Package 'brnn'

May 8, 2026

Version 0.9.4

Date 2025-04-18

Title Bayesian Regularization for Feed-Forward Neural Networks

Author Paulino Perez Rodriguez [aut, cre],
Daniel Gianola [aut]

Maintainer Paulino Perez Rodriguez <perpdgo@colpos.mx>

Depends R (>= 3.5.0), Formula, truncnorm

Description Bayesian regularization for feed-forward neural networks.

LazyLoad true

License GPL-2

NeedsCompilation yes

Repository CRAN

Date/Publication 2025-04-19 04:50:02 UTC

Contents

---

brnn *brnn*

Description

The brnn function fits a two layer neural network as described in MacKay (1992) and Foresee and Hagan (1997). It uses the Nguyen and Widrow algorithm (1990) to assign initial weights and the Gauss-Newton algorithm to perform the optimization. This function implements the functionality of the function trainbr in Matlab 2010b.

Usage

```
  brnn(x, ...)

  ## S3 method for class 'formula'
brnn(formula, data, contrasts=NULL,...)

  ## Default S3 method:
brnn(x,y,neurons=2,normalize=TRUE,epochs=1000,mu=0.005,mu_dec=0.1,
       mu_inc=10,mu_max=1e10,min_grad=1e-10,change = 0.001,cores=1,
       verbose=FALSE,Monte_Carlo = FALSE,tol = 1e-06, samples = 40,...)
```

Arguments

formula	A formula of the form y ~ x1 + x2 + ...
data	Data frame from which variables specified in formula are preferentially to be taken.
x	(numeric, $n \times p$) incidence matrix.
y	(numeric, n) the response data-vector (NAs not allowed).
neurons	positive integer that indicates the number of neurons.
normalize	logical, if TRUE will normalize inputs and output, the default value is TRUE.
epochs	positive integer, maximum number of epochs(iterations) to train, default 1000.
mu	positive number that controls the behaviour of the Gauss-Newton optimization algorithm, default value 0.005.
mu_dec	positive number, is the mu decrease ratio, default value 0.1.
mu_inc	positive number, is the mu increase ratio, default value 10.
mu_max	maximum mu before training is stopped, strict positive number, default value 1×10^{10}.
min_grad	minimum gradient.

change	The program will stop if the maximum (in absolute value) of the differences of the F function in 3 consecutive iterations is less than this quantity.
cores	Number of cpu cores to use for calculations (only available in UNIX-like operating systems). The function detectCores in the R package parallel can be used to attempt to detect the number of CPUs in the machine that R is running, but not necessarily all the cores are available for the current user, because for example in multi-user systems it will depend on system policies. Further details can be found in the documentation for the parallel package.
verbose	logical, if TRUE will print iteration history.
Monte_Carlo	If TRUE it will estimate the trace of the inverse of the hessian using Monte Carlo procedures, see Bai et al. (1996) for more details. This routine calls the function estimate.trace() to perform the computations.
tol	numeric tolerance, a tiny number useful for checking convergenge in the Bai's algorithm.
samples	positive integer, number of Monte Carlo replicates to estimate the trace of the inverse, see Bai et al. (1996) for more details.
contrasts	an optional list of contrasts to be used for some or all of the factors appearing as variables in the model formula.
...	arguments passed to or from other methods.

Details

The software fits a two layer network as described in MacKay (1992) and Foresee and Hagan (1997). The model is given by:

$y_i = g(\boldsymbol{x}_i) + e_i = \sum_{k=1}^{s} w_k g_k(b_k + \sum_{j=1}^{p} x_{ij}\beta_j^{[k]}) + e_i, i = 1, ..., n$

where:

- $e_i \sim N(0, \sigma_e^2)$.
- s is the number of neurons.
- w_k is the weight of the k-th neuron, $k = 1, ..., s$.
- b_k is a bias for the k-th neuron, $k = 1, ..., s$.
- $\beta_j^{[k]}$ is the weight of the j-th input to the net, $j = 1, ..., p$.
- $g_k(\cdot)$ is the activation function, in this implementation $g_k(x) = \frac{\exp(2x)-1}{\exp(2x)+1}$.

The software will minimize

$$F = \beta E_D + \alpha E_W$$

where

- $E_D = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2$, i.e. the error sum of squares.
- E_W is the sum of squares of network parameters (weights and biases).
- $\beta = \frac{1}{2\sigma_e^2}$.
- $\alpha = \frac{1}{2\sigma_\theta^2}$, σ_θ^2 is a dispersion parameter for weights and biases.

Value

object of class "brnn" or "brnn.formula". Mostly internal structure, but it is a list containing:

$theta	A list containing weights and biases. The first s components of the list contains vectors with the estimated parameters for the k-th neuron, i.e. $(w_k, b_k, \beta_1^{[k]}, ..., \beta_p^{[k]})'$.
$message	String that indicates the stopping criteria for the training process.
$alpha	α parameter.
$beta	β parameter.
$gamma	effective number of parameters.
$Ew	The sum of the squares of the bias and weights.
$Ed	The sum of the squares between observed and predicted values.

References

Bai, Z. J., M. Fahey and G. Golub. 1996. "Some large-scale matrix computation problems." *Journal of Computational and Applied Mathematics* **74(1-2)**, 71-89.

Foresee, F. D., and M. T. Hagan. 1997. "Gauss-Newton approximation to Bayesian regularization", *Proceedings of the 1997 International Joint Conference on Neural Networks*.

Gianola, D. Okut, H., Weigel, K. and Rosa, G. 2011. "Predicting complex quantitative traits with Bayesian neural networks: a case study with Jersey cows and wheat". *BMC Genetics*, **12**,87.

MacKay, D. J. C. 1992. "Bayesian interpolation", *Neural Computation*, **4(3)**, 415-447.

Nguyen, D. and Widrow, B. 1990. "Improving the learning speed of 2-layer neural networks by choosing initial values of the adaptive weights", *Proceedings of the IJCNN*, **3**, 21-26.

Paciorek, C. J. and Schervish, M. J. 2004. "Nonstationary Covariance Functions for Gaussian Process Regression". In Thrun, S., Saul, L., and Scholkopf, B., editors, *Advances in Neural Information Processing Systems 16*. MIT Press, Cambridge, MA.

See Also

predict.brnn

Examples

```
## Not run:

#Load the library
library(brnn)

#####################################################################
#Example 1
#Noise triangle wave function, similar to example 1 in Foresee and Hagan (1997)

#Generating the data
x1=seq(0,0.23,length.out=25)
y1=4*x1+rnorm(25,sd=0.1)
x2=seq(0.25,0.75,length.out=50)
```

```
y2=2-4*x2+rnorm(50,sd=0.1)
x3=seq(0.77,1,length.out=25)
y3=4*x3-4+rnorm(25,sd=0.1)
x=c(x1,x2,x3)
y=c(y1,y2,y3)


#With the formula interface
out=brnn(y~x,neurons=2)

#With the default S3 method the call is
#out=brnn(y=y,x=as.matrix(x),neurons=2)

plot(x,y,xlim=c(0,1),ylim=c(-1.5,1.5),
     main="Bayesian Regularization for ANN 1-2-1")
lines(x,predict(out),col="blue",lty=2)
legend("topright",legend="Fitted model",col="blue",lty=2,bty="n")

################################################################
#Example 2
#sin wave function, example in the Matlab 2010b demo.

x = seq(-1,0.5,length.out=100)
y = sin(2*pi*x)+rnorm(length(x),sd=0.1)

#With the formula interface
out=brnn(y~x,neurons=3)

#With the default method the call is
#out=brnn(y=y,x=as.matrix(x),neurons=3)

plot(x,y)
lines(x,predict(out),col="blue",lty=2)

legend("bottomright",legend="Fitted model",col="blue",lty=2,bty="n")

################################################################
#Example 3
#2 Inputs and 1 output
#the data used in Paciorek and
#Schervish (2004). The data is from a two input one output function with Gaussian noise
#with mean zero and standard deviation 0.25

data(twoinput)

#Formula interface
out=brnn(y~x1+x2,data=twoinput,neurons=10)

#With the default S3 method
#out=brnn(y=as.vector(twoinput$y),x=as.matrix(cbind(twoinput$x1,twoinput$x2)),neurons=10)

f=function(x1,x2) predict(out,cbind(x1,x2))
x1=seq(min(twoinput$x1),max(twoinput$x1),length.out=50)
```

```
x2=seq(min(twoinput$x2),max(twoinput$x2),length.out=50)
z=outer(x1,x2,f) # calculating the density values

transformation_matrix=persp(x1, x2, z,
                            main="Fitted model",
                            sub=expression(y==italic(g)~(bold(x))+e),
                            col="lightgreen",theta=30, phi=20,r=50,
                            d=0.1,expand=0.5,ltheta=90, lphi=180,
                            shade=0.75, ticktype="detailed",nticks=5)
points(trans3d(twoinput$x1,twoinput$x2, f(twoinput$x1,twoinput$x2),
               transformation_matrix), col = "red")

#################################################################
#Example 4
#Gianola et al. (2011).
#Warning, it will take a while

#Load the Jersey dataset
data(Jersey)

#Fit the model with the FULL DATA
#Formula interface
out=brnn(pheno$yield_devMilk~G,neurons=2,verbose=TRUE)

#Obtain predictions and plot them against fitted values
plot(pheno$yield_devMilk,predict(out))

#Predictive power of the model using the SECOND set for 10 fold CROSS-VALIDATION
data=pheno
data$X=G
data$partitions=partitions

#Fit the model for the TESTING DATA
out=brnn(yield_devMilk~X,
         data=subset(data,partitions!=2),neurons=2,verbose=TRUE)

#Plot the results
#Predicted vs observed values for the training set
par(mfrow=c(2,1))
plot(out$y,predict(out),xlab=expression(hat(y)),ylab="y")
cor(out$y,predict(out))

#Predicted vs observed values for the testing set
yhat_R_testing=predict(out,newdata=subset(data,partitions==2))
ytesting=pheno$yield_devMilk[partitions==2]
plot(ytesting,yhat_R_testing,xlab=expression(hat(y)),ylab="y")
cor(ytesting,yhat_R_testing)


## End(Not run)
```

brnn_extended *brnn_extended*

Description

The brnn_extended function fits a two layer neural network as described in MacKay (1992) and Foresee and Hagan (1997). It uses the Nguyen and Widrow algorithm (1990) to assign initial weights and the Gauss-Newton algorithm to perform the optimization. The hidden layer contains two groups of neurons that allow us to assign different prior distributions for two groups of input variables.

Usage

```
  brnn_extended(x, ...)

  ## S3 method for class 'formula'
brnn_extended(formula, data, contrastsx=NULL,contrastsz=NULL,...)

  ## Default S3 method:
brnn_extended(x,y,z,neurons1,neurons2,normalize=TRUE,epochs=1000,
              mu=0.005,mu_dec=0.1, mu_inc=10,mu_max=1e10,min_grad=1e-10,
              change = 0.001, cores=1,verbose =FALSE,...)
```

Arguments

formula	A formula of the form y ~ x1 + x2 ... | z1 + z2 ..., the | is used to separate the two groups of input variables.
data	Data frame from which variables specified in formula are preferentially to be taken.
y	(numeric, n) the response data-vector (NAs not allowed).
x	(numeric, $n \times p$) incidence matrix for variables in group 1.
z	(numeric, $n \times q$) incidence matrix for variables in group 2.
neurons1	positive integer that indicates the number of neurons for variables in group 1.
neurons2	positive integer that indicates the number of neurons for variables in group 2.
normalize	logical, if TRUE will normalize inputs and output, the default value is TRUE.
epochs	positive integer, maximum number of epochs to train, default 1000.
mu	positive number that controls the behaviour of the Gauss-Newton optimization algorithm, default value 0.005.
mu_dec	positive number, is the mu decrease ratio, default value 0.1.
mu_inc	positive number, is the mu increase ratio, default value 10.
mu_max	maximum mu before training is stopped, strict positive number, default value 1×10^{10}.
min_grad	minimum gradient.

change	The program will stop if the maximum (in absolute value) of the differences of the F function in 3 consecutive iterations is less than this quantity.
cores	Number of cpu cores to use for calculations (only available in UNIX-like operating systems). The function detectCores in the R package parallel can be used to attempt to detect the number of CPUs in the machine that R is running, but not necessarily all the cores are available for the current user, because for example in multi-user systems it will depend on system policies. Further details can be found in the documentation for the parallel package
verbose	logical, if TRUE will print iteration history.
contrastsx	an optional list of contrasts to be used for some or all of the factors appearing as variables in the first group of input variables in the model formula.
contrastsz	an optional list of contrasts to be used for some or all of the factors appearing as variables in the second group of input variables in the model formula.
...	arguments passed to or from other methods.

Details

The software fits a two layer network as described in MacKay (1992) and Foresee and Hagan (1997). The model is given by:

$y_i = \sum_{k=1}^{s_1} w_k^1 g_k(b_k^1 + \sum_{j=1}^{p} x_{ij}\beta_j^{1[k]}) + \sum_{k=1}^{s_2} w_k^2 g_k(b_k^2 + \sum_{j=1}^{q} z_{ij}\beta_j^{2[k]})\ e_i, i = 1, ..., n$

- $e_i \sim N(0, \sigma_e^2)$.
- $g_k(\cdot)$ is the activation function, in this implementation $g_k(x) = \frac{\exp(2x)-1}{\exp(2x)+1}$.

The software will minimize

$$F = \beta E_D + \alpha\theta_1'\theta_1 + \delta\theta_2'\theta_2$$

where

- $E_D = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2$, i.e. the sum of squared errors.
- $\beta = \frac{1}{2\sigma_e^2}$.
- $\alpha = \frac{1}{2\sigma_{\theta_1}^2}$, $\sigma_{\theta_1}^2$ is a dispersion parameter for weights and biases for the associated to the first group of neurons.
- $\delta = \frac{1}{2\sigma_{\theta_2}^2}$, $\sigma_{\theta_2}^2$ is a dispersion parameter for weights and biases for the associated to the second group of neurons.

Value

object of class "brnn_extended" or "brnn_extended.formula". Mostly internal structure, but it is a list containing:

$theta1	A list containing weights and biases. The first s_1 components of the list contain vectors with the estimated parameters for the k-th neuron, i.e. $(w_k^1, b_k^1, \beta_1^{1[k]}, ..., \beta_p^{1[k]})'$. s_1 corresponds to neurons1 in the argument list.

`$theta2` A list containing weights and biases. The first s_2 components of the list contains vectors with the estimated parameters for the k-th neuron, i.e. $(w_k^2, b_k^2, \beta_1^{2[k]}, ..., \beta_q^{2[k]})'$. s_2 corresponds to neurons2 in the argument list.

`$message` String that indicates the stopping criteria for the training process.

References

Foresee, F. D., and M. T. Hagan. 1997. "Gauss-Newton approximation to Bayesian regularization", *Proceedings of the 1997 International Joint Conference on Neural Networks*.

MacKay, D. J. C. 1992. "Bayesian interpolation", *Neural Computation*, **4(3)**, 415-447.

Nguyen, D. and Widrow, B. 1990. "Improving the learning speed of 2-layer neural networks by choosing initial values of the adaptive weights", *Proceedings of the IJCNN*, **3**, 21-26.

See Also

`predict.brnn_extended`

Examples

```
## Not run:

#Example 5
#Warning, it will take a while

#Load the Jersey dataset
data(Jersey)

#Predictive power of the model using the SECOND set for 10 fold CROSS-VALIDATION
data=pheno
data$G=G
data$D=D
data$partitions=partitions

#Fit the model for the TESTING DATA for Additive + Dominant
out=brnn_extended(yield_devMilk ~ G | D,
                                  data=subset(data,partitions!=2),
                                  neurons1=2,neurons2=2,epochs=100,verbose=TRUE)

#Plot the results
#Predicted vs observed values for the training set
par(mfrow=c(2,1))
yhat_R_training=predict(out)
plot(out$y,yhat_R_training,xlab=expression(hat(y)),ylab="y")
cor(out$y,yhat_R_training)

#Predicted vs observed values for the testing set
newdata=subset(data,partitions==2,select=c(D,G))
ytesting=pheno$yield_devMilk[partitions==2]
yhat_R_testing=predict(out,newdata=newdata)
plot(ytesting,yhat_R_testing,xlab=expression(hat(y)),ylab="y")
cor(ytesting,yhat_R_testing)
```

```
## End(Not run)
```

---

brnn_ordinal *brnn_ordinal*

Description

The brnn_ordinal function fits a Bayesian Regularized Neural Network for Ordinal data.

Usage

```
  brnn_ordinal(x, ...)

  ## S3 method for class 'formula'
brnn_ordinal(formula, data, contrasts=NULL,...)

  ## Default S3 method:
brnn_ordinal(x,
               y,
               neurons=2,
               normalize=TRUE,
               epochs=1000,
               mu=0.005,
               mu_dec=0.1,
               mu_inc=10,
               mu_max=1e10,
               min_grad=1e-10,
               change_F=0.01,
               change_par=0.01,
               iter_EM=1000,
               verbose=FALSE,
               ...)
```

Arguments

formula	A formula of the form y ~ x1 + x2 + ...
data	Data frame from which variables specified in formula are preferentially to be taken.
x	(numeric, $n \times p$) incidence matrix.
y	(numeric, n) the response data-vector (NAs not allowed).
neurons	positive integer that indicates the number of neurons.
normalize	logical, if TRUE will normalize inputs and output, the default value is TRUE.
epochs	positive integer, maximum number of epochs(iterations) to train, default 1000.

mu	positive number that controls the behaviour of the Gauss-Newton optimization algorithm, default value 0.005.
mu_dec	positive number, is the mu decrease ratio, default value 0.1.
mu_inc	positive number, is the mu increase ratio, default value 10.
mu_max	maximum mu before training is stopped, strict positive number, default value 1×10^{10}.
min_grad	minimum gradient.
change_F	the program will stop if the maximum (in absolute value) of the differences of the F function in 3 consecutive iterations is less than this quantity.
change_par	the program will stop iterations of the EM algorithm when the maximum of absolute values of differences between parameters in two consecutive iterations ins less than this quantity.
iter_EM	positive integer, maximum number of iteration for the EM algorithm.
verbose	logical, if TRUE will print iteration history.
contrasts	an optional list of contrasts to be used for some or all of the factors appearing as variables in the model formula.
...	arguments passed to or from other methods.

Details

The software fits a Bayesian Regularized Neural Network for Ordinal data. The model is an extension of the two layer network as described in MacKay (1992); Foresee and Hagan (1997), and Gianola et al. (2011). We use the latent variable approach described in Albert and Chib (1993) to model ordinal data, the Expectation maximization (EM) and Levenberg-Marquardt algorithm (Levenberg, 1944; Marquardt, 1963) to fit the model.

Following Albert and Chib (1993), suppose that $Y_1, ..., Y_n$ are observed and Y_i can take values on L ordered values. We are interested in modelling the probability $p_{ij} = P(Y_i = j)$ using the covariates $x_{i1}, ..., x_{ip}$. Let

$g(\boldsymbol{x}_i) = \sum_{k=1}^{s} w_k g_k(b_k + \sum_{j=1}^{p} x_{ij}\beta_j^{[k]})$,

where:

- s is the number of neurons.
- w_k is the weight of the k-th neuron, $k = 1, ..., s$.
- b_k is a bias for the k-th neuron, $k = 1, ..., s$.
- $\beta_j^{[k]}$ is the weight of the j-th input to the net, $j = 1, ..., p$.
- $g_k(\cdot)$ is the activation function, in this implementation $g_k(x) = \frac{\exp(2x)-1}{\exp(2x)+1}$.

Let

$Z_i = g(\boldsymbol{x}_i) + e_i$,

where:

- $e_i \sim N(0, 1)$.

- Z_i is an unobserved (latent variable).

The output from the model for latent variable is related to observed data using the approach employed in the probit and logit ordered models, that is $Y_i = j$ if $\lambda_{j-1} < Z_i < \lambda_j$, where λ_j are a set of unknown thresholds. We assign prior distributions to all unknown quantities (see Albert and Chib, 1993; Gianola et al., 2011) for further details. The Expectation maximization (EM) and Levenberg-Marquardt algorithm (Levenberg, 1944; Marquardt, 1963) to fit the model.

Value

object of class `"brnn_ordinal"`. Mostly internal structure, but it is a list containing:

`$theta`	A list containing weights and biases. The first s components of the list contains vectors with the estimated parameters for the k-th neuron, i.e. $(w_k, b_k, \beta_1^{[k]}, ..., \beta_p^{[k]})'$.
`$threshold`	A vector with estimates of thresholds.
`$alpha`	α parameter.
`$gamma`	effective number of parameters.

References

Albert J, and S. Chib. 1993. Bayesian Analysis of Binary and Polychotomus Response Data. *JASA*, **88**, 669-679.

Foresee, F. D., and M. T. Hagan. 1997. "Gauss-Newton approximation to Bayesian regularization", *Proceedings of the 1997 International Joint Conference on Neural Networks*.

Gianola, D. Okut, H., Weigel, K. and Rosa, G. 2011. "Predicting complex quantitative traits with Bayesian neural networks: a case study with Jersey cows and wheat". *BMC Genetics*, **12**,87.

Levenberg, K. 1944. "A method for the solution of certain problems in least squares", *Quart. Applied Math.*, **2**, 164-168.

MacKay, D. J. C. 1992. "Bayesian interpolation", *Neural Computation*, **4(3)**, 415-447.

Marquardt, D. W. 1963. "An algorithm for least-squares estimation of non-linear parameters". *SIAM Journal on Applied Mathematics*, **11(2)**, 431-441.

See Also

`predict.brnn_ordinal`

Examples

```
## Not run:
#Load the library
library(brnn)

#Load the dataset
data(GLS)

#Subset of data for location Harare
HarareOrd=subset(phenoOrd,Loc=="Harare")
```

```
#Eigen value decomposition for GOrdm keep those
#eigen vectors whose corresponding eigen-vectors are bigger than 1e-10
#and then compute principal components

evd=eigen(GOrd)
evd$vectors=evd$vectors[,evd$value>1e-10]
evd$values=evd$values[evd$values>1e-10]
PC=evd$vectors%*%sqrt(diag(evd$values))
rownames(PC)=rownames(GOrd)

#Response variable
y=phenoOrd$rating
gid=as.character(phenoOrd$Stock)

Z=model.matrix(~gid-1)
colnames(Z)=gsub("gid","",colnames(Z))

if(any(colnames(Z)!=rownames(PC))) stop("Ordering problem\n")

#Matrix of predictors for Neural net
X=Z%*%PC

#Cross-validation
set.seed(1)
testing=sample(1:length(y),size=as.integer(0.10*length(y)),replace=FALSE)
isNa=(1:length(y)%in%testing)
yTrain=y[!isNa]
XTrain=X[!isNa,]
nTest=sum(isNa)

neurons=2

fmOrd=brnn_ordinal(XTrain,yTrain,neurons=neurons,verbose=FALSE)

#Predictions for testing set
XTest=X[isNa,]
predictions=predict(fmOrd,XTest)
predictions



## End(Not run)
```

D *Genomic dominant relationship matrix for the Jersey dataset.*

Description

This matrix was calculated by using the dominance incidence matrix derived from 33,267 Single Nucleotide Polymorphisms (SNPs) information on 297 individually cows,

$$D = \frac{X_d X_d'}{2\sum_{j=1}^{p}(p_j^2 + q_j^2)p_j q_j},$$

where

- X_d is the design matrix for allele substitution effects for dominance.
- p_j is the frecuency of the second allele at locus j and $q_j = 1 - p_j$.

Source

University of Wisconsin at Madison, USA.

`estimate.trace` *estimate.trace*

Description

The estimate.trace function estimates the trace of the inverse of a possitive definite and symmetric matrix using the algorithm developed by Bai et al. (1996). It is specially useful when the matrix is huge.

Usage

```
estimate.trace(A,tol=1E-6,samples=40,cores=1)
```

Arguments

`A`	(numeric), positive definite and symmetric matrix.
`tol`	numeric tolerance, a very small number useful for checking convergenge in the Bai's algorithm.
`samples`	integer, number of Monte Carlo replicates to estimate the trace of the inverse.
`cores`	Number of cpu cores to use for calculations (only availible in UNIX-like operating systems).

References

Bai, Z. J., M. Fahey and G. Golub. 1996. "Some large-scale matrix computation problems." *Journal of Computational and Applied Mathematics*, **74(1-2)**, 71-89.

Examples

```
## Not run:
library(brnn)
data(Jersey)

#Estimate the trace of the inverse of G matrix
estimate.trace(G)

#The TRUE value
sum(diag(solve(G)))


## End(Not run)
```

G *Genomic additive relationship matrix for the Jersey dataset.*

Description

A matrix, similar to this was used in Gianola et al. (2011) for predicting milk, fat and protein production in Jersey cows. In this software version we do not center the incidence matrix for the additive effects.

$G = \frac{X_a X_a'}{2\sum_{j=1}^{p} p_j(1-p_j)}$,

where

- X_a is the design matrix for allele substitution effects for additivity.
- p_j is the frecuency of the second allele at locus j and $q_j = 1 - p_j$.

Source

University of Wisconsin at Madison, USA.

References

Gianola, D. Okut, H., Weigel, K. and Rosa, G. 2011. "Predicting complex quantitative traits with Bayesian neural networks: a case study with Jersey cows and wheat". *BMC Genetics*, **12**,87.

GOrd — *Genomic additive relationship matrix for the GLS dataset.*

Description

Genomic relationship matrix for the GLS dataset. The matrix was derived from 46347 markers for the 278 individuals. The matrix was calculated as follows G=MM'/p, where M is the matrix of markers centered and standarized and p is the number of markers.

Source

International Maize and Wheat Improvement Center (CIMMYT), Mexico.

References

Montesinos-Lopez, O., A. Montesinos-Lopez, J. Crossa, J. Burgueno and K. Eskridge. 2015. "Genomic-Enabled Prediction of Ordinal Data with Bayesian Logistic Ordinal Regression". *G3: Genes | Genomes | Genetics*, **5**, 2113-2126.

initnw — *Initialize networks weights and biases*

Description

Function to initialize the weights and biases in a neural network. It uses the Nguyen-Widrow (1990) algorithm.

Usage

```
initnw(neurons,p,n,npar)
```

Arguments

neurons	Number of neurons.
p	Number of predictors.
n	Number of cases.
npar	Number of parameters to be estimate including only weights and biases, and should be equal to $neurons \times (1 + 1 + p) + 1$.

Details

The algorithm is described in Nguyen-Widrow (1990) and in other books, see for example Sivanandam and Sumathi (2005). The algorithm is briefly described below.

- 1.-Compute the scaling factor $\theta = 0.7p^{1/n}$.
- 2.- Initialize the weight and biases for each neuron at random, for example generating random numbers from $U(-0.5, 0.5)$.
- 3.- For each neuron:
  - compute $\eta_k = \sqrt{\sum_{j=1}^{p}(\beta_j^{(k)})^2}$,
  - update $(\beta_1^{(k)}, ..., \beta_p^{(k)})'$,

$$\beta_j^{(k)} = \frac{\theta\beta_j^{(k)}}{\eta_k}, j = 1, ..., p,$$

  - Update the bias (b_k) generating a random number from $U(-\theta, \theta)$.

Value

A list containing initial values for weights and biases. The first s components of the list contains vectors with the initial values for the weights and biases of the k-th neuron, i.e. $(\omega_k, b_k, \beta_1^{(k)}, ..., \beta_p^{(k)})'$.

References

Nguyen, D. and Widrow, B. 1990. "Improving the learning speed of 2-layer neural networks by choosing initial values of the adaptive weights", *Proceedings of the IJCNN*, **3**, 21-26.

Sivanandam, S.N. and Sumathi, S. 2005. Introduction to Neural Networks Using MATLAB 6.0. Ed. McGraw Hill, First edition.

Examples

```
## Not run:
#Load the library
library(brnn)

#Set parameters
neurons=3
p=4
n=10
npar=neurons*(1+1+p)+1
initnw(neurons=neurons,p=p,n=n,npar=npar)


## End(Not run)
```

jacobian *Jacobian*

Description

Internal function for the calculation of the Jacobian.

normalize *normalize*

Description

Internal function for normalizing the data. This function makes a linear transformation of the inputs such that the values lie between -1 and 1.

Usage

```
normalize(x,base,spread)
```

Arguments

x	a vector or matrix that needs to be normalized.
base	If x is a vector, base is the minimum of x. If x is a matrix, base is a vector with the minimum for each of the columns of the matrix x.
spread	if x is a vector, spread=max(x)-base. If x is a matrix, spread is a vector calculated for each of the columns of x.

Details

z=2*(x-base)/spread - 1

Value

A vector or matrix with the resulting normalized values.

partitions *Partitions for cross validation (CV)*

Description

Is a vector (297×1) that assigns observations to 10 disjoint sets; the assignment was generated at random. This is used later to conduct a 10-fold CV.

Source

University of Wisconsin at Madison, USA.

pheno *Phenotypic information for Jersey*

Description

The format of the phenotype dataframe is animal ID, herd, number of lactations, average milk yield, average fat yield, average protein yield, yield deviation for milk, yield deviation for fat, and yield deviation for protein. Averages are adjusted for age, days in milk, and milking frequency. Yield deviations are adjusted further, for herd-year-season effect. You may wish to use yield deviations, because there are relatively few cows per herd (farmers don't pay to genotype all of their cows, just the good ones).

Source

University of Wisconsin at Madison, USA.

References

Gianola, D. Okut, H., Weigel, K. and Rosa, G. 2011. "Predicting complex quantitative traits with Bayesian neural networks: a case study with Jersey cows and wheat". *BMC Genetics*, **12**,87.

pheno0rd *Phenotypic information for GLS (ordinal trait)*

Description

The format of the phenotype dataframe is Location (Loc), Replicate (Rep), Genotype ID (Stock) and rating (ordinal score). Gray Leaf Spot (GLS) is a disease caused by the fungus *Cercospora zeae-maydis*. This dataset consists of genotypic and phenotypic information for 278 maize lines from the Drought Tolerance Maize (DTMA) project of CIMMYT's Global Maize Program. The dataset includes information on disease severity measured on an ordinal scale with 5 points: 1= no disease, 2= low infection, 3=moderate infection, 4=high infection and 5=totally infected.

Source

International Maize and Wheat Improvement Center (CIMMYT), Mexico.

References

Montesinos-Lopez, O., A. Montesinos-Lopez, J. Crossa, J. Burgueno and K. Eskridge. 2015. "Genomic-Enabled Prediction of Ordinal Data with Bayesian Logistic Ordinal Regression". *G3: Genes | Genomes | Genetics*, **5**, 2113-2126.

predict.brnn *predict.brnn*

Description

The function produces the predictions for a two-layer feed-forward neural network.

Usage

```
   ## S3 method for class 'brnn'
predict(object,newdata,...)
```

Arguments

object	an object of the class brnn as returned by brnn
newdata	matrix or data frame of test examples. A vector is considered to be a row vector comprising a single case.
...	arguments passed to or from other methods.

Details

This function is a method for the generic function predict() for class "brnn". It can be invoked by calling predict(x) for an object x of the appropriate class, or directly by calling predict.brnn(x) regardless of the class of the object.

Value

A vector containing the predictions

predict.brnn_extended *predict.brnn_extended*

Description

The function produces the predictions for a two-layer feed-forward neural network.

Usage

```
   ## S3 method for class 'brnn_extended'
predict(object,newdata,...)
```

Arguments

object	an object of the class brnn_extended as returned by brnn_extended
newdata	matrix or data frame of test examples. A vector is considered to be a row vector comprising a single case.
...	arguments passed to or from other methods.

Details

This function is a method for the generic function `predict()` for class `"brnn_extended"`. It can be invoked by calling `predict(x)` for an object `x` of the appropriate class, or directly by calling `predict.brnn(x)` regardless of the class of the object.

Value

A vector containig the predictions

`predict.brnn_ordinal` *predict.brnn_ordinal*

Description

The function produces the predictions for a two-layer feed-forward neural network for ordinal data.

Usage

```
   ## S3 method for class 'brnn_ordinal'
predict(object,newdata,...)
```

Arguments

`object`	an object of the class `brnn_ordinal` as returned by `brnn_ordinal`
`newdata`	matrix or data frame of test examples. A vector is considered to be a row vector comprising a single case.
`...`	arguments passed to or from other methods.

Details

This function is a method for the generic function `predict()` for class `"brnn_ordinal"`. It can be invoked by calling `predict(x)` for an object `x` of the appropriate class, or directly by calling `predict.brnn_ordinal(x)` regardless of the class of the object.

Value

A list with components:

`class`	Predicted class (an integer).
`probability`	Posterior probability of belonging to a class given the covariates.

twoinput *2 Inputs and 1 output.*

Description

The data used in Paciorek and Schervish (2004). This is a data.frame with 3 columns, columns 1 and 2 corresponds to the predictors and column 3 corresponds to the target.

References

Paciorek, C. J. and Schervish, M. J. 2004. "Nonstationary Covariance Functions for Gaussian Process Regression". In Thrun, S., Saul, L., and Scholkopf, B., editors, *Advances in Neural Information Processing Systems 16*. MIT Press, Cambridge, MA.

un_normalize *un_normalize*

Description

Internal function for going back to the original scale.

Usage

```
un_normalize(z,base,spread)
```

Arguments

z	a vector or matrix with values normalized between -1 and 1, this vector was obtained when normalizing a vector or matrix x.
base	If z is a vector, base is the minimum of x. If x is a matrix, base is a vector with the minimum for each of the columns of the matrix x.
spread	if z is a vector, spread=base-max(x). If x is a matrix, spread is a vector calculated for each of the columns of x.

Details

x=base+0.5*spread*(z+1)

Value

A vector or matrix with the resulting un normalized values.

Index