Package ‘autocart’

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Type Package

Title Autocorrelation Regression Trees

Version 1.4.5

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Description A modified version of the classification and regression tree (CART) algorithm for modelling spatial data that features coordinate information. Coordinate information can be used to evaluate measures of spatial autocorrelation and spatial compactness during the splitting phase of the tree, leading to better predictions and more physically realistic predictions on these types of datasets. These methods are described in Ancell and Bean (2021) <arXiv:2101.08258>.

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LazyData false

Depends fields, mgcv

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R topics documented:

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Create an autocart model

Usage

autocart(response, data, locations, alpha, beta, control = NULL)

Arguments

response  A vector of numeric response values with no NA entries.
data  A dataframe for the predictor variables used in the autocart tree.
locations  A two-column matrix with coordinates for the observations the predictor dataframe.
alpha  A scalar value between 0 and 1 to weight autocorrelation against reduction in variance in the tree splitting. A value of 1 indicates full weighting on measures of autocorrelation.
beta  A scalar value between 0 and 1 to weight the shape of the region in the splitting
control  An object of type "autocartControl" returned by the autocartControl function to control the splitting in the autocart tree.

Value

An S3 object of class "autocart".

Examples

# Load some data for an autocart example
snow <- na.omit(read.csv(system.file("extdata", "ut2017_snow.csv", package = "autocart")))
y <- snow$yr50[1:40]
X <- data.frame(snow$ELEVATION, snow$MCMT, snow$PPTWT, snow$HUC)[1:40, ]
locations <- as.matrix(cbind(snow$LONGITUDE, snow$LATITUDE))[1:40, ]

# Create an autocart model with 50 trees
snow_model <- autocart(y, X, locations, 0.30, 0)
autocartControl

Description
Create the object used for the controlling of the splits in the autocart model

Usage
autocartControl(
  minsplit = 20,
  minbucket = round(minsplit/3),
  maxdepth = 30,
  maxobsMtxCalc = NULL,
  distpower = 1,
  islonglat = TRUE,
  givePredAsFactor = TRUE,
  retainCoords = TRUE,
  useGearyC = FALSE,
  runParallel = TRUE,
  spatialWeightsType = "default",
  customSpatialWeights = NULL,
  spatialBandwidthProportion = 1,
  spatialBandwidth = NULL,
  asForest = FALSE
)

Arguments

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>minsplit</td>
<td>The minimum observations in a node before a split is attempted</td>
</tr>
<tr>
<td>minbucket</td>
<td>The minimum number of observations in a terminal node.</td>
</tr>
<tr>
<td>maxdepth</td>
<td>Set the maximum depth in the final tree. A root node is counted as a height of 0.</td>
</tr>
<tr>
<td>maxobsMtxCalc</td>
<td>Optional maximum number of observations in a node where computationally intensive matrix calculations like autocorrelation and compactness are performed.</td>
</tr>
<tr>
<td>distpower</td>
<td>The power of inverse distance to use when calculating spatial weights matrix.</td>
</tr>
<tr>
<td>islonglat</td>
<td>Are the coordinates longitude and latitude coordinates? If TRUE, then use great circle distance calculations</td>
</tr>
<tr>
<td>givePredAsFactor</td>
<td>In the returned autocart model, should the prediction vector also be returned as a factor?</td>
</tr>
<tr>
<td>retainCoords</td>
<td>After creating the autocart model, should the coordinates for each of the predictions be kept in the returned model?</td>
</tr>
<tr>
<td>useGearyC</td>
<td>Should autocart use Geary’s C instead of Moran’s I in the splitting function?</td>
</tr>
<tr>
<td>runParallel</td>
<td>Logical value indicating whether autocart should run using parallel processing.</td>
</tr>
</tbody>
</table>
spatialWeightsType
  What type of spatial weighting should be used when calculating spatial autocorrelation? Options are "default" or "gaussian".

customSpatialWeights
  Use this parameter to pass in an optional spatial weights matrix for use in autocorrelation calculations. Must have nrow and ncol equal to rows in training dataframe.

spatialBandwidthProportion
  What percentage of the maximum pairwise distances should be considered the maximum distance for spatial influence? Cannot be simultaneously set with spatialBandwidth

spatialBandwidth
  What is the maximum distance where spatial influence can be assumed? Cannot be simultaneously set with spatialBandwidthProportion.

asForest
  A logical indicating if the tree should be created as a forest component with random subsetting of predictors at each node. Set this to true if you are using this tree inside an ensemble.

Value
  An object passed in to the autocart function that controls the splitting.

Examples

# Load some data for an autocartControl example
snow <- na.omit(read.csv(system.file("extdata", "ut2017_snow.csv", package = "autocart")))
y <- snow$yr50[1:40]
X <- data.frame(snow$ELEVATION, snow$MCMT, snow$PPTWT)[1:40, ]
locations <- as.matrix(cbind(snow$LONGITUDE, snow$LATITUDE))[1:40, ]

# Create a control object that disallows the tree from having a depth more than 10 and give spatial weights only to observations that are a third of the distance of the longest distance between any two points in the dataset.
snow_control <- autocartControl(maxdepth = 10, spatialBandwidthProportion = 0.33)

# Pass the created control object to an autocart model
snow_model <- autocart(y, X, locations, 0.30, 0, snow_control)

autoforest
  Create a forest of autocart trees.

Description
  Create a forest of autocart trees.
autoforest

Usage

autoforest(
  response,
  data,
  locations,
  alpha,
  beta,
  control,
  numtrees,
  mtry = NULL
)

Arguments

response  The response vector that goes along with the dataframe of predictors.
data      The dataframe of predictors.
locations A matrix of the locations of the dataframe of predictors.
alpha     The percentage of weighting on spatial autocorrelation in the splitting function.
beta      The percentage of weighting on spatial compactness in the splitting function.
control   A control object from the autocartControl function that will be used for each
tree in the forest.
numtrees  The number of autocart trees to create in the forest.
mtry      The number of variables to subset at each node of the splitting in the trees. By
default, this will be 1/3 of the features.

Value

An object of type "autoforest", which is a list of the autocart trees.

Examples

# Load some data for an autoforest example
snow <- na.omit(read.csv(system.file("extdata", "ut2017_snow.csv", package = "autocart")))
y <- snow$yr50[1:40]
X <- data.frame(snow$ELEVATION, snow$MCMT, snow$PPTWT, snow$HUC)[1:40, ]
locations <- as.matrix(cbind(snow$LONGITUDE, snow$LATITUDE))[1:40, ]

# Create a control object for the autoforest tree
snow_control <- autocartControl(spatialBandwidthProportion = 1.0)

# Create an autoforest model with 5 trees
snow_model <- autoforest(y, X, locations, 0.30, 0, snow_control, numtrees = 5)
autotune

Find the best alpha, beta, and bandwidth values with k-fold cross-validation

Description

Find the best alpha, beta, and bandwidth values with k-fold cross-validation

Usage

autotune(
  response,  
  data,  
  locations,  
  k = 8,  
  control = NULL,  
  customGroups = NULL,  
  alphaVals = NULL,  
  betaVals = NULL,  
  bandwidthVals = NULL,  
  outputProgress = FALSE,  
  useSpatialNodes = FALSE,  
  spatialNodesMethod = "idw",  
  spatialNodesDistPower = 2,  
  spatialNodesDistPowerRange = c(0, 2),  
  spatialNodesModelByResidual = FALSE
)

Arguments

response  The vector of response values to test on.
data  The data frame of predictor variables.
locations  The n by 2 matrix of coordinate information for the known observations
k  The number of folds to create in k-fold cross-validation for tuning
control  An optional control function to send to the autocart creation function
customGroups  Here, you may supply custom groups for cross-validation. This parameter must be supplied as a factor and labeled from 1:numLevels.
alphaVals  Override the alpha values that are expanded in the grid in this function.
betaVals  Override the beta values that are expanded in the grid in this function.
bandwidthVals  Override the bandwidth values that are expanded in the grid in this function.
outputProgress  Print the result of the cross-validations as you are going. This is useful when the cross-validation will be very long and you do not wish to wait.
useSpatialNodes  Use an interpolative process at the terminal nodes of the autocart tree for the prediction process
**predictAutocart**

Given an autocart model object, predict for new data passed in

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**Description**

Given an autocart model object, predict for new data passed in

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**spatialNodesMethod**

The type of interpolation to use at the terminal nodes

**spatialNodesDistPower**

The power parameter to use in inverse distance weighting at terminal nodes

**spatialNodesDistPowerRange**

The ranged power parameter $p_1, p_2$ to use for a varying power parameter

**spatialNodesModelByResidual**

Do the interpolative process on the residuals of the prediction formed by response average at terminal nodes

**Value**

A list of the labeled optimal parameters that were chosen for the best predictive accuracy on cross-validation.

**Examples**

```r
# Load some data for an autotune example
# (Note that a low sample size is used here for quick example computation.
# In a practical application this function can be quite computationally
# demanding due to the grid-search nature of the function.)
snow <- na.omit(read.csv(system.file("extdata", "ut2017_snow.csv", package = "autocart")))
y <- snow$yr50[1:35]
X <- data.frame(snow$ELEVATION, snow$MCMT, snow$PPTWT)[1:35,]
locations <- as.matrix(cbind(snow$LONGITUDE, snow$LATITUDE))[1:35,]

# Find optimal parameters via cross-validation. We'll search through the
# following alpha/beta/bandwidth values:
alphaVec <- c(0.0, 0.5)
betaVec <- c(0.0, 0.2)
bandwidthVec <- c(1.0)

# We'll find the optimal values with 3-fold cross validation:
# (Due to the large number of cross-validations and trainings that occur,
# this can take a few minutes.)
myTune <- autotune(y, X, locations, k = 3, alphaVals = alphaVec,
                   betaVals = betaVec, bandwidthVals = bandwidthVec)

# Inspect the results
myTune
```

---
predictAutocart

Usage

predictAutocart(autocartModel, newdata)

Arguments

autocartModel    An S3 object of type "autocart" returned from the autocart function
newdata          A dataframe with the same amount of columns used to create the autocart model.

Value

A numeric vector containing the predicted response value for each of the rows in the passed in dataframe.

Examples

# Load some data for an autocart predict example
snow <- na.omit(read.csv(system.file("extdata", "ut2017_snow.csv", package = "autocart")))
y <- snow$yr50[1:40]
X <- data.frame(snow$ELEVATION, snow$MCMT, snow$PPTWT, snow$HUC)[1:40,]
locations <- as.matrix(cbind(snow$LONGITUDE, snow$LATITUDE))[1:40,]

# Create an autocart model with 50 trees
snow_model <- autocart(y, X, locations, 0.30, 0)

# Predict in autocart
new_X <- X[1:10,]
new_loc <- locations[1:10,]
autocart_predictions <- predictAutocart(snow_model, new_X)

predictAutoforest

Make a prediction using an autoforest model returned from the autoforest function.

Description

Make a prediction using an autoforest model returned from the autoforest function.

Usage

predictAutoforest(
    autoforestModel, newdata, newDataCoords = NULL, useSpatialNodes = FALSE,
    method = "idw", distpower = 2, distpowerRange = c(0, 2), modelByResidual = TRUE,
predictAutoforest

```r

declareByGC = FALSE
)

Arguments

- **autoforestModel**: An S3 object of type "autoforest" returned from the autoforest function.
- **newdata**: The dataframe of predictors for use in prediction.
- **newdataCoords**: the matrix of locations for all the information in newdata. Required argument if you set "useSpatialNodes" to TRUE.
- **useSpatialNodes**: If TRUE, instead of running all the observations through the autocart tree, use the spatialNodes function to make predictions.
- **method**: If using the spatial nodes type of prediction, then the type of interpolation to use. The options are "idw" and "tps".
- **distpower**: If using "idw" for the method, the power on distance. For example, setting this to 2 would mean inverse squared distance squared weighting.
- **distpowerRange**: If using "idw" for the interpolation method, the range of distance powers to use on inverse distance weighting matched to terminal node Moran I measurements.
- **modelByResidual**: When using interpolation, make a prediction using the region of interest’s average and then interpolate the residual.
- **decideByGC**: Use Geary’s C in deciding to induce a local spatial process rather than Moran’s I.

Value

A vector of predictions that correspond to the rows in newdata.

Examples

```r
# Load some data for an autoforest example
snow <- na.omit(read.csv(system.file("extdata", "ut2017_snow.csv", package = "autocart")))
y <- snow$yr50[1:40]
X <- data.frame(snow$ELEVATION, snow$MCMT, snow$PPTWT, snow$HUC)[1:40, ]
locations <- as.matrix(cbind(snow$LONGITUDE, snow$LATITUDE))[1:40, ]

# Create a control object for the autoforest tree
snow_control <- autocartControl(spatialBandwidthProportion = 1.0)

# Create an autoforest model with 5 trees (low number chosen for computation time)
snow_model <- autoforest(y, X, locations, 0.30, 0, snow_control, numtrees = 5)

# Predict for a subset of the data
new_X <- X[1:10, ]
new_loc <- locations[1:10, ]
predicted_values <- predictAutoforest(snow_model, new_X, new_loc, TRUE)
```
rmae Relative mean absolute error

Description
Relative mean absolute error

Usage
rmae(pred, obs, na.rm = TRUE)

Arguments
- pred: The vector of predictions
- obs: The actual observed values
- na.rm: Should NA values be taken out of the vectors?

Value
The relative mean average error of the two vectors.

Examples
# Create two vectors, add some noise, and evaluate the RMAE.
firstVec <- 1:10
secondVec <- 1:10 + rnorm(10)
rmae(firstVec, secondVec)

spatialNodes
Using an autocart model, use the terminal nodes to form a spatial process that uses inverse distance weighting to interpolate. The prediction for the new data that is passed in is formed by making a prediction to assign it to a group. Next, the residual for the new prediction is formed by inverse distance weighting the residual for the other points that are a part of that geometry.

Description
Using an autocart model, use the terminal nodes to form a spatial process that uses inverse distance weighting to interpolate. The prediction for the new data that is passed in is formed by making a prediction to assign it to a group. Next, the residual for the new prediction is formed by inverse distance weighting the residual for the other points that are a part of that geometry.
Usage

spatialNodes(
  autocartModel,
  newdata,
  newdataCoords,
  method = "idw",
  distpower = 2,
  distpowerRange = c(0, 2),
  modelByResidual = TRUE,
  decideByGC = FALSE
)

Arguments

autocartModel  an autocart model returned from the autocart function.
newdata        a dataframe that contains the same predictors that were used to form the tree.
newdataCoords  a matrix of coordinates for all the predictors contained in newdata
method         The type of interpolation to use. Options are "idw" for inverse distance weighting and "tps" for thin-plate splines.
distpower      the power to use if you would like to use something other than straight inverse distance, such as inverse distance squared.
distpowerRange A range of distpower to use. This is an adaptive inverse distance weighting method that linearly matches measures of spatial autocorrelation measured by Moran I to the range mentioned in distpower.
modelByResidual If true, then predict using the average of the "spatial node", and then model the residual using a spatial process. If false, fit a spatial process directly.
decideByGC     When determining if a spatial process should be ran at a terminal node, should we use the Geary C statistic instead of Moran I?

Value

a prediction for the observations that are represented by newdata and newdataCoords

Examples

# Load some data for a spatial nodes example
snow <- na.omit(read.csv(system.file("extdata", "ut2017_snow.csv", package = "autocart")))
y <- snow$yr50[1:40]
X <- data.frame(snow$ELEVATION, snow$MCMT, snow$PPTWT, snow$HUC)[1:40, ]
locations <- as.matrix(cbind(snow$LONGITUDE, snow$LATITUDE))[1:40, ]

# Create an autocart model
snow_model <- autocart(y, X, locations, 0.30, 0)

# Predict with the spatial node effect
new_X <- X[1:10, ]
new_loc <- locations[1:10, ]
spatial_node_predictions <- spatialNodes(snow_model, new_X, new_loc, distpowerRange = c(0, 2))
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