

Multilayer perceptrons

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1 Introduction

In this laboratory work you will study multilayer perceptrons (MLPs). The study is performed in low dimensional weight and pattern spaces to make visualization easy.

We start in Section 2 to consider the MLP as a function approximator that is defined by its parameter values (weights and biases) and we examine how these parameters influence the functions implemented by the nets. In Section 3 we examine how the parameter adjustments, i.e., the training is performed in the MLP. In Section 4 we examine how the MLP can be viewed as a discriminant function, solving pattern recognition problems. A comparison between the optimal discriminant function (given by Bayes' decision theory) is also performed. In this section we also examine how the performance of MLP for solving a pattern recognition problem is influenced by the number of examples in the training data.

In the beginning of each section, there is a short list of goals that you should reach. There is also a list of matlab scripts that act more or less as demos. Running these demos should help you reach the goals. Note that you sometimes might need to run the scripts a number of times with different parameter settings to get the most out of them.

2 The connection between MLP weights and the function implemented by the net

Scripts to run: `demoMLPfunc1`, `demoMLPfunc2` and `demoMLPfunc3`.

Goals:

- You should be able to sketch the function implemented by a 2-layer MLP with known weights, both for functions with 1-d and 2-d input.
- You should find the Universal Function Approximation Theorem easy to accept.

- You should understand the concept of “weight-space symmetries”.

3 Training of MLPs

Scripts to run: `demoSD`, `demoLR1`, `demoLR2`, `demoLR3`.

Goals:

- You should understand the basic disadvantages of steepest descent.
- You should know how adaptive learning rate can be used to speed up convergence.
- You should understand why the Levenberg–Marquard method converges in one iteration in `demoLR3`.

4 The MLP as a discriminant function

4.1 Separation properties and approximation of posterior probabilities

Scripts: `demosepprop`, `bayescompare`.

Goals:

- You should realize the connection between the complexity of the net and what type of decision boundaries that can be “built”.
- You should understand under what conditions an MLP can approximate posterior class probabilities.

4.2 Overtraining

Goals:

- You should understand in what sense an MLP with many degrees of freedom (many hidden neurons) can act as a “look-up table” when used as a classifier.

Scripts: `overtraining1` and `overtraining2`