

# Package: simpleNeural (via r-universe)

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**Title** An Easy to Use Multilayer Perceptron

**Description** Trains neural networks (multilayer perceptrons with one hidden layer) for bi- or multi-class classification.

**Depends** R (>= 3.6)

**Suggests** verification

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**LazyData** true

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**NeedsCompilation** no

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**Repository** <https://ac4bb21b.r-universe.dev>

**RemoteUrl** <https://github.com/cran/simpleNeural>

**RemoteRef** HEAD

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sN.MLPpredict	<i>Runs a multilayer perceptron</i>
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**Description**

Runs a multilayer perceptron

**Usage**

```
sN.MLPpredict(nnModel, X, raw = FALSE)
```

**Arguments**

nnModel	A list containing the coefficients for the MLP (as produced with sN.MLPtrain())
X	Matrix of predictors
raw	If true, returns score of each output option. If false, returns the output option with highest value.

**Value**

The predicted values obtained by the MLP

**Examples**

```
data(UCI.transfusion);
X=as.matrix(sN.normalizedF(as.data.frame(UCI.transfusion[,1:4])));
y=as.matrix(UCI.transfusion[,5]);
myMLP=sN.MLPtrain(X=X,y=y,hidden_layer_size=4,it=50,lambda=0.5,alpha=0.5);
myPrediction=sN.MLPpredict(nnModel=myMLP,X=X,raw=TRUE);
#library('verification');
#roc.area(y,myPrediction[,2]);
```

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sN.MLPtrain	<i>Trains a multilayer perceptron with 1 hidden layer</i>
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**Description**

Trains a multilayer perceptron with 1 hidden layer and a sigmoid activation function, using back-propagation and gradient descent. Don't forget to normalize the data first - sN.normalizedF(), provided in the package, can be used to do so.

**Usage**

```
sN.MLPtrain(X, y, hidden_layer_size = 5, it = 50, lambda = 0.5,
  alpha = 0.5)
```

**Arguments**

X	Matrix of predictors
y	Vector of output (the ANN learns $y=ANN(X)$ ). Classes should be assigned an integer number, starting at 0 for the first class.
hidden_layer_size	Number of units in the hidden layer
it	Number of iterations for the gradient descent. The default value of 50 may be a little low in some cases. 100 to 1000 are generally sensible values.
lambda	Penalization for model coefficients (regularization parameter)
alpha	Speed multiplier (learning rate) for gradient descent

**Value**

The coefficients of the MLP, in a list (Theta1 between input and hidden layers, Theta2 between hidden and output layers)

**References**

M.W Gardner, S.R Dorling, Artificial neural networks (the multilayer perceptron)- a review of applications in the atmospheric sciences, Atmospheric Environment, Volume 32, Issues 14-15, 1 August 1998, Pages 2627-2636, ISSN 1352-2310, doi: 10.1016/S1352-2310(97)00447-0 [<http://www.sciencedirect.com/science/article/pii/S1352231097004470>]

Jain, A.K.; Jianchang Mao; Mohiuddin, K.M., "Artificial neural networks: a tutorial," Computer , vol.29, no.3, pp.31,44, Mar 1996. doi: 10.1109/2.485891 [<http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=485891&isnumber=10412>]

Rumelhart, David E., Geoffrey E. Hinton, and R. J. Williams. "Learning Internal Representations by Error Propagation". David E. Rumelhart, James L. McClelland, and the PDP research group (editors). Parallel distributed processing: Explorations in the microstructure of cognition, Volume 1: Foundations. MIT Press, 1986.

**Examples**

```
# NB: the provided examples are just here to help use the package's functions.
# In real use cases you should perform a proper validation (cross-validation,
# external validation data...)
data(UCI.BCD.Wisconsin);
X=as.matrix(sN.normalizedF(as.data.frame(UCI.BCD.Wisconsin[,3:32])));
y=as.matrix(UCI.BCD.Wisconsin[,2]);
myMLP=sN.MLPtrain(X=X,y=y,hidden_layer_size=20,it=50,lambda=0.5,alpha=0.5);
myPrediction=sN.MLPpredict(nnModel=myMLP,X=X,raw=TRUE);
#library('verification');
#roc.area(y,myPrediction[,2]);
```

sN.normalizeDF      *Normalize data*

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### Description

Normalize all columns of a dataframe so that all values are in [0;1] and for each column the maximum value is 1 and the minimum 0.

$$\text{newx}=(x-\min(X))/(\max(X)-\min(X))$$

### Usage

```
sN.normalizeDF(dframe)
```

### Arguments

dframe      The dataframe to be normalized

### Value

The normalized dataframe

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UCI.BCD.Wisconsin      *Breast Cancer Wisconsin (Diagnostic) Data Set*

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### Description

Features are computed from a digitized image of a fine needle aspirate (FNA) of a breast mass. They describe characteristics of the cell nuclei present in the image.

### Usage

```
data(UCI.BCD.Wisconsin)
```

### Format

A data frame with 569 rows and 32 variables

### Details

Separating plane described above was obtained using Multisurface Method-Tree (MSM-T) [K. P. Bennett, "Decision Tree Construction Via Linear Programming." Proceedings of the 4th Midwest Artificial Intelligence and Cognitive Science Society, pp. 97-101, 1992], a classification method which uses linear programming to construct a decision tree. Relevant features were selected using an exhaustive search in the space of 1-4 features and 1-3 separating planes.

The actual linear program used to obtain the separating plane in the 3-dimensional space is that described in: [K. P. Bennett and O. L. Mangasarian: "Robust Linear Programming Discrimination of Two Linearly Inseparable Sets", Optimization Methods and Software 1, 1992, 23-34].

The variables are as follows:

- ID number
- Diagnosis (1 = malignant, 0 = benign)
- Ten real-valued features are computed for each cell nucleus

### Source

Dataset downloaded from the UCI Machine Learning Repository. [http://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+\(Diagnostic\)](http://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+(Diagnostic))

Creators:

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2. W. Nick Street, Computer Sciences Dept. University of Wisconsin, 1210 West Dayton St., Madison, WI 53706 street 'at' cs.wisc.edu 608-262-6619
3. Olvi L. Mangasarian, Computer Sciences Dept. University of Wisconsin, 1210 West Dayton St., Madison, WI 53706 olvi 'at' cs.wisc.edu

Donor: Nick Street

### References

W.N. Street, W.H. Wolberg and O.L. Mangasarian. Nuclear feature extraction for breast tumor diagnosis. IS&T/SPIE 1993 International Symposium on Electronic Imaging: Science and Technology, volume 1905, pages 861-870, San Jose, CA, 1993.

Lichman, M. (2013). UCI Machine Learning Repository [<http://archive.ics.uci.edu/ml>]. Irvine, CA: University of California, School of Information and Computer Science.

### Description

This data set was generated as follows. 150 subjects spoke the name of each letter of the alphabet twice. Hence, we have 52 training examples from each speaker.

**Usage**

```
data(UCI.ISOLET.ABC)
```

**Format**

A data frame with 900 rows and 618 variables

**Details**

To reduce package size, only the 3 first letters are included here. The full dataset can be obtained from <http://archive.ics.uci.edu/ml/datasets/ISOLET>.

The features are described in the paper by Cole and Fanty cited below. The features include spectral coefficients; contour features, sonorant features, pre-sonorant features, and post-sonorant features. Exact order of appearance of the features is not known.

**Source**

Dataset downloaded from the UCI Machine Learning Repository. <http://archive.ics.uci.edu/ml/datasets/ISOLET>

Creators:

Ron Cole and Mark Fanty Department of Computer Science and Engineering, Oregon Graduate Institute, Beaverton, OR 97006. [cole@cs.ogi.edu](mailto:cole@cs.ogi.edu), [fanty@cs.ogi.edu](mailto:fanty@cs.ogi.edu)

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**References**

Fanty, M., Cole, R. (1991). Spoken letter recognition. In Lippman, R. P., Moody, J., and Touretzky, D. S. (Eds). Advances in Neural Information Processing Systems 3. San Mateo, CA: Morgan Kaufmann. [<http://rexa.info/paper/bee6de062d0d168c5c5b5290b11cd6b12ca8472e>]

**Examples**

```
# NB: 50 iterations isn't enough in this case,  
# it was chosen so that the example runs fast enough on CRAN check farm  
data(UCI.ISOLET.ABC);  
X=as.matrix(sN.normalizeDF(as.data.frame(UCI.ISOLET.ABC[,1:617])));  
y=as.matrix(UCI.ISOLET.ABC[,618]-1);  
myMLP=sN.MLPtrain(X=X,y=y,hidden_layer_size=20,it=50,lambda=0.5,alpha=0.5);  
myPrediction=sN.MLPpredict(nnModel=myMLP,X=X,row=FALSE);  
table(y,myPrediction);
```

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UCI.transfusion

*Blood Transfusion Service Center Data Set*

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## Description

Data taken from the Blood Transfusion Service Center in Hsin-Chu City in Taiwan. To demonstrate the RFMTC marketing model (a modified version of RFM), this study adopted the donor database of Blood Transfusion Service Center in Hsin-Chu City in Taiwan. The center passes their blood transfusion service bus to one university in Hsin-Chu City to gather blood donated about every three months. To build a FRMTC model, we selected 748 donors at random from the donor database. These 748 donor data, each one included R (Recency - months since last donation), F (Frequency - total number of donation), M (Monetary - total blood donated in c.c.), T (Time - months since first donation), and a binary variable representing whether he/she donated blood in March 2007 (1 stand for donating blood; 0 stands for not donating blood).

## Usage

```
data(UCI.transfusion)
```

## Format

A data frame with 748 rows and 5 variables

## Details

The variables are as follows:

- R. Recency - months since last donation
- F. Frequency - total number of donations
- M. Monetary - total blood donated in c.c. (mL)
- T. Time - months since first donation
- y. a binary variable representing whether he/she donated blood in March 2007 (1=yes; 0=no)

## Source

Dataset downloaded from the UCI Machine Learning Repository. <http://archive.ics.uci.edu/ml/datasets/Blood+Transfusion+Service+Center>

Original Owner and Donor: Prof. I-Cheng Yeh Department of Information Management Chung-Hua University Hsin Chu, Taiwan 30067, R.O.C. e-mail: icyeh 'at' chu.edu.tw

## References

Yeh, I-Cheng, Yang, King-Jang, and Ting, Tao-Ming, "Knowledge discovery on RFM model using Bernoulli sequence", Expert Systems with Applications, 2008. DOI: 10.1016/j.eswa.2008.07.018

Lichman, M. (2013). UCI Machine Learning Repository [<http://archive.ics.uci.edu/ml>]. Irvine, CA: University of California, School of Information and Computer Science.

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