# Package 'bcf'

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**Type** Package

**Title** Causal Inference for a Binary Treatment and Continuous Outcome using Bayesian Causal Forests

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**Description** Causal inference for a binary treatment and continuous outcome using Bayesian Causal Forests. See Hahn, Murray and Carvalho (2017) <arXiv:1706.09523> for additional information. This implementation relies on code originally accompanying Pratola et. al. (2013) <arXiv:1309.1906>.

**License** GPL-3

**Depends** Rcpp (>= 0.10.4)

**LinkingTo** Rcpp, RcppArmadillo

**NeedsCompilation** yes

**RoxygenNote** 6.0.1

**Repository** CRAN

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## R topics documented:

bcf *Fit Bayesian Causal Forests*

## Description

Fit Bayesian Causal Forests

## Usage

```
bcf(y, z, x_control, x_moderate = x_control, pihat, nburn, nsim, nthin = 1,
  update_interval = 100, ntree_control = 200, sd_control = 2 * sd(y),
  base_control = 0.95, power_control = 2, ntree_moderate = 50,
  sd_moderate = sd(y), base_moderate = 0.25, power_moderate = 3, nu = 3,
  lambda = NULL, sigq = 0.9, sighat = NULL, include_pi = "control",
  use_muscale = TRUE, use_tauscale = TRUE)
```

## Arguments

| | |
|---|---|
| `y` | Response variable |
| `z` | Treatment variable |
| `x_control` | Design matrix for the "prognostic" function mu(x) |
| `x_moderate` | Design matrix for the covariate-dependent treatment effects tau(x) |
| `pihat` | Length n estimates of |
| `nburn` | Number of burn-in MCMC iterations |
| `nsim` | Number of MCMC iterations to save after burn-in |
| `nthin` | Save every nthin'th MCMC iterate. The total number of MCMC iterations will be nsim*nthin + nburn. |
| `update_interval` | Print status every update_interval MCMC iterations |
| `ntree_control` | Number of trees in mu(x) |
| `sd_control` | SD(mu(x)) marginally at any covariate value (or its prior median if use_muscale=TRUE) |
| `base_control` | Base for tree prior on mu(x) trees (see details) |
| `power_control` | Power for the tree prior on mu(x) trees |
| `ntree_moderate` | Number of trees in tau(x) |
| `sd_moderate` | SD(tau(x)) marginally at any covariate value (or its prior median if use_tauscale=TRUE) |
| `base_moderate` | Base for tree prior on tau(x) trees (see details) |
| `power_moderate` | Power for the tree prior on tau(x) trees (see details) |
| `nu` | Degrees of freedom in the chisq prior on $sigma^2$ |
| `lambda` | Scale parameter in the chisq prior on $sigma^2$ |
| `sigq` | Calibration quantile for the chisq prior on $sigma^2$ |
| `sighat` | Calibration estimate for the chisq prior on $sigma^2$ |

| | |
|---|---|
| `include_pi` | Takes values "control", "moderate", "both" or "none". Whether to include pihat in mu(x) ("control"), tau(x) ("moderate"), both or none. Values of "control" or "both" are HIGHLY recommended with observational data. |
| `use_muscale` | Use a half-Cauchy hyperprior on the scale of mu. |
| `use_tauscale` | Use a half-Normal prior on the scale of tau. |

## Details

Fits the Bayesian Causal Forest model (Hahn et. al. 2018): For a response variable y, binary treatment z, and covariates x,

$$y_i = \mu(x_i, \pi_i) + \tau(x_i, \pi_i)z_i + \epsilon_i$$

where $\pi_i$ is an (optional) estimate of the propensity score $\Pr(Z_i = 1|X_i = x_i)$ and $\epsilon_i \sim N(0, \sigma^2)$

Some notes:

- x_control and x_moderate must be numeric matrices. See e.g. the makeModelMatrix function in the dbarts package for appropriately constructing a design matrix from a data.frame
- sd_control and sd_moderate are the prior SD(mu(x)) and SD(tau(x)) at a given value of x (respectively). If use_muscale = FALSE, then this is the parameter $\sigma_\mu$ from the original BART paper, where the leaf parameters have prior distribution $N(0, \sigma_\mu/m)$, where m is the number of trees. If use_muscale=TRUE then sd_control is the prior median of a half Cauchy prior for SD(mu(x)). If use_tauscale = TRUE, then sd_moderate is the prior median of a half Normal prior for SD(tau(x)).
- By default the prior on $\sigma^2$ is calibrated as in Chipman, George and McCulloch (2008).

## Value

A list with elements

| | |
|---|---|
| `tau` | `nsim` by `n` matrix of posterior samples of individual treatment effects |
| `mu` | `nsim` by `n` matrix of posterior samples of individual treatment effects |
| `sigma` | Length `nsim` vector of posterior samples of sigma |

## References

Hahn, Murray, and Carvalho(2017). Bayesian regression tree models for causal inference: regularization, confounding, and heterogeneous effects. https://arxiv.org/abs/1706.09523. (Call citation("bcf") from the command line for citation information in Bibtex format.)

## Examples

```
# data generating process
p = 3 #two control variables and one moderator
n = 250
#
set.seed(1)
```

```
x = matrix(rnorm(n*p), nrow=n)

# create targeted selection
q = -1*(x[,1]>(x[,2])) + 1*(x[,1]<(x[,2]))

# generate treatment variable
pi = pnorm(q)
z = rbinom(n,1,pi)

# tau is the true (homogeneous) treatment effect
tau = (0.5*(x[,3] > -3/4) + 0.25*(x[,3] > 0) + 0.25*(x[,3]>3/4))

# generate the response using q, tau and z
mu = (q + tau*z)

# set the noise level relative to the expected mean function of Y
sigma = diff(range(q + tau*pi))/8

# draw the response variable with additive error
y = mu + sigma*rnorm(n)

# If you didn't know pi, you would estimate it here
pihat = pnorm(q)

bcf_fit = bcf(y, z, x, x, pihat, nburn=2000, nsim=2000)

# Get posterior of treatment effects
tau_post = bcf_fit$tau
tauhat = colMeans(tau_post)
plot(tau, tauhat); abline(0,1)
```

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