Aprenentatge Automàtic 1

GCED

Lluís A. Belanche belanche@cs.upc.edu





Soft Computing Research Group
Dept. de Ciències de la Computació (Computer Science)
Universitat Politècnica de Catalunya

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LECTURE 8d: Artificial neural networks (I)

The MLP in R

```
nnet(x, y, weights, size, Wts, mask,
    linout = FALSE, entropy = FALSE, softmax = FALSE,
    censored = FALSE, skip = FALSE, rang = 0.7, decay = 0,
    maxit = 100, Hess = FALSE, trace = TRUE, MaxNWts = 1000,
    abstol = 1.0e-4, reltol = 1.0e-8, ...)
```

Suppose we are dealing with a three-class problem with 4 inputs:

```
nnet(x, y, size=2, softmax = TRUE)
```

a 4-2-3 network with 19 weights

Using exactly the *same* call to **nnet** three times, we have got these results:

```
# weights: 19
                          # weights: 19
                                                     # weights: 19
initial value 143.78535
                           initial value 147.09410
                                                      initial value 140.510964
                                                      iter 10 value 87.626321
iter 10 value 82.67353
                           iter 10 value 70.01521
                                                      iter 20 value 33.779907
iter 20 value 7.343014
                           iter 20 value 34.64103
iter 30 value 3.130778
                           iter 30 value 21.04111
                                                     iter 30 value 7.576811
iter 40 value 2.817692
                           iter 40 value 6.781165
                                                      iter 40 value 7.027161
iter 50 value 2.803824
                          iter 50 value 1.729377
                                                      ..... <removed>
                                                      iter 100 value 6.448934
iter 60 value 2.781383
                          iter 60 value 1.051125
iter 70 value 2.743949
                           iter 70 value 0.725090
                                                      iter 110 value 6.448800
iter 80 value 2.310192
                           iter 80 value 0.318526
                                                      iter 120 value 6.448505
iter 90 value 0.148647
                           iter 90 value 0.136883
                                                     final value 6.446125
iter 100 value 0.031570
                           iter 100 value 0.116817
                                                     converged
iter 110 value 0.018951
                           iter 110 value 0.111052
.... <removed>
                           ..... <removed>
iter 860 value 0.000156
                           iter1940 value 0.001235
iter 870 value 0.000155
                           iter1950 value 0.001235
                           iter1960 value 0.001230
iter 880 value 0.000151
iter 890 value 0.000145
                           iter1970 value 0.001225
iter 900 value 0.000087
                           iter1980 value 0.001212
final value 0.000087
                           iter1990 value 0.001206
                           iter2000 value 0.001198
converged
                           final value 0.001198
                           stopped after 2000 iterations
```

Tricks of the trade

Activation function An MLP usually trains faster if the activation function is anti-symmetric g(-z) = -g(z) (e.g., the tanh)

Target values should not be the asymptotic values of the activation function, but leave a margin

Input values should be preprocessed so that:

- 1. their mean value is zero and their stdev is 1 (use standardization)
- 2. they are uncorrelated (use PCA)

Initial weights should be small and zero-centered, to avoid initially driving the neurons into saturation

Tricks of the trade

On-line vs. Batch

- On-line training is much faster —particularly in large redundant datasets— and often results in better solutions. It can also track changes in the data
- Batch training is better understood (convergence) and can be accelerated using second-order nformation; it is not sensitive to the ordering of examples

Today we call **mini-batches** (different) subsets of training observations used in consecutive epochs.

Number of hidden neurons

- While the number of inputs and outputs are dictated by the problem, the number of hidden neurons is not directly related to the application domain (it largely remains an unsolved problem)
 - 1. A small number may not be sufficient (underfitted model)
 - 2. A large number may be too much (overfitted model)
- Many methods abound: constructive (e.g., cascade correlation), pruning (e.g., optimal brain damage), golden search, ...
- Arguably the best method (it is more principled and arguably faster)
 is to use a large number and regularize the network

Number of hidden neurons

In order to find the best one-hidden-layer network architecture, there are two simple and common methods:

- Explore different numbers of hidden, with no regularization
- Fix a large number of hidden units, and explore different regularization values
- Both at the same time is not a sensible thing to do and usually a waste of computing resources