

# Package ‘CBPS’

July 21, 2025

**Version** 0.23

**Date** 2022-01-18

**Title** Covariate Balancing Propensity Score

**Depends** R (>= 3.4), MASS, MatchIt, nnet, numDeriv, glmnet

**Description** Implements the covariate balancing propensity score (CBPS) proposed by Imai and Ratkovic (2014) <[DOI:10.1111/rssb.12027](#)>. The propensity score is estimated such that it maximizes the resulting covariate balance as well as the prediction of treatment assignment. The method, therefore, avoids an iteration between model fitting and balance checking. The package also implements optimal CBPS from Fan et al. (in-press) <[DOI:10.1080/07350015.2021.2002159](#)>, several extensions of the CBPS beyond the cross-sectional, binary treatment setting. They include the CBPS for longitudinal settings so that it can be used in conjunction with marginal structural models from Imai and Ratkovic (2015) <[DOI:10.1080/01621459.2014.956872](#)>, treatments with three- and four-valued treatment variables, continuous-valued treatments from Fong, Hazlett, and Imai (2018) <[DOI:10.1214/17-AOAS1101](#)>, propensity score estimation with a large number of covariates from Ning, Peng, and Imai (2020) <[DOI:10.1093/biomet/asaa020](#)>, and the situation with multiple distinct binary treatments administered simultaneously. In the future it will be extended to other settings including the generalization of experimental and instrumental variable estimates.

**LazyLoad** yes

**LazyData** yes

**License** GPL (>= 2)

**NeedsCompilation** no

**Repository** CRAN

**RoxygenNote** 7.1.2

**Suggests** testthat

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**Date/Publication** 2022-01-18 18:02:52 UTC

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AsyVar	<i>Asymptotic Variance and Confidence Interval Estimation of the ATE</i>
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**Description**

AsyVar estimates the asymptotic variance of the ATE obtained with the CBPS or oCBPS method. It also returns the finite variance estimate, the finite standard error, and a CI for the ATE.

**Usage**

```

AsyVar(
  Y,
  Y_1_hat = NULL,
  Y_0_hat = NULL,
  CBPS_obj,
  method = "CBPS",
  X = NULL,
  TL = NULL,
  pi = NULL,
  mu = NULL,
  CI = 0.95
)

```

**Arguments**

Y	The vector of actual outcome values (observations).
Y_1_hat	The vector of estimated outcomes according to the treatment model. (AsyVar automatically sets the treatment model as a linear regression model and it is fitted within the function.) If CBPS_obj is specified, or if X and TL are specified, this is unnecessary.
Y_0_hat	The vector of estimated outcomes according to the control model. (AsyVar automatically sets the control model as a linear regression model and it is fitted within the function.) If CBPS_obj is specified, or if X and TL are specified, this is unnecessary.
CBPS_obj	An object obtained with the CBPS function. If this object is not specified, then X, TL, pi, and mu must all be specified instead.
method	The specific method to be considered. Either "CBPS" or "oCBPS" must be selected.
X	The matrix of covariates with the rows corresponding to the observations and the columns corresponding to the variables. The left most column must be a column of 1's for the intercept. (X is not necessary if CBPS_obj is specified.)
TL	The vector of treatment labels. More specifically, the label is 1 if it is in the treatment group and 0 if it is in the control group. (TL is not necessary if CBPS_obj is specified.)
pi	The vector of estimated propensity scores. (pi is not necessary if CBPS_obj is specified.)
mu	The estimated average treatment effect obtained with either the CBPS or oCBPS method. (mu is not necessary if CBPS_obj is specified.)
CI	The specified confidence level (between 0 and 1) for calculating the confidence interval for the average treatment effect. Default value is 0.95.

**Value**

mu.hat	The estimated average treatment effect, $\hat{\mu}$ .
--------	---

asy.var	The estimated asymptotic variance of $\sqrt{n} * \hat{\mu}$ obtained with the CBPS or oCBPS method.
var	The estimated variance of $\hat{\mu}$ obtained with the CBPS or oCBPS method.
std.err	The standard error of $\hat{\mu}$ obtained with the CBPS or oCBPS method.
CI.mu.hat	The confidence interval of $\hat{\mu}$ obtained with the CBPS or oCBPS method with the confidence level specified in the input argument.

### Author(s)

Inbeom Lee

### References

Fan, Jianqing and Imai, Kosuke and Lee, Inbeom and Liu, Han and Ning, Yang and Yang, Xiaolin. 2021. "Optimal Covariate Balancing Conditions in Propensity Score Estimation." Journal of Business & Economic Statistics. <https://imai.fas.harvard.edu/research/CBPStheory.html>

### Examples

```
#GENERATING THE DATA
n=300

#Initialize the X matrix.
X_v1 <- rnorm(n,3,sqrt(2))
X_v2 <- rnorm(n,0,1)
X_v3 <- rnorm(n,0,1)
X_v4 <- rnorm(n,0,1)
X_mat <- as.matrix(cbind(rep(1,n), X_v1, X_v2, X_v3, X_v4))

#Initialize the Y_1 and Y_0 vector using the treatment model and the control model.
Y_1 <- X_mat %*% matrix(c(200, 27.4, 13.7, 13.7, 13.7), 5, 1) + rnorm(n)
Y_0 <- X_mat %*% matrix(c(200, 0 , 13.7, 13.7, 13.7), 5, 1) + rnorm(n)

#True Propensity Score calculation.
pre_prop <- X_mat[,2:5] %*% matrix(c(0, 0.5, -0.25, -0.1), 4, 1)
propensity_true <- (exp(pre_prop))/(1+(exp(pre_prop)))

#Generate T_vec, the treatment vector, with the true propensity scores.
T_vec <- rbinom(n, size=1, prob=propensity_true)

#Now generate the actual outcome Y_outcome (accounting for treatment/control groups).
Y_outcome <- Y_1*T_vec + Y_0*(1-T_vec)

#Use oCBPS.
ocbps.fit <- CBPS(T_vec ~ X_mat, ATT=0, baseline.formula = ~X_mat[,c(1,3:5)],
  diff.formula = ~X_mat[,2])

#Use the AsyVar function to get the asymptotic variance of the
#estimated average treatment effect and its confidence interval when using oCBPS.
AsyVar(Y=Y_outcome, CBPS_obj=ocbps.fit, method="oCBPS", CI=0.95)
```

```
#Use CBPS.
cbps.fit <- CBPS(T_vec ~ X_mat, ATT=0)

#Use the AsyVar function to get the asymptotic variance of the
#estimated average treatment effect and its confidence interval when using CBPS.
AsyVar(Y=Y_outcome, CBPS_obj=cbps.fit, method="CBPS", CI=0.95)
```

---

balance	<i>Optimal Covariate Balance</i>
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### Description

Returns the mean and standardized mean associated with each treatment group, before and after weighting. To access more comprehensive diagnostics for assessing covariate balance, consider using Noah Greifer's `cobalt` package.

### Usage

```
balance(object, ...)
```

### Arguments

object	A CBPS, npCBPS, or CBMSM object.
...	Additional arguments to be passed to balance.

### Details

For binary and multi-valued treatments as well as marginal structural models, each of the matrices' rows are the covariates and whose columns are the weighted mean, and standardized mean associated with each treatment group. The standardized mean is the weighted mean divided by the standard deviation of the covariate for the whole population. For continuous treatments, returns the absolute Pearson correlation between the treatment and each covariate.

### @aliases balance balance.npCBPS balance.CBPS balance.CBMSM

### Value

Returns a list of two matrices, "original" (before weighting) and "balanced" (after weighting).

### Author(s)

Christian Fong, Marc Ratkovic, and Kosuke Imai.

**Examples**

```
###
### Example: Assess Covariate Balance
###
data(LaLonde)
## Estimate CBPS
fit <- CBPS(treat ~ age + educ + re75 + re74 +
I(re75==0) + I(re74==0),
data = LaLonde, ATT = TRUE)
balance(fit)
```

---

balance.CBPS	<i>Calculates the pre- and post-weighting difference in standardized means for covariate within each contrast</i>
--------------	---

---

**Description**

Calculates the pre- and post-weighting difference in standardized means for covariate within each contrast

**Usage**

```
## S3 method for class 'CBPS'
balance(object, ...)
```

**Arguments**

object	A CBPS, npCBPS, or CBMSM object.
...	Additional arguments to be passed to balance.

---

balance.CBPSContinuous	<i>Calculates the pre- and post-weighting correlations between each covariate and the T</i>
------------------------	---

---

**Description**

Calculates the pre- and post-weighting correlations between each covariate and the T

**Usage**

```
## S3 method for class 'CBPSContinuous'
balance(object, ...)
```

Arguments

object            A CBPS, npCBPS, or CBMSM object.  
...               Additional arguments to be passed to balance.

---

balance.npCBPS	<i>Calls the appropriate balance function based on the number of treatments</i>
----------------	---

---

Description

Calls the appropriate balance function based on the number of treatments

Usage

```
## S3 method for class 'npCBPS'  
balance(object, ...)
```

Arguments

object            A CBPS, npCBPS, or CBMSM object.  
...               Other parameters to be passed.

---

Blackwell	<i>Blackwell Data for Covariate Balancing Propensity Score</i>
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---

Description

This data set gives the outcomes as well as treatment assignments and covariates for the example from Blackwell (2013).

Format

A data frame consisting of 13 columns (including treatment assignment, time, and identifier vectors) and 570 observations.

Source

d.gone.neg is the treatment. d.gone.neg.l1, d.gone.neg.l2, and d.gone.neg.l3 are lagged treatment variables. camp.length, deminc, base.poll, base.und, and office covariates. year is the year of the particular race, and time goes from the first measurement (time = 1) to the election (time = 5). demName is the identifier, and demprcnt is the outcome.

References

Blackwell, Matthew. (2013). A framework for dynamic causal inference in political science. American Journal of Political Science 57, 2, 504-619.

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CBIV	<i>Covariate Balancing Propensity Score for Instrumental Variable Estimates (CBIV)</i>
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## Description

CBIV estimates propensity scores for compliance status in an instrumental variables setup such that both covariate balance and prediction of treatment assignment are maximized. The method, therefore, avoids an iterative process between model fitting and balance checking and implements both simultaneously.

## Usage

```
CBIV(
  Tr,
  Z,
  X,
  iterations = 1000,
  method = "over",
  twostep = TRUE,
  twosided = TRUE,
  ...
)
```

## Arguments

Tr	A binary treatment variable.
Z	A binary encouragement variable.
X	A pre-treatment covariate matrix.
iterations	An optional parameter for the maximum number of iterations for the optimization. Default is 1000.
method	Choose "over" to fit an over-identified model that combines the propensity score and covariate balancing conditions; choose "exact" to fit a model that only contains the covariate balancing conditions. Our simulations suggest that "over" dramatically outperforms "exact."
twostep	Default is TRUE for a two-step GMM estimator, which will run substantially faster than continuous-updating. Set to FALSE to use the continuous-updating GMM estimator.
twosided	Default is TRUE, which allows for two-sided noncompliance with both always-takers and never-takers. Set to FALSE for one-sided noncompliance, which allows only for never-takers.
...	Other parameters to be passed through to <code>optim()</code> .

**Details**

Fits covariate balancing propensity scores for generalizing local average treatment effect estimates obtained from instrumental variables analysis.

**Value**

<code>coefficients</code>	A named matrix of coefficients, where the first column gives the complier coefficients and the second column gives the always-taker coefficients.
<code>fitted.values</code>	The fitted $N \times 3$ compliance score matrix. The first column gives the estimated probability of being a complier, the second column gives the estimated probability of being an always-taker, and the third column gives the estimated probability of being a never-taker.
<code>weights</code>	The optimal weights: the reciprocal of the probability of being a complier.
<code>deviance</code>	Minus twice the log-likelihood of the CBIV fit.
<code>converged</code>	Convergence value. Returned from the call to <code>optim()</code> .
<code>J</code>	The J-statistic at convergence
<code>df</code>	The number of linearly independent covariates.
<code>bal</code>	The covariate balance associated with the optimal weights, calculated as the GMM loss of the covariate balance conditions.

**Author(s)**

Christian Fong

**References**

Imai, Kosuke and Marc Ratkovic. 2014. "Covariate Balancing Propensity Score." Journal of the Royal Statistical Society, Series B (Statistical Methodology). <http://imai.princeton.edu/research/CBPS.html>

**Examples**

```
###
### Example: propensity score matching
### (Need to fix when we have an actual example).

##Load the LaLonde data
data(LaLonde)
## Estimate CBPS
fit <- CBPS(treat ~ age + educ + re75 + re74 +
I(re75==0) + I(re74==0),
data = LaLonde, ATT = TRUE)
summary(fit)
```

CBMSM

*Covariate Balancing Propensity Score (CBPS) for Marginal Structural Models***Description**

CBMSM estimates propensity scores such that both covariate balance and prediction of treatment assignment are maximized. With longitudinal data, the method returns marginal structural model weights that can be entered directly into a linear model. The method also handles multiple binary treatments administered concurrently.

**Usage**

```
CBMSM(
  formula,
  id,
  time,
  data,
  type = "MSM",
  twostep = TRUE,
  msm.variance = "approx",
  time.vary = FALSE,
  init = "opt",
  ...
)
```

**Arguments**

<code>formula</code>	A formula of the form <code>treat ~ X</code> . The same covariates are used in each time period. At default values, a single set of coefficients is estimated across all time periods. To allow a different set of coefficients for each time period, set <code>time.vary = TRUE</code> . Data should be sorted by time.
<code>id</code>	A vector which identifies the unit associated with each row of <code>treat</code> and <code>X</code> .
<code>time</code>	A vector which identifies the time period associated with each row of <code>treat</code> and <code>X</code> . All data should be sorted by time.
<code>data</code>	An optional data frame, list or environment (or object coercible by <code>as.data.frame</code> to a data frame) containing the variables in the model. If not found in <code>data</code> , the variables are taken from <code>environment(formula)</code> , typically the environment from which CBMSM is called. Data should be sorted by time.
<code>type</code>	"MSM" for a marginal structural model, with multiple time periods or "Multi-Bin" for multiple binary treatments at the same time period.
<code>twostep</code>	Set to <code>TRUE</code> to use a two-step estimator, which will run substantially faster than continuous-updating. Default is <code>FALSE</code> , which uses the continuous-updating estimator described by Imai and Ratkovic (2014).
<code>msm.variance</code>	Default is <code>FALSE</code> , which uses the low-rank approximation of the variance described in Imai and Ratkovic (2014). Set to <code>TRUE</code> to use the full variance matrix.

<code>time.vary</code>	Default is FALSE, which uses the same coefficients across time period. Set to TRUE to fit one set per time period.
<code>init</code>	Default is "opt", which uses CBPS and logistic regression starting values, and chooses the one that achieves the best balance. Other options are "glm" and "CBPS"
<code>...</code>	Other parameters to be passed through to <code>optim()</code>

### Details

Fits covariate balancing propensity scores for marginal structural models.

### @aliases CBMSM CBMSM.fit

### Value

<code>weights</code>	The optimal weights.
<code>fitted.values</code>	The fitted propensity score for each observation.
<code>y</code>	The treatment vector used.
<code>x</code>	The covariate matrix.
<code>id</code>	The vector id used in CBMSM.fit.
<code>time</code>	The vector time used in CBMSM.fit.
<code>model</code>	The model frame.
<code>call</code>	The matched call.
<code>formula</code>	The formula supplied.
<code>data</code>	The data argument.
<code>treat.hist</code>	A matrix of the treatment history, with each observation in rows and time in columns.
<code>treat.cum</code>	A vector of the cumulative treatment history, by individual.

### Author(s)

Marc Ratkovic, Christian Fong, and Kosuke Imai; The CBMSM function is based on the code for version 2.15.0 of the glm function implemented in the stats package, originally written by Simon Davies. This documentation is likewise modeled on the documentation for glm and borrows its language where the arguments and values are the same.

### References

- Imai, Kosuke and Marc Ratkovic. 2014. "Covariate Balancing Propensity Score." Journal of the Royal Statistical Society, Series B (Statistical Methodology). <http://imai.princeton.edu/research/CBPS.html>
- Imai, Kosuke and Marc Ratkovic. 2015. "Robust Estimation of Inverse Probability Weights for Marginal Structural Models." Journal of the American Statistical Association. <http://imai.princeton.edu/research/MSM.html>

**See Also**[plot.CBMSM](#)**Examples**

```
##Load Blackwell data

data(Blackwell)

## Quickly fit a short model to test
form0 <- "d.gone.neg ~ d.gone.neg.l1 + camp.length"
fit0<-CBMSM(formula = form0, time=Blackwell$time,id=Blackwell$demName,
data=Blackwell, type="MSM", iterations = NULL, twostep = TRUE,
msm.variance = "approx", time.vary = FALSE)

## Not run:
##Fitting the models in Imai and Ratkovic (2014)
##Warning: may take a few mintues; setting time.vary to FALSE
##Results in a quicker fit but with poorer balance
##Usually, it is best to use time.vary TRUE
form1<-"d.gone.neg ~ d.gone.neg.l1 + d.gone.neg.l2 + d.neg.frac.l3 +
camp.length + camp.length + deminc + base.poll + year.2002 +
year.2004 + year.2006 + base.und + office"

##Note that init="glm" gives the published results but the default is now init="opt"
fit1<-CBMSM(formula = form1, time=Blackwell$time,id=Blackwell$demName,
data=Blackwell, type="MSM", iterations = NULL, twostep = TRUE,
msm.variance = "full", time.vary = TRUE, init="glm")

fit2<-CBMSM(formula = form1, time=Blackwell$time,id=Blackwell$demName,
data=Blackwell, type="MSM", iterations = NULL, twostep = TRUE,
msm.variance = "approx", time.vary = TRUE, init="glm")

##Assessing balance

bal1<-balance.CBMSM(fit1)
bal2<-balance.CBMSM(fit2)

##Effect estimation: Replicating Effect Estimates in
##Table 3 of Imai and Ratkovic (2014)

lm1<-lm(demprcnt[time==1]~fit1$treat.hist,data=Blackwell,
weights=fit1$glm.weights)
lm2<-lm(demprcnt[time==1]~fit1$treat.hist,data=Blackwell,
weights=fit1$weights)
lm3<-lm(demprcnt[time==1]~fit1$treat.hist,data=Blackwell,
weights=fit2$weights)

lm4<-lm(demprcnt[time==1]~fit1$treat.cum,data=Blackwell,
weights=fit1$glm.weights)
```

```

lm5<-lm(demprcnt[time==1]~fit1$treat.cum,data=Blackwell,
weights=fit1$weights)
lm6<-lm(demprcnt[time==1]~fit1$treat.cum,data=Blackwell,
weights=fit2$weights)

### Example: Multiple Binary Treatments Administered at the Same Time
n<-200
k<-4
set.seed(1040)
X1<-cbind(1,matrix(rnorm(n*k),ncol=k))

betas.1<-betas.2<-betas.3<-c(2,4,4,-4,3)/5
probs.1<-probs.2<-probs.3<-(1+exp(-X1 %*% betas.1))^-1

treat.1<-rbinom(n=length(probs.1),size=1,probs.1)
treat.2<-rbinom(n=length(probs.2),size=1,probs.2)
treat.3<-rbinom(n=length(probs.3),size=1,probs.3)
treat<-c(treat.1,treat.2,treat.3)
X<-rbind(X1,X1,X1)
time<-c(rep(1,nrow(X1)),rep(2,nrow(X1)),rep(3,nrow(X1)))
id<-c(rep(1:nrow(X1),3))
y<-cbind(treat.1,treat.2,treat.3) %*% c(2,2,2) +
X1 %*% c(-2,8,7,6,2) + rnorm(n,sd=5)

multibin1<-CBMSM(treat~X,id=id,time=time,type="MultiBin",twostep=TRUE)
summary(lm(y~-1+treat.1+treat.2+treat.3+X1, weights=multibin1$w))

## End(Not run)

```

---

CBMSM.fit

---

*CBMSM.fit*


---

## Description

CBMSM.fit

## Usage

```

CBMSM.fit(
  treat,
  X,
  id,
  time,
  MultiBin.fit,
  twostep,
  msm.variance,

```

```

    time.vary,
    init,
    ...
)

```

### Arguments

<code>treat</code>	A vector of treatment assignments. For $N$ observations over $T$ time periods, the length of <code>treat</code> should be $N \times T$ .
<code>X</code>	A covariate matrix. For $N$ observations over $T$ time periods, <code>X</code> should have $N \times T$ rows.
<code>id</code>	A vector which identifies the unit associated with each row of <code>treat</code> and <code>X</code> .
<code>time</code>	A vector which identifies the time period associated with each row of <code>treat</code> and <code>X</code> .
<code>MultiBin.fit</code>	A parameter for whether the multiple binary treatments occur concurrently (FALSE) or over consecutive time periods (TRUE) as in a marginal structural model. Setting <code>type = "MultiBin"</code> when calling <code>CBMSM</code> will set <code>MultiBin.fit</code> to TRUE when <code>CBMSM.fit</code> is called.
<code>twostep</code>	Set to TRUE to use a two-step estimator, which will run substantially faster than continuous-updating. Default is FALSE, which uses the continuous-updating estimator described by Imai and Ratkovic (2014).
<code>msm.variance</code>	Default is FALSE, which uses the low-rank approximation of the variance described in Imai and Ratkovic (2014). Set to TRUE to use the full variance matrix.
<code>time.vary</code>	Default is FALSE, which uses the same coefficients across time period. Set to TRUE to fit one set per time period.
<code>init</code>	Default is "opt", which uses CBPS and logistic regression starting values, and chooses the one that achieves the best balance. Other options are "glm" and "CBPS"
<code>...</code>	Other parameters to be passed through to <code>optim()</code>

---

CBPS

---

*Covariate Balancing Propensity Score (CBPS) Estimation*


---

### Description

CBPS estimates propensity scores such that both covariate balance and prediction of treatment assignment are maximized. The method, therefore, avoids an iterative process between model fitting and balance checking and implements both simultaneously. For cross-sectional data, the method can take continuous treatments and treatments with a control (baseline) condition and either 1, 2, or 3 distinct treatment conditions.

Fits covariate balancing propensity scores.

### @aliases CBPS CBPS.fit print.CBPS

**Usage**

```
CBPS(
  formula,
  data,
  na.action,
  ATT = 1,
  iterations = 1000,
  standardize = TRUE,
  method = "over",
  twostep = TRUE,
  sample.weights = NULL,
  baseline.formula = NULL,
  diff.formula = NULL,
  ...
)
```

**Arguments**

<code>formula</code>	An object of class <code>formula</code> (or one that can be coerced to that class): a symbolic description of the model to be fitted.
<code>data</code>	An optional data frame, list or environment (or object coercible by <code>as.data.frame</code> to a data frame) containing the variables in the model. If not found in <code>data</code> , the variables are taken from <code>environment(formula)</code> , typically the environment from which <code>CBPS</code> is called.
<code>na.action</code>	A function which indicates what should happen when the data contain NAs. The default is set by the <code>na.action</code> setting of options, and is <code>na.fail</code> if that is unset.
<code>ATT</code>	Default is 1, which finds the average treatment effect on the treated interpreting the second level of the treatment factor as the treatment. Set to 2 to find the ATT interpreting the first level of the treatment factor as the treatment. Set to 0 to find the average treatment effect. For non-binary treatments, only the ATE is available.
<code>iterations</code>	An optional parameter for the maximum number of iterations for the optimization. Default is 1000.
<code>standardize</code>	Default is <code>TRUE</code> , which normalizes weights to sum to 1 within each treatment group. For continuous treatments, normalizes weights to sum up to 1 for the entire sample. Set to <code>FALSE</code> to return Horvitz-Thompson weights.
<code>method</code>	Choose "over" to fit an over-identified model that combines the propensity score and covariate balancing conditions; choose "exact" to fit a model that only contains the covariate balancing conditions.
<code>twostep</code>	Default is <code>TRUE</code> for a two-step estimator, which will run substantially faster than continuous-updating. Set to <code>FALSE</code> to use the continuous-updating estimator described by Imai and Ratkovic (2014).
<code>sample.weights</code>	Survey sampling weights for the observations, if applicable. When left <code>NULL</code> , defaults to a sampling weight of 1 for each observation.

<code>baseline.formula</code>	Used only to fit iCBPS (see Fan et al). Currently only works with binary treatments. A formula specifying the balancing covariates in the baseline outcome model, i.e., $E(Y(0) X)$ .
<code>diff.formula</code>	Used only to fit iCBPS (see Fan et al). Currently only works with binary treatments. A formula specifying the balancing covariates in the difference between the treatment and baseline outcome model, i.e., $E(Y(1)-Y(0) X)$ .
<code>...</code>	Other parameters to be passed through to <code>optim()</code> .

**Value**

<code>fitted.values</code>	The fitted propensity score
<code>linear.predictor</code>	$X * \text{beta}$
<code>deviance</code>	Minus twice the log-likelihood of the CBPS fit
<code>weights</code>	The optimal weights. Let $\pi_i = f(T_i X_i)$ . For binary ATE, these are given by $\frac{T_i}{\pi_i} + \frac{(1-T_i)}{(1-\pi_i)}$ . For binary ATT, these are given by $\frac{n}{n_t} * \frac{T_i - \pi_i}{1 - \pi_i}$ . For multi_valued treatments, these are given by $\sum_{j=0}^{J-1} T_{i,j} / \pi_{i,j}$ . For continuous treatments, these are given by $\frac{f(T_i)}{f(T_i X_i)}$ . These expressions for weights are all before standardization (i.e. with <code>standardize=FALSE</code> ). Standardization will make weights sum to 1 within each treatment group. For continuous treatment, standardization will make all weights sum to 1. If sampling weights are used, the weight for each observation is multiplied by the survey sampling weight.
<code>y</code>	The treatment vector used
<code>x</code>	The covariate matrix
<code>model</code>	The model frame
<code>converged</code>	Convergence value. Returned from the call to <code>optim()</code> .
<code>call</code>	The matched call
<code>formula</code>	The formula supplied
<code>data</code>	The data argument
<code>coefficients</code>	A named vector of coefficients
<code>sigmasq</code>	The sigma-squared value, for continuous treatments only
<code>J</code>	The J-statistic at convergence
<code>mle.J</code>	The J-statistic for the parameters from maximum likelihood estimation
<code>var</code>	The covariance matrix for the coefficients.
<code>Ttilde</code>	For internal use only.
<code>Xtilde</code>	For internal use only.
<code>beta.tilde</code>	For internal use only.
<code>simgasq.tilde</code>	For internal use only.

**Author(s)**

Christian Fong, Marc Ratkovic, Kosuke Imai, and Xiaolin Yang; The CBPS function is based on the code for version 2.15.0 of the glm function implemented in the stats package, originally written by Simon Davies. This documentation is likewise modeled on the documentation for glm and borrows its language where the arguments and values are the same.

**References**

- Imai, Kosuke and Marc Ratkovic. 2014. "Covariate Balancing Propensity Score." Journal of the Royal Statistical Society, Series B (Statistical Methodology). <http://imai.princeton.edu/research/CBPS.html>
- Fong, Christian, Chad Hazlett, and Kosuke Imai. 2018. "Covariate Balancing Propensity Score for a Continuous Treatment." The Annals of Applied Statistics. <http://imai.princeton.edu/research/files/CBGPS.pdf>
- Fan, Jianqing and Imai, Kosuke and Liu, Han and Ning, Yang and Yang, Xiaolin. "Improving Covariate Balancing Propensity Score: A Doubly Robust and Efficient Approach." Unpublished Manuscript. <http://imai.princeton.edu/research/CBPStheory.html>

**See Also**

[summary.CBPS](#)

**Examples**

```
###
### Example: propensity score matching
###

##Load the LaLonde data
data(LaLonde)
## Estimate CBPS
fit <- CBPS(treat ~ age + educ + re75 + re74 +
I(re75==0) + I(re74==0),
data = LaLonde, ATT = TRUE)
summary(fit)
## Not run:
## matching via MatchIt: one to one nearest neighbor with replacement
library(MatchIt)
m.out <- matchit(treat ~ fitted(fit), method = "nearest",
data = LaLonde, replace = TRUE)

### Example: propensity score weighting
###
## Simulation from Kang and Shafer (2007).
set.seed(123456)
n <- 500
X <- mvrnorm(n, mu = rep(0, 4), Sigma = diag(4))
prop <- 1 / (1 + exp(X[,1] - 0.5 * X[,2] +
0.25*X[,3] + 0.1 * X[,4]))
treat <- rbinom(n, 1, prop)
y <- 210 + 27.4*X[,1] + 13.7*X[,2] + 13.7*X[,3] + 13.7*X[,4] + rnorm(n)
```

```

##Estimate CBPS with a misspecified model
X.mis <- cbind(exp(X[,1]/2), X[,2]*(1+exp(X[,1]))^(-1)+10,
  (X[,1]*X[,3]/25+.6)^3, (X[,2]+X[,4]+20)^2)
fit1 <- CBPS(treat ~ X.mis, ATT = 0)
summary(fit1)

## Horwitz-Thompson estimate
mean(treat*y/fit1$fitted.values)
## Inverse propensity score weighting
sum(treat*y/fit1$fitted.values)/sum(treat/fit1$fitted.values)

rm(list=c("y", "X", "prop", "treat", "n", "X.mis", "fit1"))

### Example: Continuous Treatment as in Fong, Hazlett,
### and Imai (2018). See
### https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/AIF4PI
### for a real data example.
set.seed(123456)
n <- 1000
X <- mvrnorm(n, mu = rep(0,2), Sigma = diag(2))
beta <- rnorm(ncol(X)+1, sd = 1)
treat <- cbind(1,X)%*%beta + rnorm(n, sd = 5)

treat.effect <- 1
effect.beta <- rnorm(ncol(X))
y <- rbinom(n, 1, (1 + exp(-treat.effect*treat -
  X%*%effect.beta))^(-1))

fit2 <- CBPS(treat ~ X)
summary(fit2)
summary(glm(y ~ treat + X, weights = fit2$weights,
family = "quasibinomial"))

rm(list=c("n", "X", "beta", "treat", "treat.effect",
  "effect.beta", "y", "fit2"))

### Simulation example: Improved CBPS (or iCBPS) from Fan et al
set.seed(123456)
n <- 500
X <- mvrnorm(n, mu = rep(0, 4), Sigma = diag(4))
prop <- 1 / (1 + exp(X[,1] - 0.5 * X[,2] + 0.25*X[,3] + 0.1 * X[,4]))
treat <- rbinom(n, 1, prop)
y1 <- 210 + 27.4*X[,1] + 13.7*X[,2] + 13.7*X[,3] + 13.7*X[,4] + rnorm(n)
y0 <- 210 + 13.7*X[,2] + 13.7*X[,3] + 13.7*X[,4] + rnorm(n)
##Estimate iCBPS with a misspecified model
X.mis <- cbind(exp(X[,1]/2), X[,2]*(1+exp(X[,1]))^(-1)+10,
  (X[,1]*X[,3]/25+.6)^3, (X[,2]+X[,4]+20)^2)
fit1 <- CBPS(treat ~ X.mis, baseline.formula=~X.mis[,2:4],
  diff.formula=~X.mis[,1], ATT = FALSE)
summary(fit1)

## End(Not run)

```

---

CBPS.fit	<i>CBPS.fit determines the proper routine (what kind of treatment) and calls the appropriate function. It also pre- and post-processes the data</i>
----------	---

---

### Description

CBPS.fit determines the proper routine (what kind of treatment) and calls the appropriate function. It also pre- and post-processes the data

### Usage

```
CBPS.fit(
  treat,
  X,
  baselineX,
  diffX,
  ATT,
  method,
  iterations,
  standardize,
  twostep,
  sample.weights = sample.weights,
  ...
)
```

### Arguments

treat	A vector of treatment assignments. Binary or multi-valued treatments should be factors. Continuous treatments should be numeric.
X	A covariate matrix.
baselineX	Similar to baseline.formula, but in matrix form.
diffX	Similar to diff.formula, but in matrix form.
ATT	Default is 1, which finds the average treatment effect on the treated interpreting the second level of the treatment factor as the treatment. Set to 2 to find the ATT interpreting the first level of the treatment factor as the treatment. Set to 0 to find the average treatment effect. For non-binary treatments, only the ATE is available.
method	Choose "over" to fit an over-identified model that combines the propensity score and covariate balancing conditions; choose "exact" to fit a model that only contains the covariate balancing conditions.
iterations	An optional parameter for the maximum number of iterations for the optimization. Default is 1000.

<code>standardize</code>	Default is TRUE, which normalizes weights to sum to 1 within each treatment group. For continuous treatments, normalizes weights to sum up to 1 for the entire sample. Set to FALSE to return Horvitz-Thompson weights.
<code>twostep</code>	Default is TRUE for a two-step estimator, which will run substantially faster than continuous-updating. Set to FALSE to use the continuous-updating estimator described by Imai and Ratkovic (2014).
<code>sample.weights</code>	Survey sampling weights for the observations, if applicable. When left NULL, defaults to a sampling weight of 1 for each observation.
<code>...</code>	Other parameters to be passed through to <code>optim()</code> .

**Value**

CBPS.fit object

---

hdCBPS	<i>hdCBPS high dimensional CBPS method to parses the formula object and passes the result to hdCBPS.fit, which calculates ATE using CBPS method in a high dimensional setting.</i>
--------	--

---

**Description**

hdCBPS high dimensional CBPS method to parses the formula object and passes the result to hdCBPS.fit, which calculates ATE using CBPS method in a high dimensional setting.

**Usage**

```
hdCBPS(
  formula,
  data,
  na.action,
  y,
  ATT = 0,
  iterations = 1000,
  method = "linear"
)
```

**Arguments**

<code>formula</code>	An object of class formula (or one that can be coerced to that class): a symbolic description of the model to be fitted.
<code>data</code>	An optional data frame, list or environment (or object coercible by <code>as.data.frame</code> to a data frame) containing the variables in the model. If not found in data, the variables are taken from <code>environment(formula)</code> , typically the environment from which CBPS is called.
<code>na.action</code>	A function which indicates what should happen when the data contain NAs. The default is set by the <code>na.action</code> setting of options, and is <code>na.fail</code> if that is unset.

y	An outcome variable.
ATT	Option to calculate ATT
iterations	An optional parameter for the maximum number of iterations for the optimization. Default is 1000.
method	Choose among "linear", "binomial", and "poission".

**Value**

ATT	Average treatment effect on the treated.
ATE	Average treatment effect.
s	Standard Error.
fitted.values	The fitted propensity score
coefficients1	Coefficients for the treated propensity score
coefficients0	Coefficients for the untreated propensity score
model	The model frame

**Author(s)**

Sida Peng

---

LaLonde

*LaLonde Data for Covariate Balancing Propensity Score*

---

**Description**

This data set gives the outcomes as well as treatment assignments and covariates for the econometric evaluation of training programs in LaLonde (1986).

**Format**

A data frame consisting of 12 columns (including a treatment assignment vector) and 3212 observations.

**Source**

Data from the National Supported Work Study. A benchmark matching dataset. Columns consist of an indicator for whether the observed unit was in the experimental subset; an indicator for whether the individual received the treatment; age in years; schooling in years; indicators for black and Hispanic; an indicator for marriage status, one of married; an indicator for no high school degree; reported earnings in 1974, 1975, and 1978; and whether the 1974 earnings variable is missing. Data not missing 1974 earnings are the Dehejia-Wahba subsample of the LaLonde data. Missing values for 1974 earnings set to zero. 1974 and 1975 earnings are pre-treatment. 1978 earnings is taken as the outcome variable.

## References

LaLonde, R.J. (1986). Evaluating the econometric evaluations of training programs with experimental data. *American Economic Review* 76, 4, 604-620.

---

npCBPS	<i>Non-Parametric Covariate Balancing Propensity Score (npCBPS) Estimation</i>
--------	--

---

## Description

npCBPS is a method to estimate weights interpretable as (stabilized) inverse generalized propensity score weights,  $w_i = f(T_i)/f(T_i|X)$ , without actually estimating a model for the treatment to arrive at  $f(T|X)$  estimates. In brief, this works by maximizing the empirical likelihood of observing the values of treatment and covariates that were observed, while constraining the weights to be those that (a) ensure balance on the covariates, and (b) maintain the original means of the treatment and covariates.

In the continuous treatment context, this balance on covariates means zero correlation of each covariate with the treatment. In binary or categorical treatment contexts, balance on covariates implies equal means on the covariates for observations at each level of the treatment. When given a numeric treatment the software handles it continuously. To handle the treatment as binary or categorical is must be given as a factor.

Furthermore, we apply a Bayesian variant that allows the correlation of each covariate with the treatment to be slightly non-zero, as might be expected in a given finite sample.

Estimates non-parametric covariate balancing propensity score weights.

### @aliases npCBPS npCBPS.fit

## Usage

```
npCBPS(formula, data, na.action, corprior = 0.01, print.level = 0, ...)
```

## Arguments

formula	An object of class formula (or one that can be coerced to that class): a symbolic description of the model to be fitted.
data	An optional data frame, list or environment (or object coercible by <code>as.data.frame</code> to a data frame) containing the variables in the model. If not found in data, the variables are taken from <code>environment(formula)</code> , typically the environment from which CBPS is called.
na.action	A function which indicates what should happen when the data contain NAs. The default is set by the <code>na.action</code> setting of options, and is <code>na.fail</code> if that is unset.
corprior	Prior hyperparameter controlling the expected amount of correlation between each covariate and the treatment. Specifically, the amount of correlation between the $k$ -dimensional covariates, $X$ , and the treatment $T$ after weighting is assumed to have prior distribution $MVN(0, \sigma^2 I_k)$ . We conceptualize $\sigma^2$ as

a tuning parameter to be used pragmatically. It's default of 0.1 ensures that the balance constraints are not too harsh, and that a solution is likely to exist. Once the algorithm works at such a high value of  $\sigma^2$ , the user may wish to attempt values closer to 0 to get finer balance.

<code>print.level</code>	Controls verbosity of output to the screen while npCBPS runs. At the default of <code>print.level=0</code> , little output is produced. If <code>print.level&gt;0</code> , it outputs diagnostics including the log posterior ( <code>log_post</code> ), the log empirical likelihood associated with the weights ( <code>log_el</code> ), and the log prior probability of the (weighted) correlation of treatment with the covariates.
<code>...</code>	Other parameters to be passed.

### Value

<code>weights</code>	The optimal weights
<code>y</code>	The treatment vector used
<code>x</code>	The covariate matrix
<code>model</code>	The model frame
<code>call</code>	The matched call
<code>formula</code>	The formula supplied
<code>data</code>	The data argument
<code>log.p.eta</code>	The log density for the (weighted) correlation of the covariates with the treatment, given the choice of prior ( <code>corprior</code> )
<code>log.el</code>	The log empirical likelihood of the observed data at the chosen set of IPW weights.
<code>eta</code>	A vector describing the correlation between the treatment and each covariate on the weighted data at the solution.
<code>sumw0</code>	The sum of weights, provided as a check on convergence. This is always 1 when convergence occurs unproblematically. If it differs from 1 substantially, no solution perfectly satisfying the conditions was found, and the user may consider a larger value of <code>corprior</code> .

### Author(s)

Christian Fong, Chad Hazlett, and Kosuke Imai

### References

Fong, Christian, Chad Hazlett, and Kosuke Imai. "Parametric and Nonparametric Covariate Balancing Propensity Score for General Treatment Regimes." Unpublished Manuscript. <http://imai.princeton.edu/research/files/CBGPS.pdf>

**Examples**

```
##Generate data
data(LaLonde)

## Restricted two only two covariates so that it will run quickly.
## Performance will remain good if the full LaLonde specification is used
fit <- npCBPS(treat ~ age + educ, data = LaLonde, corprior=.1/nrow(LaLonde))
plot(fit)
```

npCBPS.fit

*npCBPS.fit***Description**

npCBPS.fit

**Usage**

```
npCBPS.fit(treat, X, corprior, print.level, ...)
```

**Arguments**

treat	A vector of treatment assignments. Binary or multi-valued treatments should be factors. Continuous treatments should be numeric.
X	A covariate matrix.
corprior	Prior hyperparameter controlling the expected amount of correlation between each covariate and the treatment. Specifically, the amount of correlation between the k-dimensional covariates, X, and the treatment T after weighting is assumed to have prior distribution $MVN(0, \sigma^2 I_k)$ . We conceptualize $\sigma^2$ as a tuning parameter to be used pragmatically. It's default of 0.1 ensures that the balance constraints are not too harsh, and that a solution is likely to exist. Once the algorithm works at such a high value of $\sigma^2$ , the user may wish to attempt values closer to 0 to get finer balance.
print.level	Controls verbosity of output to the screen while npCBPS runs. At the default of <code>print.level=0</code> , little output is produced. If <code>print.level&gt;0</code> , it outputs diagnostics including the log posterior ( <code>log_post</code> ), the log empirical likelihood associated with the weights ( <code>log_el</code> ), and the log prior probability of the (weighted) correlation of treatment with the covariates.
...	Other parameters to be passed.

plot.CBMSM

*Plotting CBPS Estimation for Marginal Structural Models***Description**

Plots the absolute difference in standardized means before and after weighting.

**Usage**

```
## S3 method for class 'CBMSM'
plot(x, covars = NULL, silent = TRUE, boxplot = FALSE, ...)
```

**Arguments**

x	an object of class “CBMSM”.
covars	Indices of the covariates to be plotted (excluding the intercept). For example, if only the first two covariates from balance are desired, set covars to 1:2. The default is NULL, which plots all covariates.
silent	If set to FALSE, returns the absolute imbalance for each treatment history pair before and after weighting. This helps the user to create his or her own customized plot. Default is TRUE, which returns nothing.
boxplot	If set to TRUE, returns a boxplot summarizing the imbalance on the covariates instead of a point for each covariate. Useful if there are many covariates.
...	Additional arguments to be passed to plot.

**Details**

Covariate balance is improved if the plot’s points are below the plotted line of  $y=x$ .

**Value**

The x-axis gives the imbalance for each covariate-treatment history pair without any weighting, and the y-axis gives the imbalance for each covariate-treatment history pair after CBMSM weighting. Imbalance is measured as the absolute difference in standardized means for the two treatment histories. Means are standardized by the standard deviation of the covariate in the full sample.

**Author(s)**

Marc Ratkovic and Christian Fong

**See Also**

[CBMSM](#), [plot](#)

plot.CBPS

*Plotting Covariate Balancing Propensity Score Estimation***Description**

This function plots the absolute difference in standardized means before and after weighting. To access more sophisticated graphics for assessing covariate balance, consider using Noah Greifer's cobalt package.

**Usage**

```
## S3 method for class 'CBPS'
plot(x, covars = NULL, silent = TRUE, boxplot = FALSE, ...)
```

**Arguments**

x	an object of class "CBPS" or "npCBPS", usually, a result of a call to CBPS or npCBPS.
covars	Indices of the covariates to be plotted (excluding the intercept). For example, if only the first two covariates from balance are desired, set covars to 1:2. The default is NULL, which plots all covariates.
silent	If set to FALSE, returns the imbalances used to construct the plot. Default is TRUE, which returns nothing.
boxplot	If set to TRUE, returns a boxplot summarizing the imbalance on the covariates instead of a point for each covariate. Useful if there are many covariates.
...	Additional arguments to be passed to plot.

**Details**

The "Before Weighting" plot gives the balance before weighting, and the "After Weighting" plot gives the balance after weighting.

### @aliases plot.CBPS plot.npCBPS

**Value**

For binary and multi-valued treatments, plots the absolute difference in standardized means by contrast for all covariates before and after weighting. This quantity for a single covariate and a given pair of treatment conditions is given by  $\frac{\sum_{i=1}^n w_i * (T_i == 1) * X_i}{\sum_{i=1}^n (T_i == 1) * w_i} - \frac{\sum_{i=1}^n w_i * (T_i == 0) * X_i}{\sum_{i=1}^n (T_i == 0) * w_i}$ . For continuous treatments, plots the weighted absolute Pearson correlation between the treatment and each covariate. See [https://en.wikipedia.org/wiki/Pearson\\_product-moment\\_correlation\\_coefficient#Weighted\\_correlation\\_coefficient](https://en.wikipedia.org/wiki/Pearson_product-moment_correlation_coefficient#Weighted_correlation_coefficient).

**Author(s)**

Christian Fong, Marc Ratkovic, and Kosuke Imai.

**See Also**[CBPS](#), [plot](#)


---

plot.CBPSContinuous	<i>Plot the pre-and-post weighting correlations between X and T</i>
---------------------	---

---

**Description**

Plot the pre-and-post weighting correlations between X and T

**Usage**

```
## S3 method for class 'CBPSContinuous'
plot(x, covars = NULL, silent = TRUE, boxplot = FALSE, ...)
```

**Arguments**

x	an object of class “CBPS” or “npCBPS”, usually, a result of a call to CBPS or npCBPS.
covars	Indices of the covariates to be plotted (excluding the intercept). For example, if only the first two covariates from balance are desired, set covars to 1:2. The default is NULL, which plots all covariates.
silent	If set to FALSE, returns the imbalances used to construct the plot. Default is TRUE, which returns nothing.
boxplot	If set to TRUE, returns a boxplot summarizing the imbalance on the covariates instead of a point for each covariate. Useful if there are many covariates.
...	Additional arguments to be passed to balance.

---

plot.npCBPS	<i>Calls the appropriate plot function, based on the number of treatments</i>
-------------	---

---

**Description**

Calls the appropriate plot function, based on the number of treatments

**Usage**

```
## S3 method for class 'npCBPS'
plot(x, covars = NULL, silent = TRUE, ...)
```

**Arguments**

x	an object of class “CBPS” or “npCBPS”, usually, a result of a call to CBPS or npCBPS.
covars	Indices of the covariates to be plotted (excluding the intercept). For example, if only the first two covariates from balance are desired, set covars to 1:2. The default is NULL, which plots all covariates.
silent	If set to FALSE, returns the imbalances used to construct the plot. Default is TRUE, which returns nothing.
...	Additional arguments to be passed to balance.

---

print.CBPS	<i>Print coefficients and model fit statistics</i>
------------	--

---

**Description**

Print coefficients and model fit statistics

**Usage**

```
## S3 method for class 'CBPS'
print(x, digits = max(3, getOption("digits") - 3), ...)
```

**Arguments**

x	an object of class “CBPS” or “npCBPS”, usually, a result of a call to CBPS or npCBPS.
digits	the number of digits to keep for the numerical quantities.
...	Additional arguments to be passed to summary.

---

summary.CBPS	<i>Summarizing Covariate Balancing Propensity Score Estimation</i>
--------------	--

---

**Description**

Prints a summary of a fitted CBPS object.

**Usage**

```
## S3 method for class 'CBPS'
summary(object, ...)
```

**Arguments**

object	an object of class “CBPS”, usually, a result of a call to CBPS.
...	Additional arguments to be passed to summary.

**Details**

Prints a summary of a CBPS object, in a format similar to `glm`. The variance matrix is calculated from the numerical Hessian at convergence of CBPS.

**Value**

<code>call</code>	The matched call.
<code>deviance.residuals</code>	The five number summary and the mean of the deviance residuals.
<code>coefficients</code>	A table including the estimate for the each coefficient and the standard error, z-value, and two-sided p-value for these estimates.
<code>J</code>	Hansen's J-Statistic for the fitted model.
<code>Log-Likelihood</code>	The log-likelihood of the fitted model.

**Author(s)**

Christian Fong, Marc Ratkovic, and Kosuke Imai.

**See Also**

[CBPS, summary](#)

---

vcov.CBPS

---

*Calculate Variance-Covariance Matrix for a Fitted CBPS Object*


---

**Description**

`vcov.CBPS` Returns the variance-covariance matrix of the main parameters of a fitted CBPS object.

**Usage**

```
## S3 method for class 'CBPS'
vcov(object, ...)
```

**Arguments**

<code>object</code>	An object of class <code>formula</code> (or one that can be coerced to that class): a symbolic description of the model to be fitted.
<code>...</code>	Additional arguments to be passed to <code>vcov.CBPS</code>

**Details**

This is the CBPS implementation of the generic function `vcov()`.

**Value**

A matrix of the estimated covariances between the parameter estimates in the linear or non-linear predictor of the model.

**Author(s)**

Christian Fong, Marc Ratkovic, and Kosuke Imai.

**References**

This documentation is modeled on the documentation of the generic [vcov](#).

**See Also**

[vcov](#)

**Examples**

```
###
### Example: Variance-Covariance Matrix
###

##Load the LaLonde data
data(LaLonde)
## Estimate CBPS via logistic regression
fit <- CBPS(treat ~ age + educ + re75 + re74 + I(re75==0) + I(re74==0),
  data = LaLonde, ATT = TRUE)
## Get the variance-covariance matrix.
vcov(fit)
```

---

vcov\_outcome

*Calculate Variance-Covariance Matrix for Outcome Model*

---

**Description**

vcov\_outcome Returns the variance-covariance matrix of the main parameters of a fitted CBPS object.

This adjusts the standard errors of the weighted regression of Y on Z for uncertainty in the weights.

### @aliases vcov\_outcome vcov\_outcome.CBPSContinuous

**Usage**

```
vcov_outcome(object, Y, Z, delta, tol = 10-5, lambda = 0.01)
```

**Arguments**

object	A fitted CBPS object.
Y	The outcome.
Z	The covariates (including the treatment and an intercept term) that predict the outcome.
delta	The coefficients from regressing Y on Z, weighting by the cbpsfit\$weights.
tol	Tolerance for choosing whether to improve conditioning of the "M" matrix prior to conversion. Equal to $1/(\text{condition number})$ , i.e. the smallest eigenvalue divided by the largest.
lambda	The amount to be added to the diagonal of M if the condition of the matrix is worse than tol.

**Value**

A matrix of the estimated covariances between the parameter estimates in the weighted outcome regression, adjusted for uncertainty in the weights.

**Author(s)**

Christian Fong, Chad Hazlett, and Kosuke Imai.

**References**

Lunceford and Davididian 2004.

**Examples**

```
###
### Example: Variance-Covariance Matrix
###

##Load the LaLonde data
data(LaLonde)
## Estimate CBPS via logistic regression
fit <- CBPS(treat ~ age + educ + re75 + re74 + I(re75==0) + I(re74==0),
  data = LaLonde, ATT = TRUE)
## Get the variance-covariance matrix.
vcov(fit)
```

---

```
vcov_outcome.CBPSContinuous  
vcov_outcome
```

---

**Description**

vcov\_outcome

**Usage**

```
## S3 method for class 'CBPSContinuous'  
vcov_outcome(object, Y, Z, delta, tol = 10-5, lambda = 0.01)
```

**Arguments**

object	A fitted CBPS object.
Y	The outcome.
Z	The covariates (including the treatment and an intercept term) that predict the outcome.
delta	The coefficients from regressing Y on Z, weighting by the cbpsfit\$weights.
tol	Tolerance for choosing whether to improve conditioning of the "M" matrix prior to conversion. Equal to 1/(condition number), i.e. the smallest eigenvalue divided by the largest.
lambda	The amount to be added to the diagonal of M if the condition of the matrix is worse than tol.

**Value**

Variance-Covariance Matrix for Outcome Model

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