Artificial neural networks

Assignment 2: Bayesian learning in neural networks

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1 Context

Bayesian statistics offer a robust framework in which it is possible to build and assess models, and perform inference.

In this exercise, we explore bayesian learning applied to neural networks. Using the Bayes rule in the context of learning has several desirable properties related to the fact that one is not using point estimates in the search space of solutions (for example the weight space) but tries to obtain a distribution over the weight space. Hence, quantification of certainty of predictions is possible without the use of validation set or resampling.

2 Decision boundary of classifier

In this section, I investigated whether a simple bayesian approach (MAP) could classify correctly data generated by a perceptron (hence linearly separable). In terms of architecture, the perceptron created consisted of 1 neuron with 2 inputs taking values in $[-1; 1]$, without bias term. The output of the perceptron is in $\{-1, 1\}$

Figure 1 displays the classifiers on top of the dataset (top left-hand side figure). You can see that the classifier generated using the Bayes rule sits close to the perceptron used to generate the dataset. There seemed to be exceptions to that, and in a few cases the classifier was really off.

To note, starting with a gaussian prior, the convergence of the posterior through the iterative updates always entailed that one of the weight (w1 or w2) was set to 1, while the other varied. I did not see exception to that when running the script multiple times. The MAP weights of the bayesian classifier were often close to that of the perceptron, but given that there is an infinite amount of possible classifiers for this dataset, multiple combinations are possible. It also happened that the bayesian approach did not reach a 100% correct classification (see top left graph).

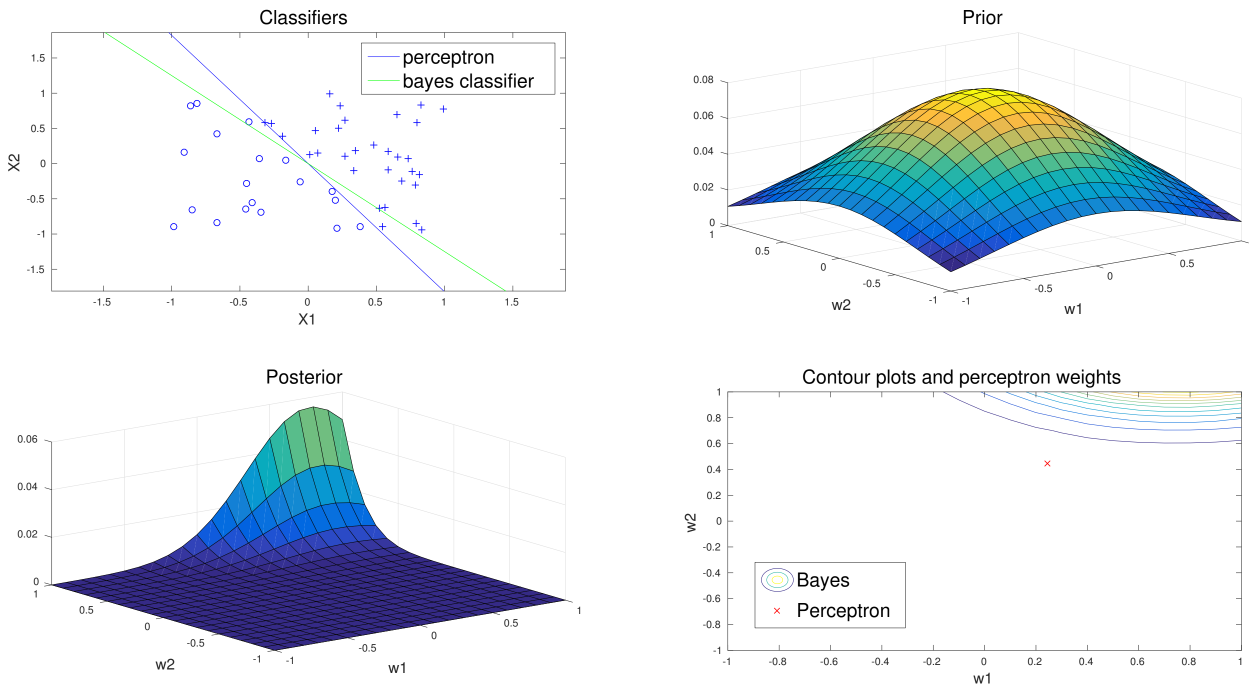

Figure 1: Comparison of perceptron and bayes classifier for dataset generated by perceptron

3 Function approximation

The underlying function considered in this section is $f(x) = sin(x)$, with some gaussian noise added for the training dataset. On figure 2, you can see the results of the function approximation using *trainlm* and *trainbr* using different amounts of neurons (but a fixed amount of epochs).

The effects of bayesian as regularization can be seen, as the overfitting seems lower compared to the *trainlm* approach.

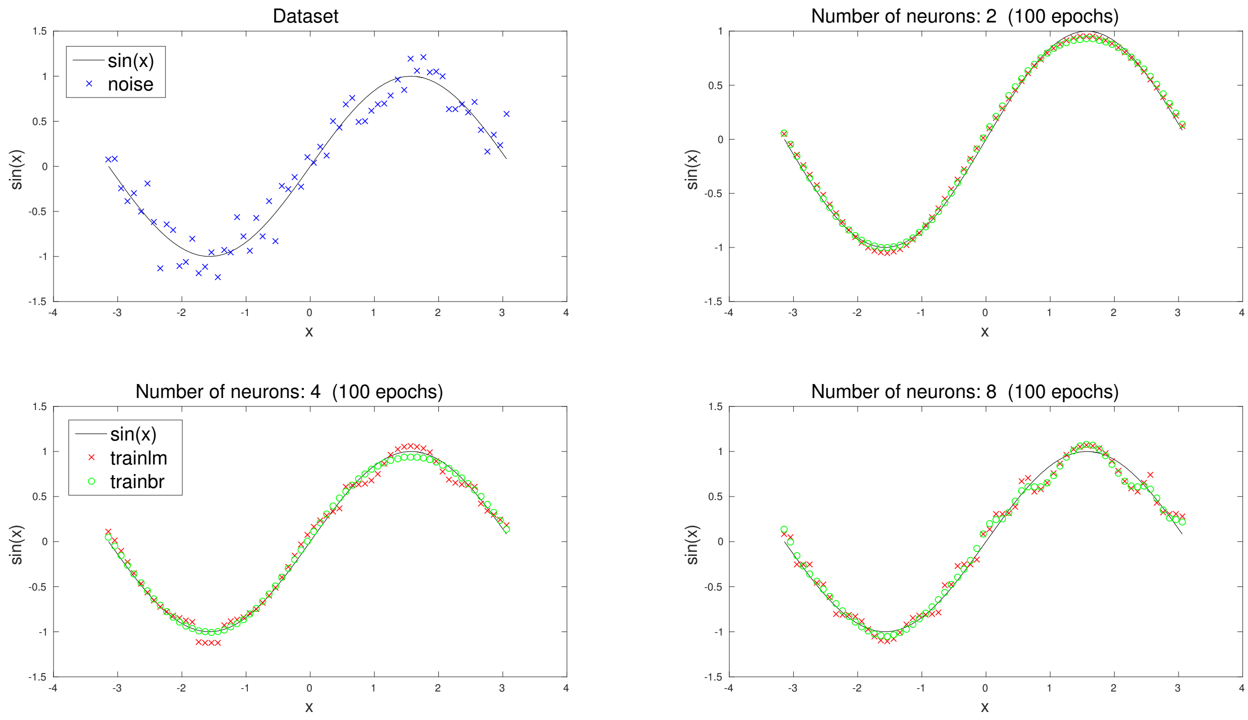

Figure 2: Influence of number of neurons on the function estimation
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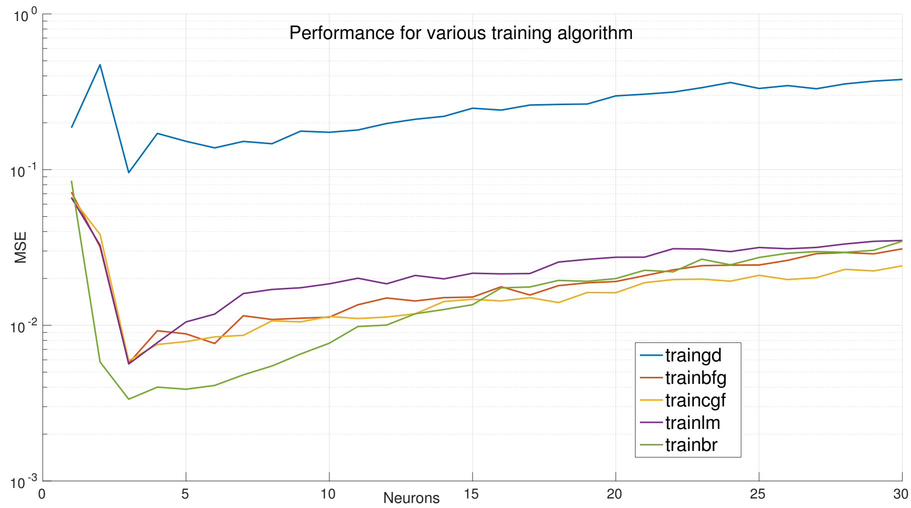
To investigate further, I took a look at the performance of the networks using the performance function MSE for different models. This is only possible because we know the true underlying function. Otherwise, I would have used a resampling approach, such as 10-fold cross validation. The results are reported on the right, for each architecture (parameter = number of neurons, and choice of training algorithm), I fixed the number of epochs to 1000, then proceeded to build 50 different datasets. For each, the performance was evaluated, and then averaged over the 50 datasets.



As can be seen on the plot above and on the right, the *trainbr* performs indeed well in the region of few neurons compared to other algorithms.