Package ‘CausalGAM’

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Title Estimation of Causal Effects with Generalized Additive Models
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Depends R (>= 2.9.0), gam (>= 1.0.1)
Description Implements various estimators for average
treatment effects - an inverse probability weighted (IPW) estimator,
an augmented inverse probability weighted (AIPW) estimator, and a standard
regression estimator - that make use of generalized additive models for
the treatment assignment model and/or outcome model. See: Glynn, Adam N.
and Kevin M. Quinn. 2010. "An Introduction to the Augmented Inverse
Propensity Weighted Estimator." Political Analysis. 18: 36-56.
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**balance.IPW**

## Description

This function calculates weighted means of covariates where weights in inverse propensity weights and then examines the differences in the weighted means across treated and control units as a diagnostic for covariate balance.

## Usage

```r
balance.IPW(pscore.formula, pscore.family, treatment.var, outcome.var, data = NULL, divby0.action = c("fail", "truncate", "discard"), divby0.tol = 1e-08, nboot = 501, suppress.warnings = TRUE, ...)
```

## Arguments

- `pscore.formula` A formula expression for the propensity score model. See the documentation of `gam` for details.
- `pscore.family` A description of the error distribution and link function to be used for the propensity score model. See the documentation of `gam` for details.
- `treatment.var` A character variable giving the name of the binary treatment variable in `data`. If `treatment.var` is a numeric variable, it is assumed that `control` corresponds to `sort(unique(treatment.values))[1]` and `treatment` corresponds to `sort(unique(treatment.values))[2]`. If `treatment.var` is a factor, it is assumed that `control` corresponds to `levels(treatment.values)[1]` and `treatment` corresponds to `levels(treatment.values)[2]`.
- `outcome.var` A character variable giving the name of the outcome variable in `data`.
- `data` A non-optional data frame containing the variables in the propensity score model along with all covariates that one wishes to assess balance for. `data` cannot contain any missing values.
- `divby0.action` A character variable describing what action to take when some estimated propensity scores are less than `divby0.tol` or greater than `1 - divby0.tol`. Options include: ‘fail’ (abort the call to estimate.ATE), ‘truncate’ (set all estimated propensity scores less than `divby0.tol` equal to `divby0.tol` and all estimated propensity scores greater than `1 - divby0.tol` equal to `1 - divby0.tol`), and ‘discard’ (discard units that have estimate propensity scores less than `divby0.tol` or greater than `1 - divby0.tol`). Note that discarding units will change the estimand.
- `divby0.tol` A scalar in `[0, 0.5)` giving the tolerance level for extreme propensity scores. Defaults to `1e - 8`. See `divby0.action` for details.
- `nboot` Number of bootstrap replications used for calculating bootstrap standard errors. If `nboot` is less than or equal to 0 then bootstrap standard errors are not calculated. Defaults to 501.
suppress.warnings

Logical value indicating whether warnings from the \texttt{gam} fitting procedures should be suppressed from printing to the screen. Defaults to \texttt{TRUE}.

... Further arguments to be passed.

\section*{Details}

This function provides diagnostic information that allows a user to judge whether the inverse propensity weights generated from a particular generalized additive model specification result in covariate balance across treated and control groups. The function is intended to be used before the \texttt{estimate.ATE} function in order to find a specification for the propensity score model that results in sufficient covariate balance.

The weighted mean differences between all variables in the dataset passed to \texttt{balance.IPW} are reported along with a \textit{z}-statistics for these weighted differences. Univariate mean covariate balance is decreasing in the absolute value of the \textit{z}-statistics (\textit{z}-statistics closer to 0 imply better univariate mean balance).

Printing the output from \texttt{balance.IPW} will result in a table with \(k - 2\) rows (one for each variable other than the treatment and outcome variables) and 6 columns. The columns are (from left to right) the observed mean of the covariate among the treated units, the observed mean of the covariate among the control units, the weighted mean of the covariate among the treated units, the weighted mean of the covariate among the control units, the weighted mean difference, and the \textit{z}-statistic for the difference.

It is often useful to include interactions and powers of the covariates in the dataset so that balance can be checked for these quantities as well.

Means, mean differences, and \textit{z}-statistics are only reported for numeric covariates.

\section*{Value}

An object of class \texttt{balance} with the following attributes:

\begin{itemize}
  \item \texttt{obs.mean.control} \hfill The observed mean of each of the covariates within the control units.
  \item \texttt{obs.mean.treated} \hfill The observed mean of each of the covariates within the treated units.
  \item \texttt{weighted.mean.control} \hfill The weighted mean of each of the covariates within the control units.
  \item \texttt{weighted.mean.treated} \hfill The weighted mean of each of the covariates within the treated units.
  \item \texttt{weighted.diff.SE} \hfill The bootstrap standard errors for the differences between \texttt{weighted.mean.treated} and \texttt{weighted.mean.control}.
\end{itemize}

\section*{Author(s)}

Adam Glynn, Emory University

Kevin Quinn, University of Michigan
References
Adam N. Glynn and Kevin M. Quinn. 2010. "An Introduction to the Augmented Inverse Propensity
Weighted Estimator." Political Analysis.

See Also
gam, estimate.ATE

Examples
```r
## Not run:
set.seed(1234)
## number of units in sample
n <- 2000

## measured potential confounders
z1 <- rnorm(n)
z2 <- rnorm(n)
z3 <- rnorm(n)
z4 <- rnorm(n)

## treatment assignment
prob.treated <- pnorm(-0.5 + 0.75*z2)
x <- rbinom(n, 1, prob.treated)

## potential outcomes
y0 <- z4 + rnorm(n)
y1 <- z1 + z2 + z3 + cos(z3*2) + rnorm(n)

## observed outcomes
y <- y0
y[x==1] <- y1[x==1]

## put everything in a data frame
examp.data <- data.frame(z1, z2, z3, z4, x, y)

## augment data with interactions and powers of covariates
examp.data$z1z1 <- examp.data$z1^2
examp.data$z2z2 <- examp.data$z2^2
examp.data$z3z3 <- examp.data$z3^2
examp.data$z4z4 <- examp.data$z4^2
examp.data$z1z2 <- examp.data$z1 * examp.data$z2
examp.data$z1z3 <- examp.data$z1 * examp.data$z3
examp.data$z1z4 <- examp.data$z1 * examp.data$z4
examp.data$z2z3 <- examp.data$z2 * examp.data$z3
examp.data$z2z4 <- examp.data$z2 * examp.data$z4
examp.data$z3z4 <- examp.data$z3 * examp.data$z4
```
## check balance of a propensity score model that is not sufficient to
## control confounding bias

```
bal.1 <- balance.IPW(pscore.formula=x~s(z3)+s(z4),
                   pscore.family=binomial(probit),
                   treatment.var="x",
                   outcome.var="y",
                   data=examp.data,
                   nboot=250)
```

```
print(bal.1) ## some big z-statistics here indicating balance not so great
```

## try again
```
bal.2 <- balance.IPW(pscore.formula=x~z1+z2+z3+z4,
                   pscore.family=binomial(probit),
                   treatment.var="x",
                   outcome.var="y",
                   data=examp.data,
                   nboot=250)
```

```
print(bal.2) ## balance looks much better--
## only 1 out of 14 zs > 2.0 in absval
```

## End(Not run)

---

**estimate.ATE**

Estimate Population Average Treatment Effects (ATE) Using Generalized Additive Models

### Description

This function implements three estimators for the population ATE— a regression estimator, an inverse propensity weighted (IPW) estimator, and an augmented inverse propensity weighted (AIPW) estimator— using generalized additive models.

### Usage

```
estimate.ATE(pscore.formula, pscore.family,
             outcome.formula.t, outcome.formula.c, outcome.family,
             treatment.var, data = NULL,
             divby0.action = c("fail", "truncate", "discard"),
             divby0.tol = 1e-08, nboot = 501,
             variance.smooth.deg = 1, variance.smooth.span = 0.75,
             var.gam.plot = TRUE, suppress.warnings = TRUE, ...)
```
Arguments

pscore.formula A formula expression for the propensity score model. See the documentation of \texttt{gam} for details.

pscore.family A description of the error distribution and link function to be used for the propensity score model. See the documentation of \texttt{gam} for details.

outcome.formula.t A formula expression for the outcome model under active treatment. See the documentation of \texttt{gam} for details.

outcome.formula.c A formula expression for the outcome model under control. See the documentation of \texttt{gam} for details.

outcome.family A description of the error distribution and link function to be used for the outcome models. See the documentation of \texttt{gam} for details.

treatment.var A character variable giving the name of the binary treatment variable in \texttt{data}. If \texttt{treatment.var} is a numeric variable, it is assumed that \texttt{control} corresponds to \texttt{sort(unique(treatment.values))[1]} and \texttt{treatment} corresponds to \texttt{sort(unique(treatment.values))[2]}. If \texttt{treatment.var} is a factor, it is assumed that \texttt{control} corresponds to \texttt{levels(treatment.values)[1]} and \texttt{treatment} corresponds to \texttt{levels(treatment.values)[2]}.

data A non-optional data frame containing the variables in the model. \texttt{data} cannot contain any missing values.

divby0.action A character variable describing what action to take when some estimated propensity scores are less than \texttt{divby0.tol} or greater than $1 - \texttt{divby0.tol}$. Options include: ‘fail’ (abort the call to \texttt{estimate.ATE}), ‘truncate’ (set all estimated propensity scores less than \texttt{divby0.tol} equal to \texttt{divby0.tol} and all estimated propensity scores greater than $1 - \texttt{divby0.tol}$ equal to $1 - \texttt{divby0.tol}$), and ‘discard’ (discard units that have estimate propensity scores less than \texttt{divby0.tol} or greater than $1 - \texttt{divby0.tol}$). Note that discarding units will change the estimand.

divby0.tol A scalar in $[0, 0.5)$ giving the tolerance level for extreme propensity scores. Defaults to $1e - 8$. See \texttt{divby0.action} for details.

nboot Number of bootstrap replications used for calculating bootstrap standard errors. If \texttt{nboot} is less than or equal to 0 then bootstrap standard errors are not calculated. Defaults to 501.

variance.smooth.deg The degree of the loess smooth used to calculate the conditional error variance of the outcome models given the estimated propensity scores. Possible values are 0, 1, or 2. Defaults to 1. If set to a value less than 0 than the conditional error variance will not be calculated and the estimated asymptotic standard errors will not be reported. See \texttt{lo} for details.

variance.smooth.span The span of the loess smooth used to calculate the conditional error variance of the outcome models given the estimated propensity scores. Defaults to 10.75. If set to a value less than or equal to 0 than the conditional error variance will not be calculated and the estimated asymptotic standard errors will not be reported. See \texttt{lo} for details.
var.gam.plot  Logical value indicating whether the estimated conditional variances should be plotted against the estimated propensity scores. Setting var.gam.plot to TRUE is useful for judging whether variance.smooth.deg and variance.smooth.span were set appropriately. Defaults to TRUE.

suppress.warnings  Logical value indicating whether warnings from the gam fitting procedures should be suppressed from printing to the screen. Defaults to TRUE.

Further arguments to be passed.

Details

The three estimators implemented by this function are a regression estimator, an IPW estimator with weights normalized to sum to 1, and an AIPW estimator. Glynn and Quinn (2010) provides details regarding how each of these estimators are implemented. The AIPW estimator requires the specification of both a propensity score model governing treatment assignment and outcome models that describe the conditional expectation of the outcome variable given measured confounders and treatment status. The AIPW estimator has the so-called double robustness property. This means that if either the propensity score model or the outcomes models are correctly specified then the estimator is consistent for ATE.

Standard errors for the regression and IPW estimators can be calculated by either the bootstrap or by estimating the large sample standard errors. The latter approach requires estimation of the conditional variance of the disturbances in the outcome models given the propensity scores (see section IV of Imbens (2004) for details). The accuracy of these standard errors is only as good as one’s estimates of these conditional variances.

Standard errors for the AIPW estimator can be calculated similarly. In addition, Lunceford and Davidian (2004) also discuss an empirical sandwich estimator of the sampling variance which is also implemented here.

Value

An object of class CausalGAM with the following attributes:

- ATE.AIPW.hat  AIPW estimate of ATE.
- ATE.reg.hat  Regression estimate of ATE.
- ATE.IPW.hat  IPW estimate of ATE.
- ATE.AIPWsand.SE  Empirical sandwich standard error for ATE.AIPW.hat.
- ATE.AIPW.asymp.SE  Estimated asymptotic standard error for ATE.AIPW.hat.
- ATE.reg.asymp.SE  Estimated asymptotic standard error for ATE.reg.hat.
- ATE.IPW.asymp.SE  Estimated asymptotic standard error for ATE.IPW.hat.
- ATE.AIPW.bs.SE  Estimated bootstrap standard error for ATE.AIPW.hat.
- ATE.reg.bs.SE  Estimated bootstrap standard error for ATE.reg.hat.
ATE.IPW.bs.SE  Estimated bootstrap standard error for ATE.IPW.hat.
ATE.AIPW.bs  Vector of bootstrap replications of ATE.AIPW.hat.
ATE.reg.bs  Vector of bootstrap replications of ATE.reg.hat.
ATE.IPW.bs  Vector of bootstrap replications of ATE.IPW.hat.
gam.t  gam object from fitted outcome model under treatment.
gam.c  gam object from the fitted outcome model under control.
gam.ps  gam object from the fitted propensity score model.
truncated.indic  Logical vector indicating which rows of data had extreme propensity scores truncated.
discarded.indic  Logical vector indicating which rows of data were discarded because of extreme propensity scores.
treated.value  Value of treatment.var that corresponds to active treatment.
control.value  Value of treatment.var that corresponds to control.
treatment.var  treatment.var
n.treated.prediscard  Number of treated units before any truncations or discards.
n.control.prediscard  Number of control units before any truncations or discards.
n.treated.postdiscard  Number of treated units after truncations or discards.
n.control.postdiscard  Number of control units after truncations or discards.
pscores.prediscard  Estimated propensity scores before any truncations or discards.
pscores.postdiscard  Estimated propensity scores after truncations or discards.
cond.var.t  Vector of conditional error variances for the outcome for each unit under treatment given the unit’s estimated propensity score.
cond.var.c  Vector of conditional error variances for the outcome for each unit under control given the unit’s estimated propensity score.
call  The initial call to estimate.ATE.
data  The data frame sent to estimate.ATE.

Author(s)
Adam Glynn, Emory University
Kevin Quinn, University of Michigan
**References**


**See Also**

gam, balance.IPW

**Examples**

```r
## Not run:
## a simulated data example with Gaussian outcomes
##
## number of units in sample
n <- 2000

## measured potential confounders
z1 <- rnorm(n)
z2 <- rnorm(n)
z3 <- rnorm(n)
z4 <- rnorm(n)

## treatment assignment
prob.treated <- pnorm(-0.5 + 0.75*z2)
x <- rbinom(n, 1, prob.treated)

## potential outcomes
y0 <- z4 + rnorm(n)
y1 <- z1 + z2 + z3 + cos(z3*2) + rnorm(n)

## observed outcomes
y <- y0
y[x==1] <- y1[x==1]

## put everything in a data frame
examp.data <- data.frame(z1, z2, z3, z4, x, y)

## estimate ATE
##
## in a real example one would want to use a larger number of
## bootstrap replications
##
```
ATE.out <- estimate.ATE(pscore.formula = x ~ s(z2),
  pscore.family = binomial,
  outcome.formula.t = y ~ s(z1) + s(z2) + s(z3) + s(z4),
  outcome.formula.c = y ~ s(z1) + s(z2) + s(z3) + s(z4),
  outcome.family = gaussian,
  treatment.var = "x",
  data=examp.data,
  divby0.action="t",
  divby0.tol=0.001,
  var.gam.plot=FALSE,
  nboot=50)

## print summary of estimates
print(ATE.out)

## a simulated data example with Bernoulli outcomes
##
## number of units in sample
n <- 2000

## measured potential confounders
z1 <- rnorm(n)
z2 <- rnorm(n)
z3 <- rnorm(n)
z4 <- rnorm(n)

## treatment assignment
prob.treated <- pnorm(-0.5 + 0.75*z2)
x <- rbinom(n, 1, prob.treated)

## potential outcomes
p0 <- pnorm(z4)
p1 <- pnorm(z1 + z2 + z3 + cos(z3*2))
y0 <- rbinom(n, 1, p0)
y1 <- rbinom(n, 1, p1)

## observed outcomes
y <- y0
y[x==1] <- y1[x==1]

## put everything in a data frame
examp.data <- data.frame(z1, z2, z3, z4, x, y)

## estimate ATE
##
## in a real example one would want to use a larger number of bootstrap replications

```r
ATE.out <- estimate.ATE(pscore.formula = x ~ s(z2),
    pscore.family = binomial,
    outcome.formula.t = y ~ s(z1) + s(z2) + s(z3) + s(z4),
    outcome.formula.c = y ~ s(z1) + s(z2) + s(z3) + s(z4),
    outcome.family = binomial,
    treatment.var = "x",
    data=examp.data,
    divby0.action="t",
    divby0.tol=0.001,
    var.gam.plot=FALSE,
    nboot=50)
```

## print summary of estimates

```r
print(ATE.out)
```

## End(Not run)
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