# Package 'DTRreg'

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Type Package
<b>Title</b> DTR Estimation and Inference via G-Estimation, Dynamic WOLS, Q-Learning, and Dynamic Weighted Survival Modeling (DWSurv)
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<b>Description</b> Dynamic treatment regime estimation and inference via G-estimation, dynamic weighted ordinary least squares (dWOLS) and Q-learning. Inference via bootstrap and (for G-estimation) recursive sandwich estimation. Estimation and inference for survival outcomes via Dynamic Weighted Survival Modeling (DWSurv).
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chooseM
confint
DTRreg
plot
predict
Index 16

2 chooseM

chooseM	Adaptive Choice of the Bootstrap Resample Size M for the m-out-of-n
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	Bootstrap with for DTR Estimation

# Description

Implementation of a double-bootstrap alogrithm for choosing the bootstrap resample size m in a data-adaptive manner. The function returns a resample size m to be used to apply the m-out-of-n bootstrap with DTRreg.

# Usage

```
chooseM(outcome, blip.mod, treat.mod, tf.mod, data = NULL,
    method = "gest", weight = "default", missing = "default",
    treat.mod.man = NULL, B1 = 500, B2 = 500)
```

# Arguments

outcome	The outcome variable.
blip.mod	A list of formula objects specifying covariates of a (linear) blip function for each stage in order. No dependent variable should be specified.
treat.mod	A list of formula objects specifying the treatment model for each stage in order. Treatment variable should be included as the dependent variable. If treatment is binary a logistic regression model will be used, otherwise a linear regression model will be used.
tf.mod	A list of formula objects specifying covariates of a (linear) treatment-free model for each stage in order. No dependent variable should be specified.
data	A data frame containing all necessary covariates contained in the above models.
method	The DTR method to be used, choose "dwols" for dynamic WOLS, "gest" for G-estimation, or "qlearn" for Q-learning.
weight	If using dynamic WOLS the option for the weights used. Default is the form $ A-E[A ] $ , "iptw" gives inverse probability of treatment style weights.
missing	If set to "ipcw" and data are missing then inverse probability of censored weights is used with the probability of censoring estimated via logistic regression on the full covariate history up to that point.
treat.mod.man	A list of vectors of known treatment weights can be specified to be used instead of those estimated by the routine.
B1	Number of first-level boostrap resamples.
B2	Number of second-level boostrap resamples.

chooseM 3

### **Details**

The m-out-of-n bootstrap is an adequate tool for constructing valid confidence intervals for the first stage parameters in DTRreg. The resample size m is:  $m = n^{\frac{1+alpha(1-pHat)}{1+alpha}}$ . The estimated non-regularity level is computed by DTRreg. The double-bootstrap algorithm is a cross-validation tool for choosing the tuning parameter alpha in a data-driven way.

The current implementation is valid for a two-stage DTR. Moreover, the current implementation may be unstable when there are many missing data.

### Value

m Resample size for using in the m-out-of-n bootstrap.

#### Author(s)

Gabrielle Simoneau

#### References

Chakraborty, B., Moodie, E. E. M. (2013) *Statistical Methods for Dynamic Treatment Regimes*. New York: Springer.

Efron B., Tibshirani R. J. (1994) An Introduction to the Bootstrap. CRC press.

Wallace, M. P., Moodie, E. M. (2015) Doubly-Robust Dynamic Treatment Regimen Estimation Via Weighted Least Squares. *Biometrics* **71**(3), 636–644 (doi:10.1111/biom.12306.)

```
##################
# example single run of a 2-stage g-estimation analysis
set.seed(1)
# expit function
expit <- function(x) \{1 / (1 + exp(-x))\}
# sample size
n <- 100
# variables (X = patient information, A = treatment)
X1 <- rnorm(n)
A1 <- rbinom(n, 1, expit(X1))
X2 <- rnorm(n)
A2 \leftarrow rbinom(n, 1, expit(X2))
# blip functions
gamma1 <- A1 * (1 + X1)
gamma2 < - A2 * (1 + X2)
# observed outcome: treatment-free outcome plus blip functions
Y \leftarrow exp(X1) + exp(X2) + gamma1 + gamma2 + rnorm(n)
# models to be passed to DTRreg
# blip model
blip.mod <- list(~X1, ~X2)</pre>
# treatment model (correctly specified)
treat.mod <- list(A1~X1, A2~X2)</pre>
# treatment-free model (incorrectly specified)
tf.mod <- list(~X1, ~X2)</pre>
```

4 confint

confint

Flexible Confidence Interval Calculations for DTRs

### **Description**

Confidence intervals for dWOLS or DWSurv parameters, with the possibility of deriving constructing the confidence intervals using the percentile method when bootstrap is used (DWSurv only).

### Usage

```
## S3 method for class 'DTRreg'
confint(object, parm = NULL, level = 0.95, type = "se", ...)
```

### **Arguments**

object A model object generated by the function DTRreg.

type Typical Wald-type confidence interval "se" (default) or confidence intervals de-

rived with the percentile method "percentile" (currently available with DWSurv

only).

parm Not available for DTRreg objects.

level the confidence level required.

... Space for additional arguments (not currently used by DTRreg).

### **Details**

**BLABLA** 

### Value

A list with columns giving lower and upper confidence limits for each parameter. These will be labelled as (1-level)/2 and 1 - (1-level)/2 in

### Author(s)

Gabrielle Simoneau

### References

**MYPAPER** 

### **Examples**

```
###################
# simulate data
expit <- function(x) exp(x) / (1 + exp(x))
theta1 <- c(4.7, 1.5, -0.8, 0.1, 0.1)
n <- 100
X1 <- runif(n, 0.1, 1.29)</pre>
X12 < - rbinom(n, 1, 0.4)
A1 <- rbinom(n, 1, expit(2*X1 - 1))
delta \leftarrow rbinom(n, 1, expit(3*X12 + 0.1))
logT < - theta1[1] + theta1[2]*X1[delta == 1] + theta1[3]*X12[delta == 1] +
theta1[4]*A1[delta == 1] + theta1[5]*A1[delta == 1]*X1[delta == 1] +
rnorm(sum(delta), sd = 0.3)
C \leftarrow rexp(n - sum(delta), rate = 1/300)
Y \leftarrow rep(NA, n)
Y[delta == 1] \leftarrow exp(logT)
Y[delta == 0] <- C
dataset <- data.frame(X1, X12, A1, delta, Y)</pre>
model <- DWSurv(time = list(~Y), blip.mod = list(~X1), treat.mod = list(A1~X1),</pre>
tf.mod = list(~X1 + X12), cens.mod = list(delta~X12), data = dataset, var.estim = "bootstrap",
boot.opt = "standard", B = 200)
confint(model, type = "percentile")
```

DTRreg

DTR Estimation and Inference via G-estimation and Dynamic WOLS

### **Description**

Dynamic treatment regimen estimation and inference via G-estimation and dynamic WOLS. Estimation of blip model parameters for multi-stage data.

# Usage

```
DTRreg(outcome, blip.mod, treat.mod, tf.mod, data = NULL,
    method = "gest", weight = "default", var.estim = "none",
    B = 200, M = 0, truncate = 0, verbose = "FALSE",
    interrupt = "FALSE", treat.range = NULL, missing = "default",
    interactive = FALSE, treat.mod.man = NULL, type = "DTR")
```

### **Arguments**

outcome The outcome variable. blip.mod A list of formula objects specifying covariates of a (linear) blip function for each stage in order. No dependent variable should be specified. treat.mod A list of formula objects specifying the treatment model for each stage in order. Treatment variable should be included as the dependent variable. If treatment is binary a logistic regression model will be used, otherwise a linear regression model will be used. tf.mod A list of formula objects specifying covariates of a (linear) treatment-free model for each stage in order. No dependent variable should be specified. data A data frame containing all necessary covariates contained in the above models. method The DTR method to be used, choose "dwols" for dynamic WOLS, "gest" for G-estimation, or "qlearn" for Q-learning. weight If using dynamic WOLS the option for the weights used. Default is the form |A - E[Al...]l, "iptw" gives inverse probability of treatment style weights. Covariance matrix estimation method, either "bootstrap" (for either dWOLS var.estim or G-estimation) or "sandwich" for recursive sandwich estimation in the Gestimation context. В Number of bootstrap samples. М Subsample size for m out of n bootstrap. If unspecified this is set to the sample size (i.e. n) truncate Bootstrap option. Truncate (a number between 0 and 0.5) will replace the lowest and highest specified proportion of parameter estimates with the relevant quantiles affording some robustness to extreme values when estimating covariance. Bootstrap option. If TRUE then estimated time to completion will be printed verbose approximately every 30 seconds. Bootstrap option. If TRUE then user will be given the option to abort if estiinterrupt mated time to completion exceeds 10 minutes. For continuous treatments. Specify the maximum/minimum value that treattreat.range ments can be take. If unspecified then the minimum/maximum value of observed treatments is used. If you wish to have unrestricted treatments set this option to c(-Inf,+Inf). missing If set to "ipcw" and data are missing then inverse probability of censored weights is used with the probability of censoring estimated via logistic regression on the full covariate history up to that point. interactive If TRUE on-screen prompts will guide the user through the specification of blip, treatment and treatment-free models. treat.mod.man A list of vectors of known treatment weights can be specified to be used instead of those estimated by the routine. type If specified as something other than "DTR", DTRreg will take an 'effect estimation' (as opposed to a DTR estimation) approach, treating the observed outcome as being equal to an outcome assuming no treatment is received at any stage, plus a blip component at each stage. The main difference is that each stage's

pseudo-outcome is generated by subtracting a blip function, rather than adding a regret function as in the DTR framework. Note that most of the DTR-specific output will either be suppressed or irrelevant.

### **Details**

DTRreg allows the estimation of optimal dynamic treatment regimens (DTRs, also known as adaptive treatment strategies) from multi-stage trials using G-estimation and dynamic weighted ordinary least squares (dWOLS). Both methods focus on estimating the parameters of the blip: a model of the difference in expected outcome under the observed treatment and some reference treatment (usually a control) at a given stage, assuming identical histories and optimal treatment thereafter. The reader is referred to Chakraborty and Moodie (2013) for a thorough introduction and review of DTR methods. The dWOLS method may be used to obtain parameter estimates identical to those from Q-learning (by setting method = "qlearn"). This option is intended primarily for exploratory purposes; the authors note that there is a dedicated R package for Q-learning (qLearn), although it is limited to the 2-stage setting.

Both of these methods require the specification of three models for each stage of the analysis: a treatment model (conditional mean of the treatment variable), a treatment-free model (conditional mean of outcome assuming only reference treatments are used), and a blip model. Only the blip model must be correctly specified (or over-specified), with consistent parameter estimates obtainable if at least one of the other two models is correctly specified. Note that all of these must be specified as lists of formula objects, even if only one stage of treatment is considered.

Note that as is conventional, it is assumed a larger value of the outcome is preferred (which can be easily achieved via transformation of your data if necessary).

When treatment is binary, if confidence intervals are computed (via specification of var.estim other than 'none'), then DTRreg will calculate the proportion of subjects at each stage for whom optimal treatment is non-unique. If this proportion exceeds 0.05 a non-regularity warning will be displayed, along with the proportion of subjects for whom this is the case. Note that this warning is only displayed if a variance estimation option is selected.

### Value

An object of class DTR, a list including elements

psi Blip parameter estimates for each stage of treatment.

opt.treat Optimal treatment decisions for each subject at each stage of treatment.

covmat Covariance matrix of blip parameter estimates.

regret Estimates of the regret for each subject based on observed treatment and blip

parameter estimates.

beta Treatment-free model parameter estimates (note that these may not be consis-

tent).

opt.Y Predicted optimal outcome under recommended regimen.

nonreg Non-regularity estimates.

The functions coef, predict and confint may be used with such model objects. The first two have specific help files for their implementation, while confint is used in the same way as the standard confint command, with the exception of the parm option, which is not available.

### Author(s)

Michael Wallace

### References

Chakraborty, B., Moodie, E. E. M. (2013) *Statistical Methods for Dynamic Treatment Regimes*. New York: Springer.

Robins, J. M. (2004) *Optimal structural nested models for optimal sequential decisions*. In Proceedings of the Second Seattle Symposium on Biostatistics, D. Y. Lin and P. J. Heagerty (eds), 189–326. New York: Springer.

Wallace, M. P., Moodie, E. M. (2015) Doubly-Robust Dynamic Treatment Regimen Estimation Via Weighted Least Squares. *Biometrics* **71**(3), 636–644 (doi:10.1111/biom.12306.)

```
###################
# example single run of a 2-stage g-estimation analysis
set.seed(1)
# expit function
expit <- function(x) \{1 / (1 + exp(-x))\}
# sample size
n <- 10000
# variables (X = patient information, A = treatment)
X1 <- rnorm(n)
A1 <- rbinom(n, 1, expit(X1))
X2 <- rnorm(n)
A2 <- rbinom(n, 1, expit(X2))
# blip functions
gamma1 <- A1 * (1 + X1)
gamma2 <- A2 * (1 + X2)
# observed outcome: treatment-free outcome plus blip functions
Y \leftarrow exp(X1) + exp(X2) + gamma1 + gamma2 + rnorm(n)
# models to be passed to DTRreg
# blip model
blip.mod <- list(~X1, ~X2)</pre>
# treatment model (correctly specified)
treat.mod <- list(A1~X1, A2~X2)</pre>
# treatment-free model (incorrectly specified)
tf.mod <- list(~X1, ~X2)</pre>
# perform G-estimation
mod1 <- DTRreg(Y, blip.mod, treat.mod, tf.mod, method = "gest")</pre>
#####################
```

DWSurv 9

DWSurv	DTR estimation and inference for time-to-event data using DWSurv
DNSul V	DIR estimation and inference for time-to-event data using Dwsurv

# Description

Dynamic treatment regimen estimation and inference via dynamic weighted survival modeling (DWSurv). Inference for the blip estimators with single- and multi-stage data.

# Usage

```
DWSurv(time, blip.mod, treat.mod, tf.mod, cens.mod, data = NULL, weight = "default",
    var.estim = "none", asymp.opt = "adjusted", boot.opt = "standard", B = 500,
    optimization = "max", quiet = FALSE)
```

# Arguments

time	A list of formula specifying the survival time variable for each stage in order. The time variable should be specified on the right hand side of the formula. No dependent variable should be specified. The list should be as long as the maximum number of stages.
blip.mod	A list of formula objects specifying covariates of a (linear) blip function for each stage in order. No dependent variable should be specified.
treat.mod	A list of formula objects specifying the treatment model for each stage in order. The treatment variable should be binary and included as the dependent variable. Logistic regression models are used.
tf.mod	A list of formula objects specifying covariates of a (linear) treatment-free model for each stage in order. No dependent variable should be specified.
cens.mod	A list of formula objects specifying the censoring model for each stage in order. The censoring indicator should be included as the dependent variable and should be the same across stages. In the absence of censoring, one still needs to specify a censoring indicator variable across stages.
data	A data frame containing all necessary covariates contained in the above models.
weight	A user-supplied function for the weights to be used in DWSurv. The function must have the four following arguments: treatment received A, probability of receiving treatment A=1, status, probability of being observed status = 1. Default is the inverse probability of censoring weights combined with  A - E[A ] .
var.estim	Covariance matrix estimation method, either "asymptotic", "bootstrap" or "none" (default).
asymp.opt	If the asymptotic variance estimation is used, specify either the "adjusted" (default) or "naive" version.
boot.opt	If bootstrap is used for variance estimation, specify either the "standard" (default), "empirical" or "normal". The last two are parametric bootstraps.
В	Number of bootstrap resamples, if applicable.

10 DWSurv

optimization If "max" (default), it is assumed that larger values/longer survival times are pre-

ferred. Set to "min" if the sequence of optimal decision rules should minimize

survival time.

quiet To suppress warnings when bootstrapping.

### **Details**

The function DWSurv() allows estimating an optimal dynamic treatment regime from multi-stage trials or observational data when the outcome of interest is survival time subject to right-censoring. The dynamic weighted survival modeling (DWSurv) algorithm is implemented. The method focuses on estimating the parameters of the blip: a model of the difference in expected outcome under the observed treatment and some reference treatment (usually a control) at a given stage, assuming identical histories and optimal treatment thereafter.

The method requires the specification of four models for each stage of the analysis: a treatment model (conditional mean of the treatment variable), a censoring model, a treatment-free model (conditional mean of outcome assuming only reference treatments are used), and a blip model. Only the blip model must be correctly specified (or over-specified), with consistent parameter estimates obtainable if at least one of the treatment-free or the treatment and censoring models are correctly specified. Note that all of these must be specified as lists of formula objects, even if only one stage of treatment is considered.

Note that as is conventional, it is assumed a larger survival time is preferred (which can be easily achieved via transformation of your data if necessary).

#### Value

An object of class DTR, a list including elements

psi Blip parameter estimates for each stage of treatment.

opt. treat Optimal treatment decisions for each subject at each stage of treatment.

covmat Covariance matrix of blip parameter estimates.

log.regret Estimates of the log-transformed regret for each subject based on observed treat-

ment and blip parameter estimates.

beta Treatment-free model parameter estimates (note that these may not be consis-

tent).

opt.Y Predicted optimal survival time under recommended regimen.

nonreg Non-regularity estimates.

psi.boot If applicable, the B bootstrap estimates of the blip parameters across stages.

The functions coef and confint may be used with such model objects. The first has specific help files for their implementation, while confint is used in the same way as the standard confint command, with an additional type options which can be set to "percentile" when bootstrap is used to derive confidence intervals. The parm option is not available.

### Author(s)

Gabrielle Simoneau

DWSurv 11

#### References

Simoneau, G., Moodie, E. E. M., Nijjar, J. S., Platt, R. W. (2018) Estimating Optimal Dynamic Treatment with Survival Outcomes. *JASA*, under review.

Wallace, M. P., Moodie, E. E. M., Stephens, D. A. (2017) Dynamic Treatment Regimen Estimation via Regression-Based Techniques: Introducing R Package DTRreg. *Journal of Statistical Software* **80**(2), 1–20 (doi:10.18637/jss.v080.i02).

```
####################
# example single run of a 2-stage DWSurv analysis
set.seed(1)
# expit function
expit <- function(x) \{1 / (1 + \exp(-x))\}
# sample size and parameters
n <- 1000
theta1 <- c(6.3, 1.5, -0.8, 0.1, 0.1)
theta2 < c(4, 1.1, -0.2, -0.9, 0.6, -0.1)
lambda <- 1/300
p < -0.9
beta <- 2
# covariates and treatment (X = patient information, A = treatment)
X1 \leftarrow runif(n, 0.1, 1.29)
X14 <- X1^4
A1 <- rbinom(n, size = 1, prob = expit(2*X1 - 1))
X2 <- runif(n, 0.9, 2)
X23 <- X2<sup>3</sup>
A2 <- rbinom(n, size = 1, prob = expit(-2*X2 + 2.8))
delta <- rbinom(n, size = 1, prob = expit(2*X1 - 0.4))
eta2 <- rbinom(n, 1, prob = 0.8)
delta2 <- delta[eta2 == 1]</pre>
# survival time
logY2 <- logT2 <- theta2[1] + theta2[2]*X2[eta2 == 1]
  + theta2[3]*X23[eta2 == 1] + theta2[4]*A2[eta2 == 1]
  + theta2[5]*A2[eta2 == 1]*X2[eta2 == 1]
  + theta2[6]*X1[eta2 == 1] + rnorm(sum(eta2), sd = 0.3)
trueA2opt <- ifelse(theta2[4]*A2[eta2 == 1]</pre>
  + theta2[5]*A2[eta2 == 1]*X2[eta2 == 1] > 0, 1, 0)
logT2opt <- logT2</pre>
  + (trueA2opt - A2[eta2 == 1])*(theta2[4]*A2[eta2 == 1]
  + theta2[5]*A2[eta2 == 1]*X2[eta2 == 1])
logT <- theta1[1] + theta1[2]*X1 + theta1[3]*X14</pre>
  + theta1[4]*A1 + theta1[5]*A1*X1 + rnorm(n, sd = 0.3)
T1 \leftarrow \exp(\log T[eta2 == 1 \& delta == 1]) - \exp(\log T2 \circ t[delta2 == 1])
logT[eta2 == 1 \& delta == 1] <- log(T1 + exp(logT2[delta2 == 1]))
# censoring time
C \leftarrow (-\log(\text{runif}(n - \text{sum}(\text{delta}), 0, 1))/(\text{lambda}))
  * exp(beta * X1[delta == 0])))^(1/p)
eta2d0 \leftarrow eta2[delta == 0]
C1 <- rep(NA, length(C))
C2 <- rep(NA, length(C))
```

12 plot

```
for(i in 1:length(C))
  if(eta2d0[i] == 0){
    C1[i] \leftarrow C[i]
    C2[i] <- 0
  }else{
    C1[i] <- runif(1, 0, C[i])</pre>
    C2[i] \leftarrow C[i] - C1[i]
  }
}
# observed survival time
Y2 \leftarrow rep(NA, n)
Y1 \leftarrow rep(NA, n)
Y2[delta == 0] <- C2
Y1[delta == 0] <- C1
Y1[delta == 1 & eta2 == 1] <- T1
Y1[delta == 1 \& eta2 == 0] \leftarrow exp(logT[delta == 1 \& eta2 == 0])
Y2[delta == 1 & eta2 == 0] <- 0
Y2[delta == 1 \& eta2 == 1] \leftarrow exp(logT2[delta2 == 1])
logY \leftarrow log(Y1 + Y2)
logY2 <- log(Y2[eta2 == 1])
# data and run DWSurv
mydata <- data.frame(X1,X14,A1,X2,X23,A2,delta,Y1,Y2)</pre>
mod <- DWSurv(time = list(~Y1, ~Y2), blip.mod = list(~X1, ~X2),</pre>
  treat.mod = list(A1~X1, A2~X2), tf.mod = list(~X1 + X14, ~X2 + X23 + X1),
  cens.mod = list(delta~X1, delta~X1), var.estim = "asymptotic", data = mydata)
###################
```

plot

Diagnostic Plots for DTR Estimation

### Description

Diagnostic plots for assessment of treatment, treatment-free and blip models following DTR estimation using DTRreg and DWSurv.

### Usage

```
## S3 method for class 'DTRreg'
plot(x, ...)
```

## Arguments

x A model object generated by the functions DTRreg and DWSurv.

. . . Space for additional arguments (not currently used by DTRreg)

plot 13

#### **Details**

DTR estimation using G-estimation and dWOLS requires the specification of three models: the treatment, treatment-free and blip. The treatment model may be assessed via standard diagnostics, whereas the treatment-free and blip models may be simultaneously assessed using diagnostic plots introduced by Rich et al. The plot() function first presents diagnostic plots that assess the latter, plotting fitted values against residuals and covariates following DTR estimation. If there is any evidence of a relationship between the variables in these plots, this is evidence that at least one of the blip or treatment-free models is mis-specified.

Following these plots, the plot() function will present standard diagnostic plots for the treatment model. These are produced directly by the standard plot() command applied to the models that were fit. For example, if treatment is binary, the resulting plots are the same as those that are generated by the plot() command applied to a glm object for logistic regression.

### Author(s)

Michael Wallace

#### References

Chakraborty, B., Moodie, E. E. M. (2013) *Statistical Methods for Dynamic Treatment Regimes*. New York: Springer.

Rich B., Moodie E. E. M., Stephens D. A., Platt R. W. (2010) Model Checking with Residuals for G-estimation of Optimal Dynamic Treatment Regimes. *International Journal of Biostatistics* **6**(2), Article 12.

Robins, J. M. (2004) *Optimal structural nested models for optimal sequential decisions*. In Proceedings of the Second Seattle Symposium on Biostatistics, D. Y. Lin and P. J. Heagerty (eds), 189–326. New York: Springer.

Wallace, M. P., Moodie, E. M. (2015) Doubly-Robust Dynamic Treatment Regimen Estimation Via Weighted Least Squares. *Biometrics* **71**(3), 636–644 (doi:10.1111/biom.12306.)

### **Examples**

# ###################

```
# example single run of a 2-stage g-estimation analysis
set.seed(1)
# expit function
expit <- function(x) {1 / (1 + exp(-x))}
# sample size
n <- 10000
# variables (X = patient information, A = treatment)
X1 <- rnorm(n)
A1 <- rbinom(n, 1, expit(X1))
X2 <- rnorm(n)
A2 <- rbinom(n, 1, expit(X2))
# blip functions
gamma1 <- A1 * (1 + X1)
gamma2 <- A2 * (1 + X2)
# observed outcome: treatment-free outcome plus blip functions
Y <- exp(X1) + exp(X2) + gamma1 + gamma2 + rnorm(n)</pre>
```

14 predict

predict

Optimal Outcome Prediction for DTRs

### **Description**

Predicted outcome assuming optimal treatment (according to analysis via G-estimation or dWOLS) was followed. Assumes blip and treatment-free models correctly specified.

### Usage

```
## S3 method for class 'DTRreg'
predict(object, newdata, treat.range = NULL, ...)
```

### **Arguments**

object A model object generated by the function DTRreg.

newdata A dataset (usually the data analyzed by DTRreg for which predicted outcomes

are desired. If a new dataset is provided, variable names should correspond to

those presented to DTRreg

treat.range If treatment is continuous (rather than binary), a list of vectors of the form

c(min,max) which specify the minimum and maximum value the treatment may take. If unspecified, this will be inferred from the treat.range provided with use of the original DTRreg command. As such, if no treatment range was specified there either, treat.range will be the minimum and maximum observed treatment

value at each stage.

... Space for additional arguments (not currently used by DTRreg)

### **Details**

This function may be used in a similar fashion to more traditional modelling commands (such as lm). Users are referred to the primary DTRreg help command (and associated literature) for information concerning model specification. In particular, we note that the predict function assumes that the treatment-free model has been correctly specified, as the treatment-free parameters are used in the prediction process.

predict 15

### Value

An n x 1 matrix of predicted outcome values.

#### Author(s)

Michael Wallace

#### References

Chakraborty, B., Moodie, E. E. M. (2013) *Statistical Methods for Dynamic Treatment Regimes*. New York: Springer.

Robins, J. M. (2004) *Optimal structural nested models for optimal sequential decisions*. In Proceedings of the Second Seattle Symposium on Biostatistics, D. Y. Lin and P. J. Heagerty (eds), 189–326. New York: Springer.

Wallace, M. P., Moodie, E. M. (2015) Doubly-Robust Dynamic Treatment Regimen Estimation Via Weighted Least Squares. *Biometrics* **71**(3), 636–644 (doi:10.1111/biom.12306.)

```
###################
# example single run of a 2-stage g-estimation analysis
set.seed(1)
# expit function
expit <- function(x) \{1 / (1 + exp(-x))\}
# sample size
n <- 10000
# variables (X = patient information, A = treatment)
X1 <- rnorm(n)
A1 <- rbinom(n, 1, expit(X1))
X2 <- rnorm(n)
A2 <- rbinom(n, 1, expit(X2))
# blip functions
gamma1 <- A1 * (1 + X1)
gamma2 <- A2 * (1 + X2)
# observed outcome: treatment-free outcome plus blip functions
Y \leftarrow exp(X1) + exp(X2) + gamma1 + gamma2 + rnorm(n)
# models to be passed to DTRreg
# blip model
blip.mod <- list(~X1, ~X2)</pre>
# treatment model (correctly specified)
treat.mod <- list(A1~X1, A2~X2)</pre>
# treatment-free model (incorrectly specified)
tf.mod <- list(~X1, ~X2)
# perform G-estimation
mod1 <- DTRreg(Y, blip.mod, treat.mod, tf.mod, method = "gest")</pre>
# predicted Y for optimal treatment
dat <- data.frame(X1,X2,A1,A2)</pre>
predict(mod1, newdata = dat)
#####################
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# **Index**

```
chooseM, 2
confint, 4

DTRreg, 5
DWSurv, 9

plot, 12
predict, 14
print.DTRreg (DTRreg), 5
```