

Package: monmlp (via r-universe)

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Type Package

Title Multi-Layer Perceptron Neural Network with Optional Monotonicity Constraints

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Description Train and make predictions from a multi-layer perceptron neural network with optional partial monotonicity constraints.

License GPL-2

LazyLoad yes

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Description

The monmlp package implements one and two hidden-layer multi-layer perceptron neural network (MLP) models. An optional monotone constraint, which guarantees monotonically increasing behaviour of model outputs with respect to specified covariates, can be added to the MLP. The resulting monotone MLP (MONMLP) regression model is based on Zhang and Zhang (1999).

Early stopping can be combined with bootstrap aggregation to control overfitting. The model reduces to a standard MLP neural network if the monotone constraint is not invoked.

MLP and MONMLP models are fit using the `monmlp.fit` function. Predictions from a fitted model are made using the `monmlp.predict` function. The `gam.style` function can be used to investigate fitted covariate/response relationships.

Details

Package: monmlp
Type: Package
License: GPL-2
LazyLoad: yes

References

Lang, B., 2005. Monotonic multi-layer perceptron networks as universal approximators. In: W. Duch et al. (eds.): ICANN 2005, Lecture Notes in Computer Science, 3697:31-37.

doi:10.1007/11550907

Minin, A., Velikova, M., Lang, B., and Daniels, H., 2010. Comparison of universal approximators incorporating partial monotonicity by structure. *Neural Networks*, 23:471-475.

doi:10.1016/j.neunet.2009.09.002

Zhang, H. and Zhang, Z., 1999. Feedforward networks with monotone constraints. In: International Joint Conference on Neural Networks, vol. 3, p. 1820-1823. doi:10.1109/IJCNN.1999.832655

Examples

```
set.seed(123)
x <- as.matrix(seq(-10, 10, length = 100))
y <- logistic(x) + rnorm(100, sd = 0.2)

dev.new()
plot(x, y)
lines(x, logistic(x), lwd = 10, col = "gray")
```

```
## MLP w/ 2 hidden nodes
w.mlp <- monmlp.fit(x = x, y = y, hidden1 = 2, iter.max = 500)
lines(x, attr(w.mlp, "y.pred"), col = "red", lwd = 3)

## MLP w/ 2 hidden-layers (2 nodes each) and early stopping
w.stp <- monmlp.fit(x = x, y = y, hidden1 = 2, hidden2 = 2,
                  bag = TRUE, iter.max = 500, iter.stopped = 10)
lines(x, attr(w.stp, "y.pred"), col = "orange", lwd = 3)

## MONMLP w/ 2 hidden nodes
w.mon <- monmlp.fit(x = x, y = y, hidden1 = 2, monotone = 1,
                  iter.max = 500)
lines(x, attr(w.mon, "y.pred"), col = "blue", lwd = 3)
```

gam.style

GAM-style effects plots for interpreting MLP and MONMLP models

Description

GAM-style effects plots provide a graphical means of interpreting fitted covariate/response relationships. From Plate et al. (2000): The effect of the i th input variable at a particular input point Δx_i is the change in f resulting from changing x_i to $x_i + \Delta x_i$ from b_i (the baseline value [...]) while keeping the other inputs constant. The effects are plotted as short line segments, centered at $(x_i, \Delta x_i)$, where the slope of the segment is given by the partial derivative. Variables that strongly influence the function value have a large total vertical range of effects. Functions without interactions appear as possibly broken straight lines (linear functions) or curves (nonlinear functions). Interactions show up as vertical spread at a particular horizontal location, that is, a vertical scattering of segments. Interactions are present when the effect of a variable depends on the values of other variables.

Usage

```
gam.style(x, weights, column, baseline = mean(x[,column]),
         epsilon = 1e-5, seg.len = 0.02, seg.cols = "black",
         plot = TRUE, return.results = FALSE, ...)
```

Arguments

<code>x</code>	matrix with number of rows equal to the number of samples and number of columns equal to the number of covariate variables.
<code>weights</code>	list returned by <code>monmlp.fit</code> .
<code>column</code>	column of <code>x</code> for which effects plots should be returned.
<code>baseline</code>	value of <code>x[,column]</code> to be used as the baseline for calculation of covariate effects; defaults to <code>mean(x[,column])</code> .
<code>epsilon</code>	step-size used in the finite difference calculation of the partial derivatives.
<code>seg.len</code>	length of effects line segments expressed as a fraction of the range of <code>x[,column]</code> .

`seg.cols` colors of effects line segments.
`plot` if TRUE (the default) then an effects plots for each response variable is produced.
`return.results` if TRUE then values of effects and partial derivatives for each response variable are returned.
`...` further arguments to be passed to `plot`.

Value

A list with elements:

`effects` a matrix of covariate effects.
`partials` a matrix of covariate partial derivatives.

References

Cannon, A.J. and I.G. McKendry, 2002. A graphical sensitivity analysis for interpreting statistical climate models: Application to Indian monsoon rainfall prediction by artificial neural networks and multiple linear regression models. *International Journal of Climatology*, 22:1687-1708.

Plate, T., J. Bert, J. Grace, and P. Band, 2000. Visualizing the function computed by a feedforward neural network. *Neural Computation*, 12(6): 1337-1354.

See Also

[monmlp.fit](#), [monmlp.predict](#)

Examples

```

set.seed(1)
x <- matrix(runif(350*6), ncol=6)
y <- as.matrix(5*sin(10*x[,1]*x[,2]) + 20*(x[,3]-0.5)^2 -
              10*x[,4] + 20*x[,5]*x[,6])

w <- monmlp.fit(x = x, y = y, hidden1 = 4, n.trials = 1,
               iter.max = 500)

for (i in seq(ncol(x))) gam.style(x, weights = w, column = i)
  
```

linear

Identity function

Description

Computes a trivial identity function. Used as the hidden layer transfer function for linear MLP or MONMLP models.

Usage

`linear(x)`

Arguments

x numeric vector.

See Also

[linear.prime](#)

linear.prime *Derivative of the linear function*

Description

Derivative of the linear function.

Usage

linear.prime(x)

Arguments

x numeric vector.

See Also

[linear](#)

logistic *Logistic sigmoid function*

Description

Computes the logistic sigmoid function. Used as a hidden layer transfer function for nonlinear MLP or MONMLP models.

Usage

logistic(x)

Arguments

x numeric vector.

See Also

[logistic.prime](#)

logistic.prime	<i>Derivative of the logistic sigmoid function</i>
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Description

Derivative of the logistic sigmoid function.

Usage

```
logistic.prime(x)
```

Arguments

x numeric vector.

See Also

[logistic](#)

monmlp.fit	<i>Fit one or more MLP or MONMLP models</i>
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Description

Fit an individual model or ensemble of MLP or MONMLP regression models using [optimx](#) optimization routines to minimize a least squares cost function. Optional stopped training and bootstrap aggregation (bagging) can be used to help avoid overfitting.

If invoked, the `monotone` argument enforces increasing behaviour between specified columns of `x` and model outputs. In this case, the `exp` function is applied to the relevant weights following initialization and during optimization; manual adjustment of `init.weights` may be needed.

Note: `x` and `y` are automatically standardized prior to fitting and predictions are automatically rescaled by [monmlp.predict](#). This behaviour can be suppressed for `y` by the `scale.y` argument.

Usage

```
monmlp.fit(x, y, hidden1, hidden2 = 0, iter.max = 5000,
           n.trials = 1, n.ensemble = 1, bag = FALSE,
           cases.specified = NULL, iter.stopped = NULL,
           scale.y = TRUE, Th = tansig, To = linear,
           Th.prime = tansig.prime, To.prime = linear.prime,
           monotone = NULL, init.weights = NULL,
           max.exceptions = 10, silent = FALSE, method = "BFGS",
           control = list(trace = 0))
```

Arguments

<code>x</code>	covariate matrix with number of rows equal to the number of samples and number of columns equal to the number of covariates.
<code>y</code>	response matrix with number of rows equal to the number of samples and number of columns equal to the number of response variables.
<code>hidden1</code>	number of hidden nodes in the first hidden layer.
<code>hidden2</code>	number of hidden nodes in the second hidden layer.
<code>iter.max</code>	maximum number of iterations of the optimization algorithm.
<code>n.trials</code>	number of repeated trials used to avoid local minima.
<code>n.ensemble</code>	number of ensemble members to fit.
<code>bag</code>	logical variable indicating whether or not bootstrap aggregation (bagging) should be used.
<code>cases.specified</code>	if <code>bag = TRUE</code> , a list that specifies the bootstrapped cases to be used in each ensemble member.
<code>iter.stopped</code>	if <code>bag = TRUE</code> , specifies the number of stopped training iterations between calculation of the cost function on the out-of-bootstrap cases.
<code>scale.y</code>	logical determining if columns of the response matrix should be scaled to zero mean and unit variance prior to fitting. Set this to <code>FALSE</code> if using an output layer transfer function that limits the range of predictions.
<code>Th</code>	hidden layer transfer function.
<code>To</code>	output layer transfer function.
<code>Th.prime</code>	derivative of the hidden layer transfer function.
<code>To.prime</code>	derivative of the output layer transfer function.
<code>monotone</code>	column indices of covariates for which the monotonicity constraint should hold.
<code>init.weights</code>	either a vector giving the minimum and maximum allowable values of the random weights, an initial weight vector, or <code>NULL</code> to calculate based on fan-in.
<code>max.exceptions</code>	maximum number of exceptions of the optimization routine before fitting is terminated with an error.
<code>silent</code>	logical determining if diagnostic messages should be suppressed.
<code>method</code>	<code>optimx</code> optimization method.
<code>control</code>	list of <code>optimx</code> control parameters.

Value

list containing fitted weight matrices with attributes including called values of `x`, `y`, `Th`, `To`, `Th.prime`, `To.prime`, `monotone`, `bag`, `iter.max`, and `iter.stopped`, along with values of covariate/response column means and standard deviations (`x.center`, `x.scale`, `y.center`, `y.scale`), out-of-bootstrap cases `oob`, predicted values `y.pred`, and, if stopped training is switched on, the iteration `iter.best` and value of the cost function `cost.best` that minimized the out-of-bootstrap validation error.

See Also

[monmlp.predict](#), [gam.style](#)

Examples

```

set.seed(123)
x <- as.matrix(seq(-10, 10, length = 100))
y <- logistic(x) + rnorm(100, sd = 0.2)

dev.new()
plot(x, y)
lines(x, logistic(x), lwd = 10, col = "gray")

## MLP w/ 2 hidden nodes
w.mlp <- monmlp.fit(x = x, y = y, hidden1 = 2, iter.max = 500)
lines(x, attr(w.mlp, "y.pred"), col = "red", lwd = 3)

## MLP w/ 2 hidden nodes and stopped training
w.stp <- monmlp.fit(x = x, y = y, hidden1 = 2, bag = TRUE,
                  iter.max = 500, iter.stopped = 10)
lines(x, attr(w.stp, "y.pred"), col = "orange", lwd = 3)

## MONMLP w/ 2 hidden nodes
w.mon <- monmlp.fit(x = x, y = y, hidden1 = 2, monotone = 1,
                  iter.max = 500)
lines(x, attr(w.mon, "y.pred"), col = "blue", lwd = 3)

```

monmlp.predict

Make predictions from a fitted MLP or MONMLP model

Description

Make predictions from a fitted model or ensemble of MLP or MONMLP models.

Usage

```
monmlp.predict(x, weights)
```

Arguments

x	covariate matrix with number of rows equal to the number of samples and number of columns equal to the number of covariates.
weights	list containing weight matrices and other parameters from monmlp.fit .

Value

a matrix with number of rows equal to the number of samples and number of columns equal to the number of response variables. If `weights` is from an ensemble of models, the matrix is the ensemble mean and the attribute `ensemble` contains a list with predictions for each ensemble member.

See Also

[monmlp.fit](#)

Examples

```
set.seed(123)
x <- as.matrix(seq(-10, 10, length = 100))
y <- logistic(x) + rnorm(100, sd = 0.2)

dev.new()
plot(x, y)
lines(x, logistic(x), lwd = 10, col = "gray")

## Ensemble of MONMLP models w/ 3 hidden nodes
w.mon <- monmlp.fit(x = x, y = y, hidden1 = 3, monotone = 1,
                  n.ensemble = 15, bag = TRUE, iter.max = 500,
                  control = list(trace = 0))
p.mon <- monmlp.predict(x = x, weights = w.mon)

## Plot predictions from ensemble members
matlines(x = x, y = do.call(cbind, attr(p.mon, "ensemble")),
         col = "cyan", lty = 2)

## Plot ensemble mean
lines(x, p.mon, col = "blue", lwd = 3)
```

tansig

Hyperbolic tangent sigmoid function

Description

Computes the hyperbolic tangent sigmoid function. Used as a hidden layer transfer function for nonlinear MLP or MONMLP models.

Usage

```
tansig(x)
```

Arguments

x numeric vector.

See Also

[tansig.prime](#)

`tansig.prime`*Derivative of the hyperbolic tangent function*

Description

Derivative of the hyperbolic tangent function.

Usage

```
tansig.prime(x)
```

Arguments

`x` numeric vector.

See Also

[tansig](#)

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