UNIVERSITY OF WEST BOHEMIA

MASTER THESIS

Optimization of Neural Network

Author:
Martin BULÍN MSc.

Supervisor:
Ing. Luboš ŠMÍDL Phd.

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Declaration of Authorship

I, Martin Bulín MSc., declare that this thesis titled, "Optimization of Neural Network" and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
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- I have acknowledged all main sources of help.

Signed:

Date:

"*Look deep into nature, and then you will understand everything better.*"

A. Einstein

UNIVERSITY OF WEST BOHEMIA

Abstract

Faculty of Applied Sciences
Department of Cybernetics

Engineer (Ing.)

Optimization of Neural Network

by Martin BULÍN MSc.

abstract text...

Acknowledgements

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AI	**A**rtificial **I**ntelligence
ANN	**A**rtificial **N**eural **N**etwork

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Chapter 3

Examples

The pruning algorithm is presented on several examples, where each of them has its purpose of being shown. The XOR problem (section 3.1) should verify the ability of finding an optimal network structure. Section 3.2 comes with another 2D problem, where one feature carries more information than the other one. The Rule-plus-Exception problem in section 3.3 deals with a minority of samples that has to be treated by a different net part than rule-based samples. The train problem (section 3.4) is a working example of feature selection procedure. The MNIST database (section 3.5) is widely used in machine learning and can be regarded as commonly known. Therefore it is a good example for presentation of new methods. Finally, in section 3.6 the pruning algorithm is applied on a large dataset of phonemes.

3.1 2D-problem: XOR Function

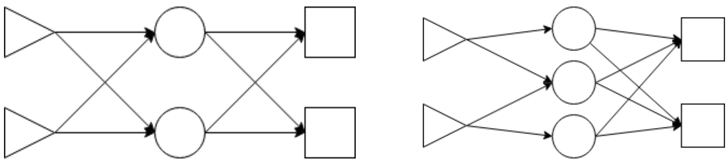
The standard Exclusive OR (XOR) function is defined by truth Table 3.1. Based on this function one can build a classification problem with two features and two classes.

x_1	x_2	y
0	0	0
0	1	1
1	0	1
1	1	0

TABLE 3.1: XOR function.

This problem serves perfectly for demonstration of network optimization methods, as two optimal architectural solutions producing the XOR function are known (Fig. 3.1) [1].

[1]The known (e.g. from (Bradley, 2006)) minimal network architectures producing the XOR function $[2, 2, 1]$ and $[2, 3, 1]$ are adjusted to $[2, 2, 2]$ and $[2, 3, 2]$ in Fig. 3.1 in order to comply with the conventions introduced in chapter 2. The number of output neurons always equals the number of classes. The number of synapses connected to the output layer is a subject to think about.



(A) Solution A. (B) Solution B.

FIGURE 3.1: Optimal network architectures producing the XOR function.

With this knowledge we can prove that the pruning algorithm is (or is not) able to find the optimal solution. If the method is correct, it should end up with one of the shown architectures (Fig. 3.1a or Fig. 3.1b).

The truth Table 3.1 ruled the generation of a 2D dataset illustrated in Fig. 3.2. The two classes can be linearly separated by two lines (two neurons, see Fig. 3.1a) and each class consists of 1000 samples. Each sample was randomly assigned to one of the two possible points belonging to its class (e.g. (0,0) or (1,1) for class 0) and then randomly placed in the surounding area within a specified range ($r = \frac{\sqrt{2}}{4}$).

The samples of each class were then splitted into three sets in the following manner: 80% to a training set, 10% to a validation set and 10% to a testing set.

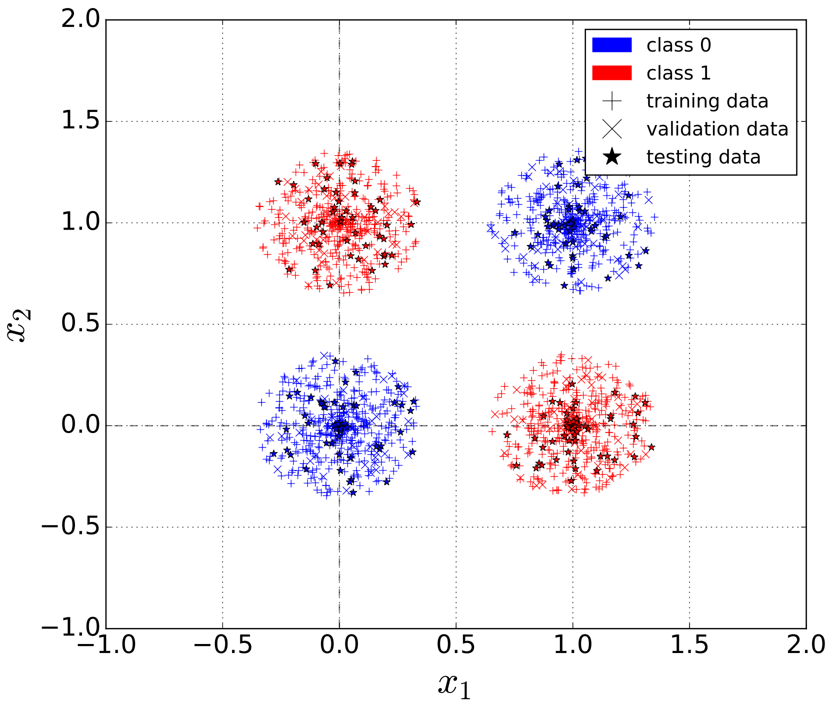


FIGURE 3.2: The XOR dataset.

The goal of this example is to show that the pruning algorithm finds one of the known minimal network structures (Fig. 3.1). An oversized network $[2, 50, 2]$ is used as the starting point. The following Table 3.2 shows all the experiment settings.

initial network		*learning parameters*		*pruning parameters*	
structure	[2, 50, 2]	learning rate	0.3	required accuracy	1.0
transfer fcn	sigmoid	number of epochs	50	retrain	True
		minibatch size	1	retraining epochs	50

TABLE 3.2: Experiment settings for XOR dataset.

Results: XOR Function

Fig. 3.3 describes the pruning process. We can see the number of synapses (starting with 200 for fully-connected structure $[2, 50, 2]$), the network structure and classification accuracy at single pruning steps (see [PA]). When the required accuracy (1.0) was not reached, the corresponding steps are transparent in the figure, indicating they were forgotten.

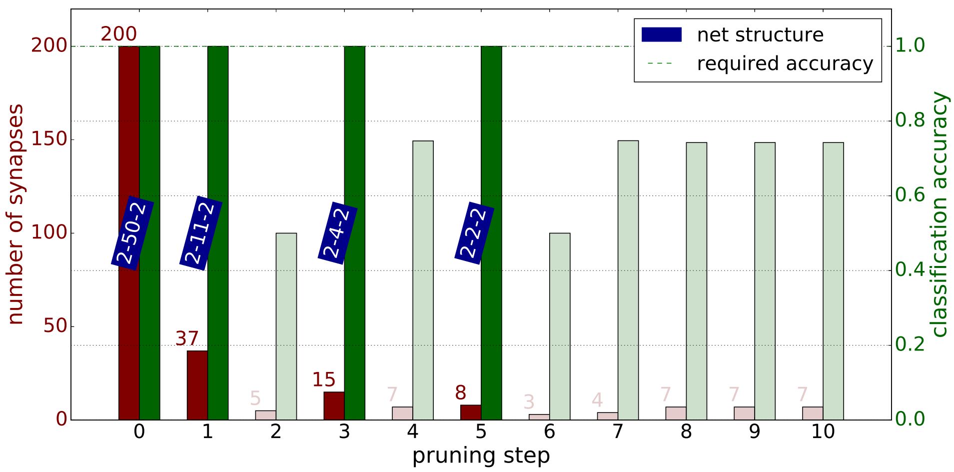
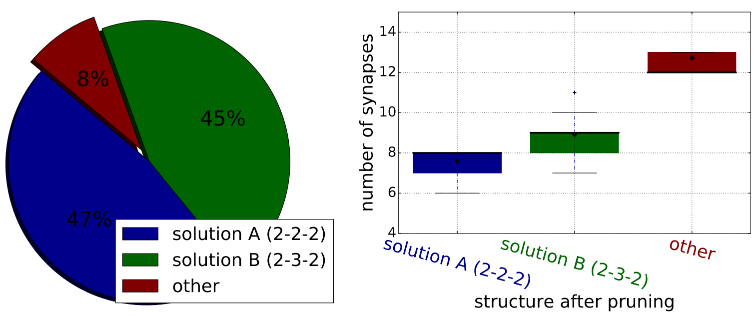


FIGURE 3.3: Illustration of the pruning procedure applied on XOR dataset (selected observation).

In Fig. 3.4 the hypothesis of this experiment is confirmed. In Fig. 3.4a we can see that in 47 out of 100 cases the pruning algorithm changed the network to $[2, 2, 2]$ architecture (Fig. 3.1a), in 45% of the cases it resulted with $[2, 3, 2]$ (Fig. 3.1b) and only in 8% it failed to find the optimal architecture. Fig. 3.4b gives statistics for the final number of synapses in these three cases.



(A) Network structure after pruning (100 observations).

(B) Number of synapses after pruning (100 observations).

FIGURE 3.4: Pruning results for XOR dataset.

3.2 2D-problem: Unbalanced Feature Information

This example is adopted from (Karnin, 1990). The problem is again two-dimensional having two non-overlapping classes as depicted in Fig. 3.5. The samples are uniformly distributed in $[-1, 1]$ x $[-1, 1]$ and the classes are equally probable, separated by two lines in 2D space ($x_1 = a$ and $x_2 = b$, where $a = 0.1$ and $b = \frac{2}{a+1} - 1 \approx 0.82$). Clearly, the problem can be solved by two neurons, similarly as the previous one.

What is interesting about this two-classes layout is that feature x_1 is much more important for the global classification accuracy than feature x_2. Having x_1 information, based on Fig. 3.5 one could potentially classify more than 90% of the samples. Opposite of that, we cannot say much with information from feature x_2 only. And this is something what also the pruning algorithm should find out.

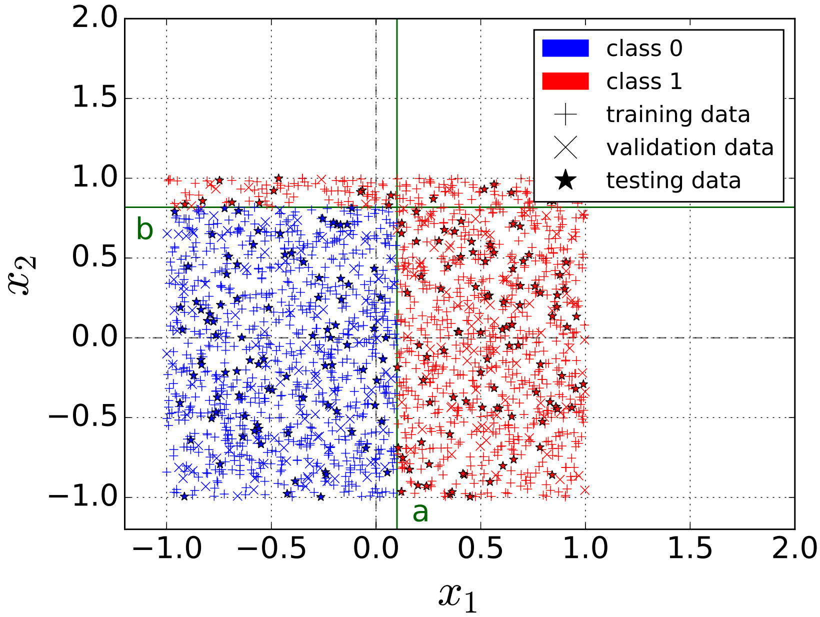
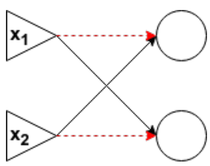
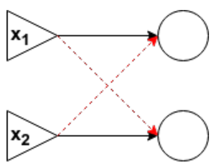


FIGURE 3.5: Dataset with unbalanced feature information.

Hence, we focus on synapses connecting the input and hidden layer. We know the required network structure is $[2, 2, 2]$, as two lines are needed to separate the data in 2D space. Actually, we even know the lines must be parallel to coordinate axes, which means that each of the hidden units needs one of the features only. Therefore, the first hypothesis here is that pruning of input-hidden synapses should result in one of the cases in Fig. 3.6.



(A) Pruning result 1.



(B) Pruning result 2.

FIGURE 3.6: Expected pruning of input-hidden synapses.

To prove this behaviour, we ran an experiment with settings in Table 3.3.

initial network		*learning parameters*		*pruning parameters*	
structure	[2, 2, 2]	learning rate	0.7	required accuracy	0.98
transfer fcn	sigmoid	number of epochs	50	retrain	True
		minibatch size	1	retraining epochs	50

TABLE 3.3: Experiment settings for dataset with unbalanced feature information.

The second hypothesis is that the synapse connected to the first feature (x_1) is more important and therefore, the other synapse (the one connected to feature x_2) will always be removed first.

Results: Unbalanced Feature Information

In Fig. 3.7 the first hypothesis is confirmed. The pruning of input-hidden synapses finished with the result shown in Fig. 3.6a in 48 out of 100 observations and with the result in Fig. 3.6b in 44% of the cases.

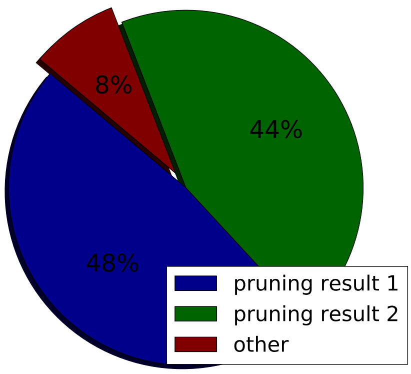


FIGURE 3.7: Results of pruning in input-hidden layer (100 observations).

In other words, with a probability of 92% the algorithm is able to find the axes-parallel lines and reveals that each of the lines needs information from one feature only. In the remaining 8% of the cases the pruning resulted with more than two input-hidden synapses.

The second hypothesis is confirmed in Fig. 3.8. As we can see, the coefficient of synapses's significance was always (100 observations) greater for the synapse coming from feature x_1 than for the synapse connected to x_2. By definition (see [PA]), the pruning method eliminates the synapses with low coefficients first, therefore information coming from feature x_1 would live longer in the network than x_2 information.

This result is not surprising at all. Having w_{r1} the weight of synapse connecting the x_1 feature and r^{th} hidden neuron (with bias b_r) and w_{s2} the weight of synapse coming from feature x_2 to s^{th} hidden neuron (with bias b_s), then by neuron definition (Rosenblatt, 1958) we created two lines, perpendicular one to each other.

$$w_{r1} \cdot x_1 + 0 \cdot x_2 + b_r = 0 \tag{3.1}$$
$$x_1 = -\frac{b_r}{w_{r1}} \tag{3.2}$$
$$0 \cdot x_1 + w_{s2} \cdot x_2 + b_s = 0 \tag{3.3}$$
$$x_2 = -\frac{b_s}{w_{s2}} \tag{3.4}$$

The feature vectors are normalised (described in chapter 2) and in Fig. 3.5 we see that $|b| > |a|$, hence we want:

$$|-\frac{b_s}{w_{s2}}| > |-\frac{b_r}{w_{r1}}| \tag{3.5}$$
$$\frac{|b_s|}{|w_{s2}|} > \frac{|b_r|}{|w_{r1}|} \tag{3.6}$$
$$|w_{s2}| < |w_{r1}| \tag{3.7}$$

Out of this we expect greater magnitudes for weights of more important synapses - so the magnitude measure [eqref] would fit here.

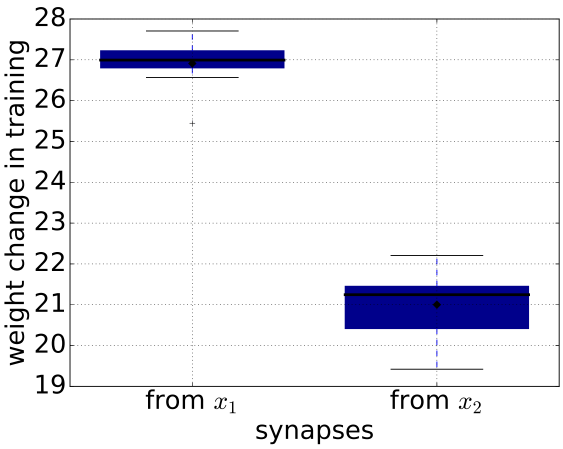


FIGURE 3.8: Weight change in training for the remaining synapses in the input-hidden layer (100 observations).

However, as we do not use a weight decay (see the learning approach in chapter 2), in general the more epochs we learn the greater the weight magnitudes are. Therefore small initial weight values does not effect the result significantly and so we can state:

$$|w_{ji}| \approx |w_{ji} - w0_{ji}| \tag{3.8}$$

where $w0_{ji} \in [0, 1]$ is the initial value of weight w_{ji}. Summing it up we can say that the *kitt* measure [ref] based on weight change is equally good as the magnitude measure assuming enough training epochs (e.g. 50).

3.3 The Rule-plus-Exception Problem

This four-dimensional problem is originally adopted from (Mozer and Smolensky, 1989) and is also used in (Karnin, 1990). The task is to learn another Boolean function: $AB + \overline{ABCD}$. A single function output should be on (i.e. equals 1) when both A and B are on, which is the *rule*. It should also be on when the *exception* $\overline{ABCD}$ occurs.

Clearly, the *rule* occurs more often than the *exception*, therefore the samples corresponding with the *rule* should be more important for the global classification accuracy. The hypothesis is that the pruning method will reveal the part of network, which deals with the *exception*, to be eliminated first - before the part of network dealing with the *rule*.

Results: The Rule-plus-Exception

3.4 The Train Problem

The Michalski's train problem...

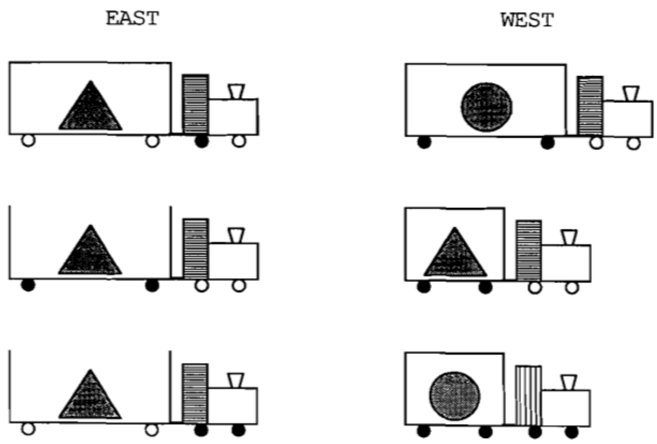


FIGURE 3.9: Michalski's train problem.

3.5 Handwritten digits (MNIST)

MNIST data... (LeCun and Cortes, 1998)

3.6 Phonemes (Speech Data)

PHONES data...

Chapter 4

Discussion

Discussion text...

4.1 Methods Recapitulation

Methods recapitulation text...

4.2 Comparison of Pruning Methods

Comparison of results text...

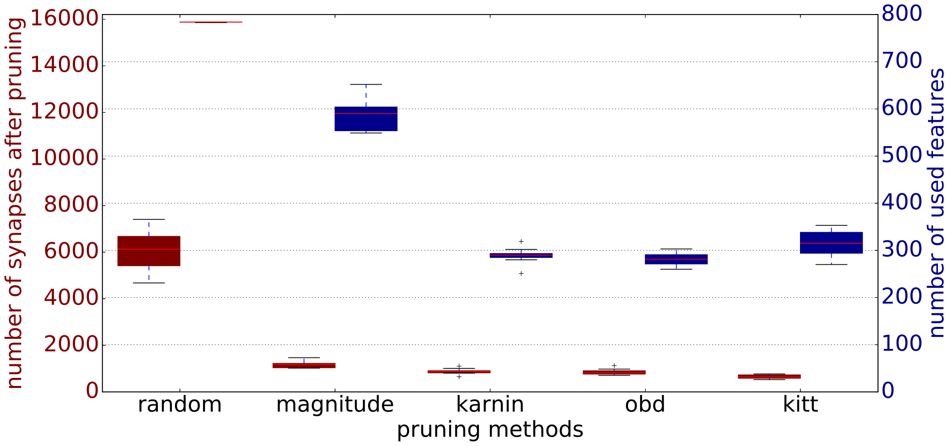


FIGURE 4.1: MNIST, req_acc = 0.95, retraining: 5 epochs

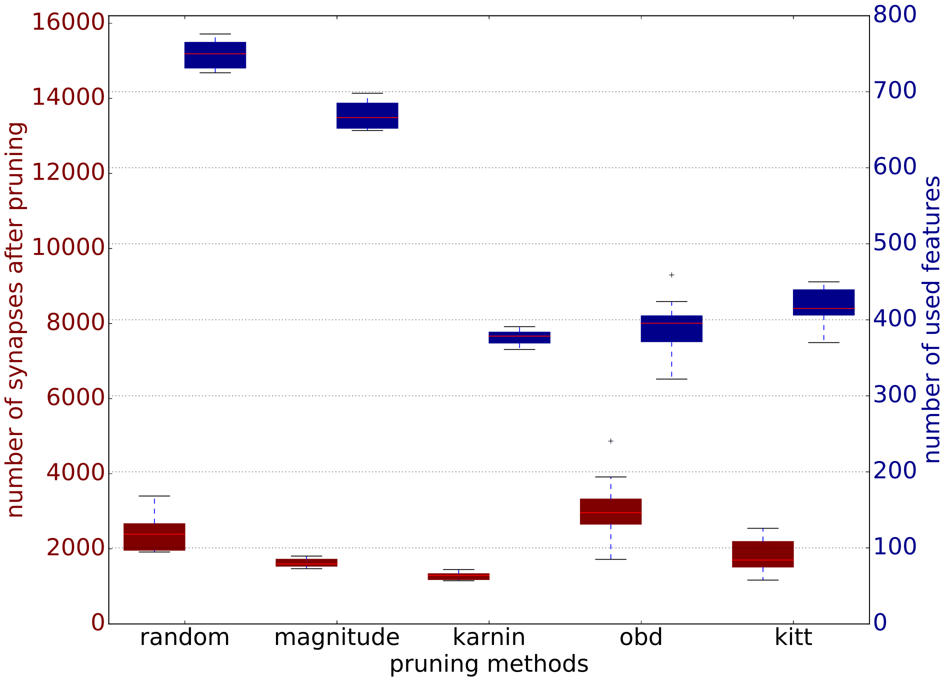


FIGURE 4.2: MNIST, req_acc = 0.95, no retraining

Chapter 5

Conclusion and Outlook

Conclusion text...

Outlook text... shrinking layers?

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Appendix A1

Structure of the Workspace

Appendix A2

Implementation

Appendix A3

Code Documentation