman type a' for zero-inflated outcomes.
mtype	A character string indicating mediator type, either 'binary' or 'continuous'. Default is 'binary'.
x.IV	Specifies baseline variable(s) to construct Instrumental Variable(s), Use cbind() for 2 or more IVs.
x.nonIV	Specifies baseline variable(s) that are not used to construct Instrumental Variable(s) as covariates. Use cbind() for 2 or more non IVs. Default is NULL.

tol	Numeric tolerance value for parameter convergence. When the square root of sum of squared difference between two consecutive set of optimized parameters less than `tol`, then the convergence is reached. Default is 1e-5.
n.init	Number of set of initial parameter values. Default is 3.
control	A list of parameters governing the nonlinear optimization algorithm behavior (to minimize the profile empirical log-likelihood). This list is the same as that for `BBoptim()`, which is a wrapper for `spg()`. `control` default is `list(maxit = 1500,M = c(50,10),ftol=1e-10,gtol = 1e-05,maxfeval = 10000,maximize = FALSE,trace = FALSE,triter = 10,eps = 1e-07,checkGrad=NULL)`. See `spg` for more details.
conf.level	Level of the returned two-sided bootstrap confidence intervals. The default value, 0.95, is to return the 2.5 and 97.5 percentiles of the simulated quantities.
sims	Number of Monte Carlo draws for nonparametric bootstrap. Default is 1000.

Details

'mediate_iv' is to estimate the controlled and natural direct and indirect ratios of randomized treatment around and through mediators when there is unmeasured confounding. This function considers count and zero-inflated count outcomes, and binary and continuous mediators. The estimation uses an instrumental variable approach with empirical likelihood and estimating equations, where no parametric assumption is needed for the outcome distribution.

Controlled effect ratio

Given the generalized linear model for the expected potential outcomes:

$$f[E(Y(z,m)|x,u)] = \beta_0 + \beta_z z + \beta_m m + \beta_x x + u,$$

where f is a log-link function, β_0 is the intercept, z is the treatment, m is pre-specified mediator value, x are baseline covariates, β_z, β_m, β_x are their corresponding coefficients, u are unmeasured confounders and $Y(z,m)$ is the potential outcome under treatment z and mediator m. Then the controlled direct effect ratio when the treatment changes from z^* to z while keeping the mediator at m:

$$\frac{E[Y(z,m)|x,u]}{E[Y(z^*,m)|x,u]} = \exp[\beta_z(z - z^*)]$$

and the controlled indirect effect ratio when the mediator changes from m^* to m while keeping the treatment at z:

$$\frac{E[Y(z,m)|x,u]}{E[Y(z,m^*)|x,u]} = \exp[\beta_m(m - m^*)]$$

Natural effect ratio

Given a generalized linear model for the expected potential outcomes and a model for the mediator:

$$f[E(Y(z,M^{z^*}|x,u))] = \beta_0 + \beta_z z + \beta_m M^{z^*} + \beta_x x + u,$$

where f is a log-link function, M^{z^*} is the potential mediator under treatment z^*, and $Y(z,M^{z^*})$ is the potential outcome under treatment z and potential mediator M^{z^*}

$$h[E(M^{z^*}|x,u)] = \alpha_0 + \alpha_z z^* + \alpha_x x + \alpha_{IV} z^* x^{IV} + u,$$

where h is an identity function for continuous mediators and logit function for binary mediators; α_{IV} is the coefficient for instrumental variables x^{IV}, $z^* x^{IV}$, interaction of randomized treatment

and instrumental variables, and M^z is the potential mediator under treatment z^*. Then the natural direct effect ratio is:

$$\frac{E[Y(z, M^{z^*})|x, u]}{E[Y(z^*, M^{z^*}|x, u]} = \exp[\beta_z(z - z^*)].$$

And the natural indirect effect ratio with a continuous mediator is:

$$\frac{E[Y(z, M^z)|x, u]}{E[Y(z, M^{z^*})|x, u]} = \exp[\beta_m \alpha_z(z - z^*) + \beta_m \alpha_{IV} x^{IV}(z - z^*)].$$

The natural indirect effect ratio with a binary mediator is:

$$\frac{E[Y(z, M^z)|x, u]}{E[Y(z, M^{z^*})|x, u]} = \frac{P(M^z = 1|x, u) \exp(\beta_m) + P(M^z = 0|x, u)}{P(M^{z^*} = 1|x, u) \exp(\beta_m) + P(M^{z^*} = 0|x, u)}.$$

The parameters are estimated by the maximized empirical likelihood estimates, which are solutions to the estimating equations that maximizes the empirical likelihood. See details in Guo, Z., Small, D.S., Gansky, S.A., Cheng, J. (2018).

Value

mediate_iv returns a list with the following components and prints them out in a matrix format:

beta   parameter estimates from optimized profile empirical log-likelihood.

ter, ter.ci   point estimate for total effect ratio and its bootstrap confidence interval.

If the interaction between treatment and mediator is not specified, ie, zm.int=FALSE, a list of additional components are:

der, der.ci   point estimate for controlled direct effect ratio and its bootstrap confidence interval.

der.nat, der.nat.ci
                point estimate for natural direct effect ratio and its bootstrap confidence interval.

ier, ier.ci   point estimate for controlled indirect effect ratio and its bootstrap confidence interval.

ier.nat, ier.nat.ci
                point estimate for natural indirect effect ratio and its bootstrap confidence interval; They are only applicable to continuous mediator.

If the interaction between treatment and mediator is specified, ie, zm.int=TRUE, which is only supported for binary mediator, a list of additional components are:

der.m0, der.m0.ci
                point estimate for controlled direct effect ratio when m = 0 and its bootstrap confidence interval.

der.m1, der.m1.ci
                point estimate for controlled direct effect ratio when m = 1 and its bootstrap confidence interval.

der.nat.m0, der.nat.m0.ci
                point estimate for natural direct effect ratio when m = 0 and its bootstrap confidence interval.

der.nat.m1, der.nat.m1.ci
                point estimate for natural direct effect ratio when m = 1 and its bootstrap confidence interval.

ier.z0, ier.z0.ci

> point estimate for controlled indirect effect ratio when z = 0 and its bootstrap confidence interval.

ier.z1, ier.z1.ci

> point estimate for controlled indirect effect ratio when z = 1 and its bootstrap confidence interval.

Author(s)

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References

Guo, Z., Small, D.S., Gansky, S.A., Cheng, J. (2018), Mediation analysis for count and zero-inflated count data without sequential ignorability and its application in dental studies. Journal of the Royal Statistical Society, Series C.; 67(2):371-394.

Ismail AI, Ondersma S, Willem Jedele JM, et al. (2011) Evaluation of a brief tailored motivational intervention to prevent early childhood caries. Community Dentistry and Oral Epidemiology 39: 433–448.

See Also

el.test, BBoptim, spg

Examples

```
# For illustration purposes a small number of bootstrap iterations are used
data("midvd_bt100")
# The outcome is Poisson distribution
ee <- mediate_iv(y = midvd_bt100$Untreated_W3,
                 z = midvd_bt100$intervention,
                 m = midvd_bt100$PBrush_6, ydist = "poisson",
                 mtype = "binary", x.IV = midvd_bt100$BrushTimes_W2,
                 tol = 0.5, n.init = 1,
                 control = list(maxit = 15, ftol = 0.5, gtol = 0.5,
                                trace = FALSE),
                 sims = 3)
```

---

mediate_zi *Mediation Analysis for Count and Zero-Inflated Count Data*

Description

'mediate_zi' is modified from the mediate function in mediation package (version 4.0.1) with the new feature added to handle Zero-inflated count outcomes including Zero-inflated Poisson and Zero-inflated Negative Binomial outcomes. This function is used to estimate various quantities for causal mediation analysis, including average causal mediation effects (ACME) or indirect effect, average direct effects (ADE), proportions mediated, and total effect. The Usage, Argument, Value, and Details of this function are the same as mediate() in mediation package version 4.0.1 (see below) except for the description of the 'model.y' argument, which has class 'zeroinfl' added.

Usage

```
mediate_zi(
  model.m,
  model.y,
  sims = 1000,
  boot = FALSE,
  treat = "treat.name",
  mediator = "med.name",
  covariates = NULL,
  outcome = NULL,
  control = NULL,
  conf.level = 0.95,
  control.value = 0,
  treat.value = 1,
  long = TRUE,
  dropobs = FALSE,
  robustSE = FALSE,
  cluster = NULL,
  ...
)
```

Arguments

model.m	A fitted model object for mediator. Can be of class 'lm', 'polr', 'bayespolr', 'glm', 'bayesglm', 'gam', 'rq', or 'survreg'.
model.y	A fitted model object for outcome. Can be of class 'lm', 'polr', 'bayespolr', 'glm', 'bayesglm', 'gam', 'vglm', 'rq', 'survreg', or 'zeroinfl'
sims	Number of Monte Carlo draws for nonparametric bootstrap or quasi-Bayesian approximation.
boot	A logical value. if 'FALSE' a quasi-Bayesian approximation is used for confidence intervals; if 'TRUE' nonparametric bootstrap will be used. Default is 'FALSE'.
treat	A character string indicating the name of the treatment variable used in the models. The treatment can be either binary (integer or a two-valued factor) or continuous (numeric).
mediator	A character string indicating the name of the mediator variable used in the models.
covariates	A list or data frame containing values for a subset of the pre-treatment covariates in 'model.m' and 'model.y'. If provided, the function will return the estimates conditional on those covariate values.
outcome	A character string indicating the name of the outcome variable in 'model.y'. Only necessary if 'model.y' is of class 'survreg'; otherwise ignored.
control	A character string indicating the name of the control group indicator. Only relevant if 'model.y' is of class 'gam'. If provided, 'd0', 'z0' and 'n0' are allowed to differ from 'd1', 'z1' and 'n1', respectively.
conf.level	Level of the returned two-sided confidence intervals. Default is to return the 2.5 and 97.5 percentiles of the simulated quantities.
control.value	Value of the treatment variable used as the control condition. Default is 0.
treat.value	Value of the treatment variable used as the treatment condition. Default is 1.

long
: A logical value. If 'TRUE', the output will contain the entire sets of simulation draws of the the average causal mediation effects, direct effects, proportions mediated, and total effect. Default is 'TRUE'.

dropobs
: A logical value indicating the behavior when the model frames of 'model.m' and 'model.y' (and the 'cluster' variable if included) are composed of different observations. If 'TRUE', models will be re-fitted using common data rows. If 'FALSE', error is returned. Default is 'FALSE'.

robustSE
: A logical value. If 'TRUE', heteroskedasticity-consistent standard errors will be used in quasi-Bayesian simulations. Ignored if 'boot' is 'TRUE' or neither 'model.m' nor 'model.y' has a method for vcovHC in the sandwich package. Default is 'FALSE'.

cluster
: A variable indicating clusters for standard errors. Note that this should be a vector of cluster indicators itself, not a character string for the name of the variable.

...
: other arguments passed to vcovHC in the sandwich package: typically the 'type' argument, which is ignored if 'robustSE' is 'FALSE'. Arguments to the boot in the boot package may also be passed, e.g. 'parallel' and 'ncpus'.

Details

This is the workhorse function for estimating causal mediation effects for a variety of data types. The average causal mediation effect (ACME) represents the expected difference in the potential outcome when the mediator took the value that would realize under the treatment condition as opposed to the control condition, while the treatment status itself is held constant. That is,

$$\delta(t) \;=\; E[Y(t, M(t_1)) - Y(t, M(t_0))],$$

where t, t_1, t_0 are particular values of the treatment T such that $t_1 \neq t_0$, $M(t)$ is the potential mediator, and $Y(t, m)$ is the potential outcome variable. The average direct effect (ADE) is defined similarly as,

$$\zeta(t) \;=\; E[Y(t_1, M(t)) - Y(t_0, M(t))],$$

which represents the expected difference in the potential outcome when the treatment is changed but the mediator is held constant at the value that would realize if the treatment equals t. The two quantities on average add up to the total effect of the treatment on the outcome, τ. See the references for more details.

When both the mediator model ('model.m') and outcome model ('model.y') are normal linear regressions, the results will be identical to the usual LSEM method by Baron and Kenny (1986). The function can, however, accommodate other data types including binary, ordered and count outcomes and mediators as well as censored outcomes. Variables can also be modeled nonparametrically, semiparametrically, or using quantile regression.

If it is desired that inference be made conditional on specific values of the pre-treatment covariates included in the model, the 'covariates' argument can be used to set those values as a list or data frame. The list may contain either the entire set or any strict subset of the covariates in the model; in the latter case, the effects will be averaged over the other covariates. The 'covariates' argument will be particularly useful when the models contain interactions between the covariates and the treatment and/or mediator (known as "moderated mediation").

The prior weights in the mediator and outcome models are taken as sampling weights and the estimated effects will be weighted averages when non-NULL weights are used in fitting 'model.m' and 'model.y'. This will be useful when data does not come from a simple random sample, for example.

As of version 4.0, the mediator model can be of either 'lm', 'glm' (or 'bayesglm'), 'polr' (or 'bayespolr'), 'gam', 'rq', or 'survreg' class corresponding respectively to the linear regression models, generalized linear models, ordered response models, generalized additive models, quantile regression models, or parametric duration models. For binary response models, the 'mediator' must be a numeric variable with values 0 or 1 as opposed to a factor. Quasi-likelihood-based inferences are not allowed for the mediator model because the functional form must be exactly specified for the estimation algorithm to work. The 'binomial' family can only be used for binary response mediators and cannot be used for multiple-trial responses. This is due to conflicts between how the latter type of models are implemented in glm and how 'mediate' is currently written.

For the outcome model, the censored regression model fitted via package VGAM (of class 'vglm' with 'family@vfamily' equal to "tobit") can be used in addition to the models listed above for the mediator. The 'mediate' function is not compatible with censored regression models fitted via other packages. When the quantile regression is used for the outcome model ('rq'), the estimated quantities are quantile causal mediation effects, quantile direct effects and etc., instead of the average effects. If the outcome model is of class 'survreg', the name of the outcome variable must be explicitly supplied in the 'outcome' argument. This is due to the fact that 'survreg' objects do not contain that information in an easily extractable form. It should also be noted that for survreg models, the Surv function must be directly used in the model formula in the call to the survreg function, and that censoring types requiring more than two arguments to Surv (e.g., interval censoring) are not currently supported by 'mediate'.

The quasi-Bayesian approximation (King et al. 2000) cannot be used if 'model.m' is of class 'rq' or 'gam', or if 'model.y' is of class 'gam', 'polr' or 'bayespolr'. In these cases, either an error message is returned or use of the nonparametric bootstrap is forced. Users should note that use of the nonparametric bootstrap often requires significant computing time, especially when 'sims' is set to a large value.

The 'control' argument must be provided when 'gam' is used for the outcome model and user wants to allow ACME and ADE to vary as functions of the treatment (i.e., to relax the "no interaction" assumption). Note that the outcome model must be fitted via package mgcv with appropriate formula using s constructs (see Imai et al. 2009 in the references). For other model types, the interaction can be allowed by including an interaction term between T and M in the linear predictor of the outcome model. As of version 3.0, the 'INT' argument is deprecated and the existence of the interaction term is automatically detected (except for 'gam' outcome models).

When the treatment variable is continuous or a factor with multiple levels, user must specify the values of t_1 and t_0 using the 'treat.value' and 'control.value' arguments, respectively. The value of t in the above expressions is set to t_0 for 'd0', 'z0', etc. and to t_1 for 'd1', 'z1', etc.

Value

mediate returns an object of class "mediate", (or "mediate.order" if the outcome model used is 'polr' or 'bayespolr'), a list that contains the components listed below. Some of these elements are not available if 'long' is set to 'FALSE' by the user.

The function summary (i.e., summary.mediate, or summary.mediate.order) can be used to obtain a table of the results. The function plot (i.e., plot.mediate, or plot.mediate.order) can be used to produce a plot of the estimated average causal mediation, average direct, and total effects along with their confidence intervals.

d0, d1	point estimates for average causal mediation effects under the control and treatment conditions.
d0.ci, d1.ci	confidence intervals for average causal mediation effects. The confidence level is set at the value specified in 'conf.level'.
d0.p, d1.p	two-sided p-values for average causal mediation effects.

`d0.sims, d1.sims`	
	vectors of length 'sims' containing simulation draws of average causal mediation effects.
`z0, z1`	point estimates for average direct effect under the control and treatment conditions.
`z0.ci, z1.ci`	confidence intervals for average direct effects.
`z0.p, z1.p`	two-sided p-values for average causal direct effects.
`z0.sims, z1.sims`	
	vectors of length 'sims' containing simulation draws of average direct effects.
`n0, n1`	the "proportions mediated", or the size of the average causal mediation effects relative to the total effect.
`n0.ci, n1.ci`	confidence intervals for the proportions mediated.
`n0.p, n1.p`	two-sided p-values for proportions mediated.
`n0.sims, n1.sims`	
	vectors of length 'sims' containing simulation draws of the proportions mediated.
`tau.coef`	point estimate for total effect.
`tau.ci`	confidence interval for total effect.
`tau.p`	two-sided p-values for total effect.
`tau.sims`	a vector of length 'sims' containing simulation draws of the total effect.
`d.avg, z.avg, n.avg`	
	simple averages of d0 and d1, z0 and z1, n0 and n1, respectively, which users may want to use as summary values when those quantities differ.
`d.avg.ci, z.avg.ci, n.avg.ci`	
	confidence intervals for the above.
`d.avg.p, z.avg.p, n.avg.p`	
	two-sided p-values for the above.
`d.avg.sims, z.avg.sims, n.avg.sims`	
	vectors of length 'sims' containing simulation draws of d.avg, z.avg and n.avg, respectively.
`boot`	logical, the 'boot' argument used.
`treat`	a character string indicating the name of the 'treat' variable used.
`mediator`	a character string indicating the name of the 'mediator' variable used.
`INT`	a logical value indicating whether the model specification allows the effects to differ between the treatment and control conditions.
`conf.level`	the confidence level used.
`model.y`	the outcome model used.
`model.m`	the mediator model used.
`control.value`	value of the treatment variable used as the control condition.
`treat.value`	value of the treatment variable used as the treatment condition.
`nobs`	number of observations in the model frame for 'model.m' and 'model.y'. May differ from the numbers in the original models input to 'mediate' if 'dropobs' was 'TRUE'.
`robustSE`	'TRUE' or 'FALSE'.
`cluster`	the clusters used.

Author(s)

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References

Cheng, J., Cheng, N.F., Guo, Z., Gregorich, S., Ismail, A.I., Gansky, S.A (2018) Mediation analysis for count and zero-inflated count data. Statistical Methods in Medical Research. 27(9):2756-2774.

Tingley, D., Yamamoto, T., Hirose, K., Imai, K. and Keele, L. (2014). "mediation: R package for Causal Mediation Analysis", Journal of Statistical Software, Vol. 59, No. 5, pp. 1-38.

Imai, K., Keele, L., Tingley, D. and Yamamoto, T. (2011). Unpacking the Black Box of Causality: Learning about Causal Mechanisms from Experimental and Observational Studies, American Political Science Review, Vol. 105, No. 4 (November), pp. 765-789.

Imai, K., Keele, L. and Tingley, D. (2010) A General Approach to Causal Mediation Analysis, Psychological Methods, Vol. 15, No. 4 (December), pp. 309-334.

Imai, K., Keele, L. and Yamamoto, T. (2010) Identification, Inference, and Sensitivity Analysis for Causal Mediation Effects, Statistical Science, Vol. 25, No. 1 (February), pp. 51-71.

Imai, K., Keele, L., Tingley, D. and Yamamoto, T. (2009) "Causal Mediation Analysis Using R" in Advances in Social Science Research Using R, ed. H. D. Vinod New York: Springer.

See Also

summary.mediate, plot.mediate

Examples

```
# For illustration purposes a small number of simulations are used
# Example: Zero-inflated Count Outcome and Binary Mediator
# Generate example data
n <- 50
# Generate binary treatment variable
z <- rep(0, n)
z[sample(1:n, n/2)] <- 1
# Generate binary covariate variable
x1 <- rbinom(n, 1, p = 0.5)
# Generate continuous covariate variable
x2 <- rnorm(n)
# Create binary mediator
m <- c(1, 1, 0, 1, 1, 1, 1, 0, 1, 1,
       0, 1, 1, 1, 1, 0, 1, 0, 1, 0,
       1, 1, 0, 1, 0, 1, 1, 1, 1, 0,
       1, 1, 0, 1, 0, 1, 1, 0, 1, 1,
       0, 1, 1, 0, 0, 1, 1, 1, 0, 1)
# Create Zero-inflated Count Outcome
y <- c(0, 7, 0, 0, 8, 0, 7, 3, 5, 0,
       5, 0, 0, 1, 10,0, 3, 4, 5, 7,
       9, 7, 0, 6, 2, 4, 0, 0, 0, 6,
       0, 11,0, 5, 6, 0, 0, 12,0, 0,
       13,6, 8, 6, 5, 0, 4, 0, 6, 8)
sdata <- data.frame(z, x1, x2, m, y)
mFit <- glm(m ~ z + x1 + x2, data = sdata, family = binomial)
# Fit with Zero-inflated Poisson model
yzipFit <- zeroinfl(y ~ z + m + x1 + x2, data = sdata)
# Estimation via Quasi-Bayesian approximation
```

```
zipMA <- mediate_zi(mFit, yzipFit, sims = 100, treat = "z", mediator = "m")
summary(zipMA)
```

---

mediate_zi_vcoef   *Mediation Sensitivity Analysis for Count and Zero-Inflated Count Data with a Post-Treatment Confounder*

Description

'mediate_zi_vcoef' is modified from mediate_zi function with 3 confounder-related parameters ('model.u', 'delta.beta.u', and 'confounder') added. It is used to estimate causal mediation effects when there is a treatment-induced mediator-outcome confounder, and the coefficient of treatment in the confounder model is specified by users. Users can perform sensitivity analysis with a range of specified coefficient values when there is a post-treatment confounder.

Usage

```
mediate_zi_vcoef(
  model.u,
  delta.beta.u,
  model.m,
  model.y,
  sims = 1000,
  boot = FALSE,
  treat = "treat.name",
  mediator = "med.name",
  confounder = "confd.name",
  covariates = NULL,
  outcome = NULL,
  control = NULL,
  conf.level = 0.95,
  control.value = 0,
  treat.value = 1,
  long = TRUE,
  dropobs = FALSE,
  robustSE = FALSE,
  cluster = NULL,
  ...
)
```

Arguments

model.u   A fitted model object for confounder. Can be of class 'lm', 'polr', 'bayespolr', 'glm', 'bayesglm', 'gam', 'rq', or 'survreg'.

delta.beta.u   Sensitivity parameter as difference from the estimated treatment coefficient in the confounder model (model.u) based on the observed data.

model.m   A fitted model object for mediator. Can be of class 'lm', 'polr', 'bayespolr', 'glm', 'bayesglm', 'gam', 'rq', or 'survreg'.

model.y   A fitted model object for outcome. Can be of class 'lm', 'polr', 'bayespolr', 'glm', 'bayesglm', 'gam', 'vglm', 'rq', 'survreg', or 'zeroinfl'

sims	Number of Monte Carlo draws for nonparametric bootstrap or quasi-Bayesian approximation.
boot	A logical value. if 'FALSE' a quasi-Bayesian approximation is used for confidence intervals; if 'TRUE' nonparametric bootstrap will be used. Default is 'FALSE'.
treat	A character string indicating the name of the treatment variable used in the models. The treatment can be either binary (integer or a two-valued factor) or continuous (numeric).
mediator	A character string indicating the name of the mediator variable used in the models.
confounder	A character string indicating the name of the confounder variable used in the models.
covariates	A list or data frame containing values for a subset of the pre-treatment covariates in 'model.m' and 'model.y'. If provided, the function will return the estimates conditional on those covariate values.
outcome	A character string indicating the name of the outcome variable in 'model.y'. Only necessary if 'model.y' is of class 'survreg'; otherwise ignored.
control	A character string indicating the name of the control group indicator. Only relevant if 'model.y' is of class 'gam'. If provided, 'd0', 'z0' and 'n0' are allowed to differ from 'd1', 'z1' and 'n1', respectively.
conf.level	Level of the returned two-sided confidence intervals. Default is to return the 2.5 and 97.5 percentiles of the simulated quantities.
control.value	Value of the treatment variable used as the control condition. Default is 0.
treat.value	Value of the treatment variable used as the treatment condition. Default is 1.
long	A logical value. If 'TRUE', the output will contain the entire sets of simulation draws of the the average causal mediation effects, direct effects, proportions mediated, and total effect. Default is 'TRUE'.
dropobs	A logical value indicating the behavior when the model frames of 'model.m' and 'model.y' (and the 'cluster' variable if included) are composed of different observations. If 'TRUE', models will be re-fitted using common data rows. If 'FALSE', error is returned. Default is 'FALSE'.
robustSE	A logical value. If 'TRUE', heteroskedasticity-consistent standard errors will be used in quasi-Bayesian simulations. Ignored if 'boot' is 'TRUE' or neither 'model.m' nor 'model.y' has a method for vcovHC in the sandwich package. Default is 'FALSE'.
cluster	A variable indicating clusters for standard errors. Note that this should be a vector of cluster indicators itself, not a character string for the name of the variable.
...	other arguments passed to vcovHC in the sandwich package: typically the 'type' argument, which is ignored if 'robustSE' is 'FALSE'. Arguments to the boot in the boot package may also be passed, e.g. 'parallel' and 'ncpus'.

Value

mediate_zi_vcoef returns an object of class "mediate", (or "mediate.order" if the outcome model used is 'polr' or 'bayespolr'), a list that contains the components listed below. Some of these elements are not available if 'long' is set to 'FALSE' by the user.

The function summary (i.e., summary.mediate, or summary.mediate.order) can be used to obtain a table of the results. The function plot (i.e., plot.mediate, or plot.mediate.order) can be

used to produce a plot of the estimated average causal mediation, average direct, and total effects along with their confidence intervals.

d0, d1	point estimates for average causal mediation effects under the control and treatment conditions.
d0.ci, d1.ci	confidence intervals for average causal mediation effects. The confidence level is set at the value specified in 'conf.level'.
d0.p, d1.p	two-sided p-values for average causal mediation effects.
d0.sims, d1.sims	
	vectors of length 'sims' containing simulation draws of average causal mediation effects.
z0, z1	point estimates for average direct effect under the control and treatment conditions.
z0.ci, z1.ci	confidence intervals for average direct effects.
z0.p, z1.p	two-sided p-values for average causal direct effects.
z0.sims, z1.sims	
	vectors of length 'sims' containing simulation draws of average direct effects.
n0, n1	the "proportions mediated", or the size of the average causal mediation effects relative to the total effect.
n0.ci, n1.ci	confidence intervals for the proportions mediated.
n0.p, n1.p	two-sided p-values for proportions mediated.
n0.sims, n1.sims	
	vectors of length 'sims' containing simulation draws of the proportions mediated.
tau.coef	point estimate for total effect.
tau.ci	confidence interval for total effect.
tau.p	two-sided p-values for total effect.
tau.sims	a vector of length 'sims' containing simulation draws of the total effect.
d.avg, z.avg, n.avg	
	simple averages of d0 and d1, z0 and z1, n0 and n1, respectively, which users may want to use as summary values when those quantities differ.
d.avg.ci, z.avg.ci, n.avg.ci	
	confidence intervals for the above.
d.avg.p, z.avg.p, n.avg.p	
	two-sided p-values for the above.
d.avg.sims, z.avg.sims, n.avg.sims	
	vectors of length 'sims' containing simulation draws of d.avg, z.avg and n.avg, respectively.
boot	logical, the 'boot' argument used.
treat	a character string indicating the name of the 'treat' variable used.
mediator	a character string indicating the name of the 'mediator' variable used.
INT	a logical value indicating whether the model specification allows the effects to differ between the treatment and control conditions.
conf.level	the confidence level used.
model.y	the outcome model used.
model.m	the mediator model used.

control.value	value of the treatment variable used as the control condition.
treat.value	value of the treatment variable used as the treatment condition.
nobs	number of observations in the model frame for 'model.m' and 'model.y'. May differ from the numbers in the original models input to 'mediate' if 'dropobs' was 'TRUE'.
robustSE	'TRUE' or 'FALSE'.
cluster	the clusters used.

Author(s)

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References

Cheng, J., Cheng, N.F., Guo, Z., Gregorich, S., Ismail, A.I., Gansky, S.A (2018) Mediation analysis for count and zero-inflated count data. Statistical Methods in Medical Research. 27(9):2756-2774.

Ismail AI, Ondersma S, Willem Jedele JM, et al. (2011) Evaluation of a brief tailored motivational intervention to prevent early childhood caries. Community Dentistry and Oral Epidemiology 39: 433–448.

Tingley, D., Yamamoto, T., Hirose, K., Imai, K. and Keele, L. (2014). "mediation: R package for Causal Mediation Analysis", Journal of Statistical Software, Vol. 59, No. 5, pp. 1-38.

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Imai, K., Keele, L. and Tingley, D. (2010) A General Approach to Causal Mediation Analysis, Psychological Methods, Vol. 15, No. 4 (December), pp. 309-334.

Imai, K., Keele, L. and Yamamoto, T. (2010) Identification, Inference, and Sensitivity Analysis for Causal Mediation Effects, Statistical Science, Vol. 25, No. 1 (February), pp. 51-71.

Imai, K., Keele, L., Tingley, D. and Yamamoto, T. (2009) "Causal Mediation Analysis Using R" in Advances in Social Science Research Using R, ed. H. D. Vinod New York: Springer.

See Also

plot_sensitivity, mediate_zi, summary.mediate, plot.mediate

Examples

```
data("midvd_bt100")
uFit <- glm (PDVisit_6 ~ intervention + BrushTimes_W2 + HealthyMeals_W2
                        + PDVisit_W2,
            family = 'binomial', data = midvd_bt100)
mFit <- glm (PBrushBedt_6 ~ intervention + BrushTimes_W2 + HealthyMeals_W2
                        + PBrush_W2 + PDVisit_6,
            family = 'binomial', data = midvd_bt100)
yFit <- zeroinfl(Untreated_W3 ~ intervention + PBrushBedt_6 + BrushTimes_W2
                        + HealthyMeals_W2 + PBrush_W2+ PDVisit_6,
                data = midvd_bt100)
# For illustration purposes a small number of simulations are used
ee <-mediate_zi_vcoef(uFit, delta.beta.u = 0.01, mFit, yFit, sims = 100,
                    treat = "intervention", mediator = "PBrushBedt_6",
                    confounder ="PDVisit_6")
```

```
summary(ee)
```

---

midvd_bt100 *Example Data for mediate_zi_vcoef, plot_sensitivity and mediate_iv Functions*

Description

A bootstrap random subsample of the DDHP MI-DVD trial data used in Cheng, J., Cheng, N.F., Guo, Z., Gregorich, S., Ismail, A.I., Gansky, S.A. (2018). In the trial, the enrolled families were examined at Wave 1 (randomization), wave 2 (dental examination and study started, considered as baseline), 6-month follow up, and end of the study (wave 3, 2-year). This bootstrap subsample data contain 100 rows and 9 columns with no missing values. The data are provided only for illustrative purposes.

Usage

```
midvd_bt100
```

Format

A data frame containing the following variables:

BrushTimes_W2: Number of times child brushed per day in a typical week measured at wave 2 (baseline).

HealthyMeals_W2: A binary variable indicating whether caregivers gave child healthy meals measured at wave 2 (baseline) (1=Yes, 0=No).

PBrush_W2: A binary variable indicating whether caregivers made sure child brushed 2 times per day measured at wave 2 (baseline) (1=Yes, 0=No).

PDVisit_W2: A binary variable indicating whether caregiver makes sure child sees dentists every 6 mos measured at wave 2 (baseline) (1=Yes, 0=No).

PDVisit_6: A binary variable indicating whether caregiver makes sure child sees dentists every 6 mos measured at 6-month follow up (1=Yes, 0=No).

PBrushBedt_6: A binary variable indicating whether caregivers made sure child brushes teeth at bedtime measured at 6-month follow up (1=Yes, 0=No).

PBrush_6: A binary variable indicating whether caregivers made sure child brushed 2 times per day measured at 6-month follow up (1=Yes, 0=No).

intervention: A binary treatment variable (1=intervention 0=Control).

Untreated_W3: The number of new untreated lesions measured at end of the 2-year study.

Source

Ismail AI, Ondersma S, Willem Jedele JM, et al. (2011) Evaluation of a brief tailored motivational intervention to prevent early childhood caries. Community Dentistry and Oral Epidemiology 39: 433–448.

Cheng, J., Cheng, N.F., Guo, Z., Gregorich, S., Ismail, A.I., Gansky, S.A. (2018) Mediation analysis for count and zero-inflated count data. Statistical Methods in Medical Research. 27(9):2756-2774.

plot_sensitivity *Plot Sensitivity Graph*

Description

'plot_sensitivity' performs sensitivity analysis when there is a treatment- induced mediator-outcome confounder by varying coefficient of treatment in the confounder model and plots sensitivity graph.

Usage

```
plot_sensitivity(
  model.u,
  n.beta.u = 10,
  model.m,
  model.y,
  sims = 1000,
  boot = FALSE,
  confounder = "confd.name",
  treat = "treat.name",
  mediator = "med.name",
  covariates = NULL,
  outcome = NULL,
  xlab = "Beta.u",
  ylab = "Effect",
  xlim = NULL,
  ylim = NULL,
  main = NULL,
  type = "l",
  col = c("black", "black", "black"),
  pch = NULL,
  lty = c(1, 2, 3),
  legend.x,
  legend.y = NULL,
  legend.inset = 0.05,
  legend = c("Direct Effect", "Mediation Effect", "Total Effect"),
  legend.horiz = FALSE
)
```

Arguments

model.u	A fitted model object for confounder. Can be of class 'lm', 'polr', 'bayespolr', 'glm', 'bayesglm', 'gam', 'rq', or 'survreg'.
n.beta.u	Number of varying coefficient of treatment in the confounder model. This number is adjusted as n.beta.u + 1 if n.beta.u is an even number.
model.m	A fitted model object for mediator. Can be of class 'lm', 'polr', 'bayespolr', 'glm', 'bayesglm', 'gam', 'rq', or 'survreg'.
model.y	A fitted model object for outcome. Can be of class 'lm', 'polr', 'bayespolr', 'glm', 'bayesglm', 'gam', 'vglm', 'rq', 'survreg', or 'zeroinfl'.
sims	Number of Monte Carlo draws for quasi-Bayesian approximation.

boot	A logical value. if 'FALSE' a quasi-Bayesian approximation is used for confidence intervals; if 'TRUE' nonparametric bootstrap will be used. Default is 'FALSE'.
confounder	A character string indicating the name of the confounder variable used in the models.
treat	A character string indicating the name of the treatment variable used in the models. The treatment can be either binary (integer or a two-valued factor) or continuous (numeric).
mediator	A character string indicating the name of the mediator variable used in the models.
covariates	A list or data frame containing values for a subset of the pre-treatment covariates in 'model.m' and 'model.y'. If provided, the function will return the estimates conditional on those covariate values. Default is NULL.
outcome	A character string indicating the name of the outcome variable in 'model.y'. Only necessary if 'model.y' is of class 'survreg'; otherwise ignored. Default is NULL.
xlab, ylab	Labels for x and y axes, as in plot. Default xlab = "Beta.u", ylab = "Effect".
xlim, ylim	Ranges of x and y axes, as in plot. The default value, NULL, indicates that the range of the finite values to be plotted should be used.
main	A main title for the plot, as in plot.
type	A character string (length 1 vector) or vector of 1-character strings indicating the type of plot for 3 columns of y, as in plot. Default is 'l' for lines.
col	A vector of strings indicating the colors for 3 lines of y. Default is ("black","black","black").
pch	A vector of plotting characters or symbols, as in plot. Default is NULL.
lty	A vector of line types, as in plot. Default is c(1,2,3).
legend.x, legend.y	
	The x and y co-ordinates to be used to position the legend, see x, y in legend. Default legend.y = NULL.
legend.inset	Inset distance(s) from the margins as a fraction of the plot region when legend is placed by keyword, as inset in legend. Default is 0.05.
legend	A character or expression vector of 3 to appear in the legend, as in legend. Default is c("Direct Effect", "Mediation Effect", "Total Effect")
legend.horiz	A logical value. If TRUE, set the legend horizontally Default is FALSE, which sets the legend vertically.

Details

The function uses the estimated coefficient of treatment in the fitted confounder model with observed data (see Cheng et al 2018) as the middle point (mid.beta.u), and calculates 1 unit change in the coefficient as |2*mid.beta.u/3/(n-1)| where n = n.beta.u if n.beta.u is an odd number and n = n.beta.u+1 if n.beta.u is an even number, and n.beta.u is the number of varying coefficient of treatment specified by users. mediate_zi_vcoef is then used to estimate average causal mediation effects (indirect effect), average direct effects, and total effect for each value of the treatment coefficient in the confounder model. The function prints all the effect estimates, and produces the sensitivity graph.

Value

`plot_sensitivity` produces sensitivity graph and returns an object of data frame with the following columns:

`beta.u`	coefficient of treatment in the confounder model.
`d0, d1`	point estimates for average causal mediation effects under the control and treatment conditions.
`z0, z1`	point estimates for average direct effect under the control and treatment conditions.
`d.avg, z.avg`	simple averages of d0 and d1, z0 and z1, respectively.
`tau.coef`	point estimate for total effect.

Author(s)

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References

Cheng, J., Cheng, N.F., Guo, Z., Gregorich, S., Ismail, A.I., Gansky, S.A (2018) Mediation analysis for count and zero-inflated count data. Statistical Methods in Medical Research. 27(9):2756-2774.

Ismail AI, Ondersma S, Willem Jedele JM, et al. (2011) Evaluation of a brief tailored motivational intervention to prevent early childhood Community Dentistry and Oral Epidemiology 39: 433–448.

See Also

mediate_zi_vcoef

Examples

```
data("midvd_bt100")
uFit <- glm(PDVisit_6 ~ intervention + BrushTimes_W2 + HealthyMeals_W2
                       + PDVisit_W2,
            family = 'binomial', data = midvd_bt100)
mFit <- glm(PBrushBedt_6 ~ intervention + BrushTimes_W2 + HealthyMeals_W2
                          + PBrush_W2 + PDVisit_6,
            family = 'binomial', data = midvd_bt100)
yFit <- zeroinfl(Untreated_W3 ~ intervention + PBrushBedt_6 + BrushTimes_W2
                               + HealthyMeals_W2 + PBrush_W2 + PDVisit_6,
                 data = midvd_bt100)
# For illustration purposes a small number of simulations are used
plot_sensitivity(uFit, n.beta.u = 5, mFit, yFit, sims = 25,
                 treat = "intervention", mediator = "PBrushBedt_6",
                 confounder = "PDVisit_6",
                 main = "Effects on the number of new untreated cavities at 2 years",
                 legend.x = "right")
```

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