Package ‘plotBart’

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Type Package

Title Diagnostic and Plotting Functions to Supplement 'bartCause'

Version 0.1.7

Description Functions to assist in diagnostics and plotting during the causal inference modeling process. Supplements the 'bartCause' package.

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BugReports https://github.com/priism-center/plotBart/issues

Encoding UTF-8

LazyData true

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Depends R (>= 2.10), bartCause (>= 1.0.4), ggplot2 (>= 3.3.2)

Imports dplyr (>= 1.0.5), tidyr (>= 1.1.3), rpart (>= 4.1.15), stats (>= 3.6.2), ggdendro (>= 0.1.22)

Suggests testthat, vdiffr, arm (>= 1.10.1), covr, knitr, rmarkdown

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Author Joseph Marlo [aut, cre], George Perrett [aut]

Maintainer Joseph Marlo <jpm770@nyu.edu>

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lalonde Lalonde dataset

Description

Lalonde dataset

Usage

lalonde

Format

An object of class `data.frame` with 445 rows and 12 columns.

Source

https://CRAN.R-project.org/package=arm
plot_balance

Plot the balance

Description

Visualize balance of variables between treatment and control groups. Balance plot reflects balance in standardized units.

Usage

plot_balance(.data, treatment, confounders)

Arguments

.data dataframe
.treatment the column denoted treatment. Must be binary.
.confounders character list of column names denoting the X columns of interest

Value

ggplot object

Author(s)

Joseph Marlo

Examples

data(lalonde)
plot_balance(lalonde, 'treat', c('re78', 'age', 'educ')) + labs(title = 'My new title')

plot_CATE

Plot the histogram or density of the Conditional Average Treatment Effect

Description

Plot the conditional average treatment effect (CATE) of a 'bartCause' model. The conditional average treatment effect is derived from taking the difference between predictions for each individual under the control condition and under the treatment condition averaged over the population. Means of the CATE distribution will resemble SATE and PATE but the CATE distribution accounts for more uncertainty than SATE and less uncertainty than PATE.
Usage

plot_CATE(
  .model,  
  type = c("histogram", "density"), 
  ci_80 = FALSE, 
  ci_95 = FALSE, 
  reference = NULL, 
  .mean = FALSE, 
  .median = FALSE
)

Arguments

.model      a model produced by 'bartCause::bartc()'
type        histogram or density
.ci_80      TRUE/FALSE. Show the 80% credible interval?
.ci_95      TRUE/FALSE. Show the 95% credible interval?
.reference  numeric. Show a vertical reference line at this value
 mean       TRUE/FALSE. Show the mean reference line
.median     TRUE/FALSE. Show the median reference line

Value

ggplot object

Author(s)

George Perrett, Joseph Marlo

Examples

data(lalonde)
confounders <- c('age', 'educ', 'black', 'hisp', 'married', 'nodegr')
model_results <- bartCause::bartc(
  response = lalonde[['re78']],
  treatment = lalonde[['treat']],
  confounders = as.matrix(lalonde[, confounders]),
estimand = 'ate',
commonSup.rule = 'none'
)
plot_CATE(model_results)
plot_common_support

Plot common support based on the standard deviation rule, chi squared rule, or both.

Description

Plot common support based on the standard deviation rule, chi squared rule, or both.

Usage

plot_common_support(.model, rule = c("both", "sd", "chi"))

Arguments

.model a model produced by 'bartCause::bartc()'
rule one of c('both', 'sd', 'chi') denoting which rule to use to identify lack of support

Details

Sufficient overlap/common support is an assumption of causal inference. BART models use the uncertainty of counterfactual uncertainty. When the posterior distribution of an individual's counterfactual prediction extends beyond a specified cut-point, that point likely has insufficient common support. 'bartCause' model offer the option to automatically remove points without common support from analyses, however, this must be specified during model fitting. Cut-points are determined through one of two rules: the standard deviation (sd) or chi-squared (chi). Under the standard deviation rule, a point has weak common support if its posterior distribution of the counterfactual deviation is greater than the maximum posterior of the observed predictions with 1 standard deviation of the distribution of standard deviations for each individual's predicted outcome under the observed assignment. Under the chi-squared rule, a point is discarded if the variance between its counterfactual prediction over observed prediction are statistically different under a chi-squared distribution with 1 degree of freedom. For more details on discard rules see Hill and Su 2013.

When called this plot will show how many points would have been removed under the standard deviation and chi-squared rules. This plot should be used as a diagnostic for 'bartCause' models fit without a common-support rule.

Value

ggplot object

Author(s)

George Perrett, Joseph Marlo

References

Examples

data(lalonde)
confounders <- c('age', 'educ', 'black', 'hisp', 'married', 'nodegr')
model_results <- bartCause::bartc(
  response = lalonde[['re78']],
  treatment = lalonde[['treat']],
  confounders = as.matrix(lalonde[, confounders]),
  estimand = 'ate',
  commonSuprule = 'none'
)
plot_common_support(model_results)

plot_ICATE  
Plot Individual Conditional Average Treatment effects

Description

Plots a histogram of Individual Conditional Average Treatment effects (ICATE). ICATEs are the difference in each individual's predicted outcome under the treatment and predicted outcome under the control averaged over the individual. Plots of ICATEs are useful to identify potential heterogeneous treatment effects between different individuals. ICATE plots can be grouped by discrete variables.

Usage

plot_ICATE(.model, .group_by = NULL, n_bins = 30, .alpha = 0.7)

Arguments

.model       a model produced by `bartCause::bartc()`
.group_by    a grouping variable as a vector
.n_bins      number of bins
.alpha       transparency of histograms

Value

ggplot object

Author(s)

George Perrett
Examples

```r
data(lalonde)
confounders <- c('age', 'educ', 'black', 'hisp', 'married', 'nodegr')
model_results <- bartCause::bartc(
  response = lalonde[['re78']],
  treatment = lalonde[['treat']],
  confounders = as.matrix(lalonde[, confounders]),
  estimand = 'ate',
  commonSup.rule = 'none'
)
plot_ICATE(model_results, lalonde$married)
```

Description

Plot the LOESS prediction of ICATEs by a continuous covariate. This is an alternative to partial dependency plots to assess treatment effect heterogeneity by a continuous covariate. See Carnegie, Dorie and Hill 2019.

Usage

```r
plot_moderator_c_loess(.model, moderator, line_color = "blue")
```

Arguments

- `.model`: a model produced by `bartCause::bartc()`
- `moderator`: the moderator as a vector
- `line_color`: the color of the loess line

Value

`ggplot` object

Author(s)

George Perrett, Joseph Marlo

References

Examples

```r
data(lalonde)
confounders <- c('age', 'educ', 'black', 'hisp', 'married', 'nodegr')
model_results <- bartCause::bartc(
  response = lalonde[['re78']],
  treatment = lalonde[['treat']],
  confounders = as.matrix(lalonde[, confounders]),
  estimand = 'ate',
  commonSuprule = 'none'
)
plot_moderator_c_loess(model_results, lalonde$age)
```

Description

Plot a partial dependency plot with a continuous covariate from a `bartCause` model. Identify treatment effect variation predicted across levels of a continuous variable.

Usage

```r
plot_moderator_c_pd(.model, moderator, n_bins = NULL)
```

Arguments

- `.model`: a model produced by `bartCause::bartc()`
- `moderator`: the moderator as a vector
- `n_bins`: number of bins to cut the moderator with. Defaults to the lesser of 15 and number of distinct levels of the moderator

Details

Partial dependency plots are one way to evaluate heterogeneous treatment effects that vary by values of a continuous covariate. For more information on partial dependency plots from BART causal inference models see Green and Kern 2012.

Value

`ggplot` object

Author(s)

George Perrett, Joseph Marlo
 References

 Examples

```r
data(lalonde)
confounders <- c('age', 'educ', 'black', 'hisp', 'married', 'nodegr')
model_results <- bartCause::bartc(
  response = lalonde[['re78']],
  treatment = lalonde[['treat']],
  confounders = as.matrix(lalonde[, confounders]),
  estimand = 'ate',
  commonSuprule = 'none',
  keepTrees = TRUE
)
plot_moderator_c_pd(model_results, lalonde$age)
```

---

**plot_moderator_d_density**

*Plot the Conditional Average Treatment Effect conditional on a discrete moderator*

Description
Plot the Conditional Average Treatment Effect split by a discrete moderating variable. This plot will provide a visual test of moderation by discrete variables.

Usage

```r
plot_moderator_d_density(
  .model,
  moderator,
  .alpha = 0.7,
  facet = FALSE,
  ncol = 1
)
```

Arguments
- `.model` a model produced by `bartCause::bartc()`
- `moderator` the moderator as a vector
- `.alpha` transparency value [0, 1]
- `facet` TRUE/FALSE. Create panel plots of each moderator level?
- `ncol` number of columns to use when faceting
Value

ggplot object

Author(s)

George Perrett

Examples

data(lalonde)
confounders <- c('age', 'educ', 'black', 'hisp', 'married', 'nodegr')
model_results <- bartCause::bartc(
  response = lalonde[['re78']],
  treatment = lalonde[['treat']],
  confounders = as.matrix(lalonde[, confounders]),
  estimand = 'ate',
  commonSuprule = 'none'
)
plot_moderator_d_density(model_results, lalonde$educ)

plot_moderator_d_linerange

Plot the posterior interval of the Conditional Average Treatment Effect grouped by a discrete variable

Description

Plots the range of the Conditional Average Treatment Effect grouped by a discrete variable. This is analogous to plot_moderator_d_density but is preferable for moderators with many categories. Rather than plotting the full density, the posterior range is shown.

Usage

plot_moderator_d_linerange(.model, moderator, .alpha = 0.7, horizontal = FALSE)

Arguments

.model a model produced by ‘bartCause::bartc()’
moderator the moderator as a vector
.alpha transparency value [0, 1]
horizontal flip the plot horizontal?

Value

ggplot object
**plot_moderator_search**  

**Author(s)**  
George Perrett, Joseph Marlo

**Examples**

```r
data(lalonde)
confounders <- c('age', 'educ', 'black', 'hisp', 'married', 'nodegr')
model_results <- bartCause::bartc(
  response = lalonde[['re78']],
  treatment = lalonde[['treat']],
  confounders = as.matrix(lalonde[, confounders]),
  estimand = 'ate',
  commonSuprule = 'none'
)
plot_moderator_d_linerange(model_results, lalonde$educ)
```

**Description**

Plot a single regression tree for exploratory heterogeneous effects. Fit single regression tree on bartc() ICATEs to produce variable importance plot. This plot is useful for identifying potential moderating variables. Tree depth may be set to depths 1, 2 or 3. Terminal nodes signal the Conditional Average Treatment effect within levels of moderation variables. Trees with different values across terminal nodes suggest strong treatment effect moderation.

**Usage**

```r
plot_moderator_search(.model, max_depth = c(2, 1, 3))
```

**Arguments**

- `.model` a model produced by `bartCause::bartc()`
- `max_depth` one of c(1, 2, 3). Maximum number of node levels within the tree. 2 is recommended

**Value**

`ggplot` object

**Author(s)**

George Perrett, Joseph Marlo
Examples

data(lalonde)
confounders <- c('age', 'educ', 'black', 'hisp', 'married', 'nodegr')
model_results <- bartCause::bartc(
  response = lalonde[['re78']],
  treatment = lalonde[['treat']],
  confounders = as.matrix(lalonde[, confounders]),
  estimand = 'ate',
  commonSuprule = 'none'
)
plot_moderator_search(model_results)

Description

Plot histograms showing the overlap between propensity scores by treatment status.

Usage

plot_overlap_pScores(
  .data,
  treatment,
  response,
  confounders,
  plot_type = c("histogram", "density"),
  pscores = NULL,
  ...
)

Arguments

.data dataframe
treatment character. Name of the treatment column within .data
response character. Name of the response column within .data
confounders character list of column names denoting confounders within .data
plot_type the plot type, one of c('Histogram', 'Density')
pscores propensity scores. If not provided, then propensity scores will be calculated using BART
... additional arguments passed to ‘bartCause::bartc’ propensity score calculation

Value

ggplot object
**plot_overlap_vars**

**Author(s)**
George Perrett, Joseph Marlo

**See Also**
plot_overlap_vars

**Examples**

```r
data(lalonde)
plot_overlap_pscores(
  .data = lalonde,
  treatment = 'treat',
  response = 're78',
  confounders = c('age', 'educ'),
  plot_type = 'histogram',
  pscores = NULL,
  seed = 44
)
```

---

**plot_overlap_vars**  
*Plot the overlap of variables*

**Description**
Plot histograms showing the overlap between variables by treatment status.

**Usage**

```r
plot_overlap_vars(
  .data, treatment, confounders, plot_type = c("histogram", "density")
)
```

**Arguments**

- **.data**: dataframe
- **treatment**: character. Name of the treatment column within .data
- **confounders**: character list of column names denoting confounders within .data
- **plot_type**: the plot type, one of c('histogram', 'density'). Defaults to 'histogram'

**Value**

ggplot object
Author(s)
George Perrett, Joseph Marlo

See Also
plot_overlap_pScores

Examples
```r
data(lalonde)
plot_overlap_vars(
  .data = lalonde,
  treatment = 'treat',
  confounders = c('age', 'educ'),
  plot_type = 'Histogram'
)
```

plot_PATE

Plot histogram or density of Population Average Treatment Effect

Description
Plot shows the Population Average Treatment Effect which is derived from the posterior predictive distribution of the difference between $y|z = 1, X$ and $y|z = 0, X$. Mean of PATE will resemble CATE and SATE but PATE will account for more uncertainty and is recommended for informing inferences on the average treatment effect.

Usage
```r
plot_PATE(
  .model,
  type = c("histogram", "density"),
  ci_80 = FALSE,
  ci_95 = FALSE,
  reference = NULL,
  .mean = FALSE,
  .median = FALSE
)
```

Arguments
- `.model` a model produced by `bartCause::bartc`
- `type` histogram or density
- `ci_80` TRUE/FALSE. Show the 80% credible interval?
- `ci_95` TRUE/FALSE. Show the 95% credible interval?
- `reference` numeric. Show a vertical reference line at this value
- `.mean` TRUE/FALSE. Show the mean reference line
- `.median` TRUE/FALSE. Show the median reference line
**Value**

ggplot object

**Author(s)**

George Perrett, Joseph Marlo

**Examples**

```r
data(lalonde)
confounders <- c('age', 'educ', 'black', 'hisp', 'married', 'nodegr')
model_results <- bartCause::bartc(
  response = lalonde[['re78']],
  treatment = lalonde[['treat']],
  confounders = as.matrix(lalonde[, confounders]),
  estimand = 'ate',
  commonSup.rule = 'none'
)
plot_PATE(model_results)
```

---

**plot_SATE**

Plot histogram or density of Sample Average Treatment Effects

**Description**

Plot a histogram or density of the Sample Average Treatment Effect (SATE). The Sample Average Treatment Effect is derived from taking the difference of each individual’s observed outcome and a predicted counterfactual outcome from a BART model averaged over the population. The mean of SATE will resemble means of CATE and PATE but will account for the least uncertainty.

**Usage**

```r
plot_SATE(
  .model,
  type = c("histogram", "density"),
  ci_80 = FALSE,
  ci_95 = FALSE,
  reference = NULL,
  .mean = FALSE,
  .median = FALSE
)
```
plot_trace

Arguments

- `.model` a model produced by `bartCause::bartc()`
- `type` histogram or density
- `ci_80` TRUE/FALSE. Show the 80% credible interval?
- `ci_95` TRUE/FALSE. Show the 95% credible interval?
- `reference` numeric. Show a vertical reference line at this x-axis value
- `.mean` TRUE/FALSE. Show the mean reference line
- `.median` TRUE/FALSE. Show the median reference line

Value

ggplot object

Author(s)

George Perrett, Joseph Marlo

Examples

data(lalonde)
confounders <- c('age', 'educ', 'black', 'hisp', 'married', 'nodegr')
model_results <- bartCause::bartc(
  response = lalonde[['re78']],
  treatment = lalonde[['treat']],
  confounders = as.matrix(lalonde[, confounders]),
  estimand = 'ate',
  commonSup.rule = 'none'
)
plot_SATE(model_results)

Description

Returns a ggplot of the estimated effect over each iteration of the model fit. This is used to visually assess the convergence of Markov chain Monte Carlo (MCMC) sampling. Chains should be well mixed such that no single color is notably separate from others.

Usage

plot_trace(.model)
Arguments

.model  a model produced by `bartCause::bartc()`

Value

ggplot object

Author(s)

Joseph Marlo, George Perrett

Examples

data(lalonde)
confounders <- c('age', 'educ', 'black', 'hisp', 'married', 'nodegr')
model_results <- bartCause::bartc(
  response = lalonde[['re78']].
  treatment = lalonde[['treat']].
  confounders = as.matrix(lalonde[, confounders]),
  estimand = 'ate',
  commonSup.rule = 'none'
)
plot_trace(.model = model_results)

plot_waterfall  

Plot a waterfall of the ICATEs

Description

Plots the point and posterior intervals of each individual’s ICATE ordered by the ICATE or a continuous variable. Points can be colored by a discrete variable. Waterfall plots are a useful visual diagnostic of possible treatment effect heterogeneity. A flat line implies little treatment effect heterogeneity while a steeper curve implies that the treatment effect varies across individuals in the sample. Ordering points by a continuous variable or coloring points by a discrete variable can be helpful to identify potential moderators of the treatment effect.

Usage

plot_waterfall(  
  .model,
  descending = TRUE,
  .order = NULL,
  .color = NULL,
  .alpha = 0.5
)
Arguments

- .model: a model produced by ‘bartCause::bartc()’
- descending: order the ICATEs by value?
- .order: a vector representing a custom order
- .color: a vector representing colors
- .alpha: transparency value [0, 1]

Value

ggplot object

Author(s)

George Perrett

Examples

data(lalonde)
confounders <- c('age', 'educ', 'black', 'hisp', 'married', 'nodegr')
model_results <- bartCause::bartc(
  response = lalonde[['re78']],
  treatment = lalonde[['treat']],
  confounders = as.matrix(lalonde[, confounders]),
  estimand = 'ate',
  commonSuprule = 'none'
)
plot_waterfall(model_results)
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