KATHOLIEKE UNIVERSITEIT LEUVEN

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Artificial Neural Networks & Deep Learning

Exercise Reports

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Contents

1 Supervised Learning and Generalization

1.3 In the Wide Jungle of the Training

Task 1.3.1

The noise parameter controls the deviation of the training data from the true function. Figure 1 shows the impact of noise on the optimization process. For $noise = 0$, the data exactly matches the true function and the model will converge to the true function quickly. For $noise > 0$, the data is perturbed by noise and the model will take longer to converge. For $noise = 1$, the data is completely random and the model will only converge to the mean of the training data without being able to capture the underlying function.

Task 1.3.2

Vanilla gradient descent is the slowest of the three methods. It computes the gradient of the loss function for the entire training set at each iteration. Stochastic gradient descent (SGD) is faster than vanilla gradient descent, because it computes the gradient for a random subset of the training data at each iteration. However it has a higher variance in the loss function. Accelerated gradient descent is the fastest of the three methods. It uses a momentum term to speed up convergence and reduce oscillations in the loss function.

Task 1.3.3

For small networks, vanilla gradient descent is sufficient, because the computation of the gradient is not very expensive. For larger networks, SGD is more appropriate due to its lower computational cost. Accelerated gradient descent is the best choice for very large networks, because it converges faster than the other two methods.

Task 1.3.4

The model is trained for 2500 epochs. In Figure 2, we can see that SGD with a learning rate of 0.05 and without momentum has an average training time, but very slow convergence. Using a learning rate of 0.1 already converges much faster, but also takes longer to compute. Momentum has a similar convergence rate and is much quicker to compute, but also has high variance. The Adam and the LBFGS optimizers converge the fastest, but LBFGS has the longest computational time. The Adam optimizer is the best choice for this problem, because it converges quickly and has low variance. All optimizers except for vanilla SGD with learning rate 0.05 can be considered to have converged after at most 1000 epochs.

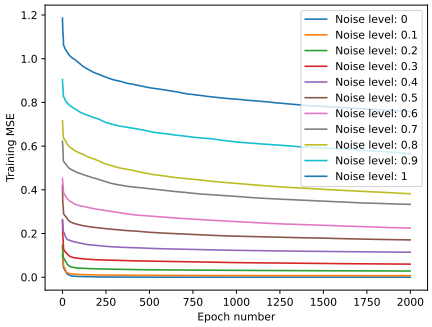


Figure 1: Impact of noise on the optimization process

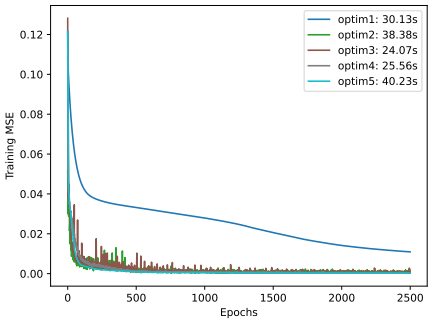


Figure 2: Comparison of optimizers

A bigger model

Task 1.3.5

The model has 34826 parameters in total as shown in Table 1.

Layer Type	Shape	# Param
(Input)	(28, 28, 1)	0
Conv2D	(26, 26, 32)	320
MaxPooling2D	(13, 13, 32)	0
Conv2D	(11, 11, 64)	18496
MaxPooling2D	(5, 5, 64)	0
Flatten	(1600,)	0
Dropout	(1600,)	0
Dense	(10,)	16010
Total		**34826**

Table 1: Model parameters

Task 1.3.6

The SGD optimizer has a much slower convergence rate than the Adam optimizer as shown in Figure 3. The Adadelta optimizer achieves very good performance after the first epoch already and has a low variance. The Adam optimizer is in between the two in terms of convergence rate and variance. Compared to the Adam optimizer, the Adadelta optimizer does not require a learning rate to be set, because it uses the gradient and the average of the squared gradient over a window of time steps to adapt the learning rate.

1.4 A Personal Regression Exercise

Task 1.4.1

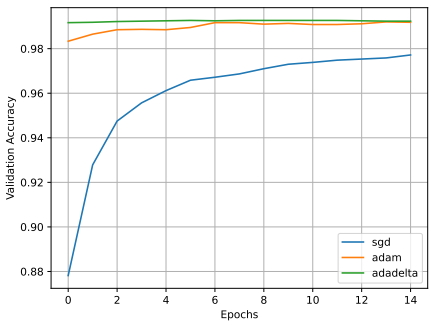


Figure 3: Validation accuracy

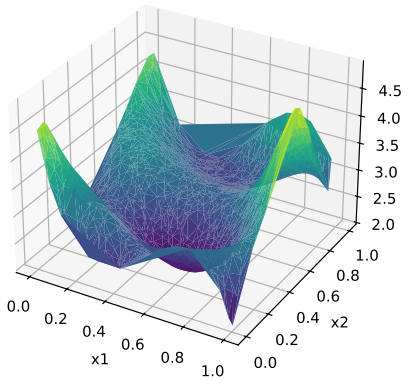


Figure 4: Function surface of the training data

If the same dataset is used for training and testing, the model will overfit the data and not generalize well to unseen data. Moreover, the evaluation of the model will be biased, because the model has already seen the test data during training. If two independent datasets are used, the performance on the test data corresponds more to real-world performance, where

the model has not seen the data before. Also, the performance on the test data will be bad, if the model has overfit the training data. The surface associated to the training set is shown in Figure 4.

Task 1.4.2

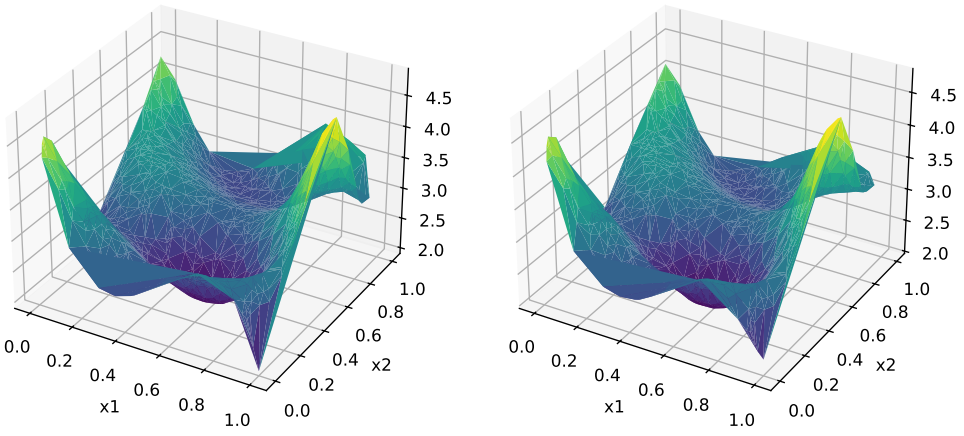
The model architecture is shown in Table 2. The choice of the activation functions seemed to have the biggest impact on the performance. The `mish` activation function performed much better than the other functions I tried. Increasing the number of layers and neurons also improved the performance. However, the model was overfitting the training data when using too many neurons. The choice of the optimizer and the learning rate did not have a big impact on the performance. Here, I used the Adam optimizer with a learning rate of 0.05. All choices were validated by calculating the mean squared error on the test data.

Layer Type	Shape	Activation Function	# Param
Dense	(16)	mish	48
Dense	(16)	mish	272
Dense	(16)	tanh	272
Dense	(1)	(None)	17
Total			**609**

Table 2: Regression model parameters

Task 1.4.3

The surfaces of the test data and the predicted data are shown in Figure 5. The model has already converged and further training would not improve the performance. The final mean squared error on the test data is 0.0017132.



(a) Test data (b) Predicted

Figure 5: Function surface

Task 1.4.4

I used early stopping to avoid overfitting. The training was stopped when the validation loss did not improve for 10 epochs. Another strategy to avoid overfitting is to use dropout layers, which sets a few neurons to zero during training.

2 Recurrent Neural Networks

2.1 Hopfield Networks

Task 2.1.1

All of the attractor states $[1, 1]$, $[-1, -1]$ and $[1, -1]$ are reached after a few iterations, as shown in Figure 6. We also get the unwanted attractor $[-1, 1]$ because the network is not able to distinguish between the patterns $[1, -1]$ and $[-1, 1]$. The ten random points in Figure 6 converged after an average of 8.6 iterations. The attractors are stable, as further iterations do not change the state of the network. However, if initial points are placed exactly in the middle between two attractors, they stay unaffected by updates, as shown in Figure 7. These points are additional attractors, which are not part of the target patterns. They are unstable, as small perturbations will make the network converge to one of the stable attractors.

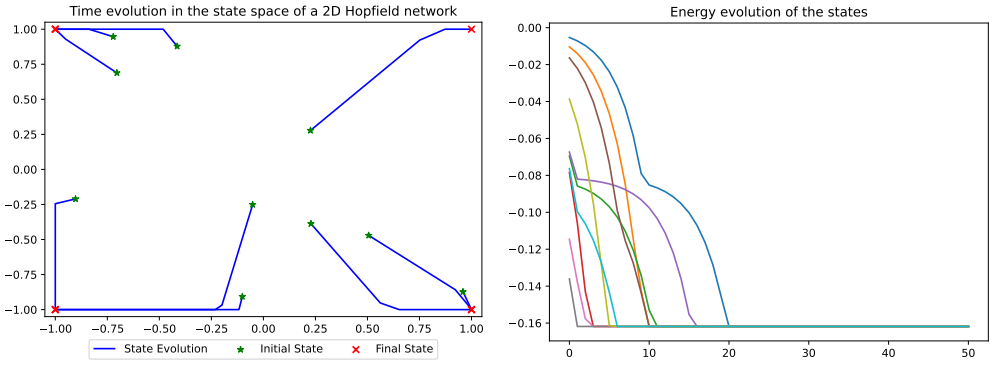


Figure 6: 2D network: random inputs

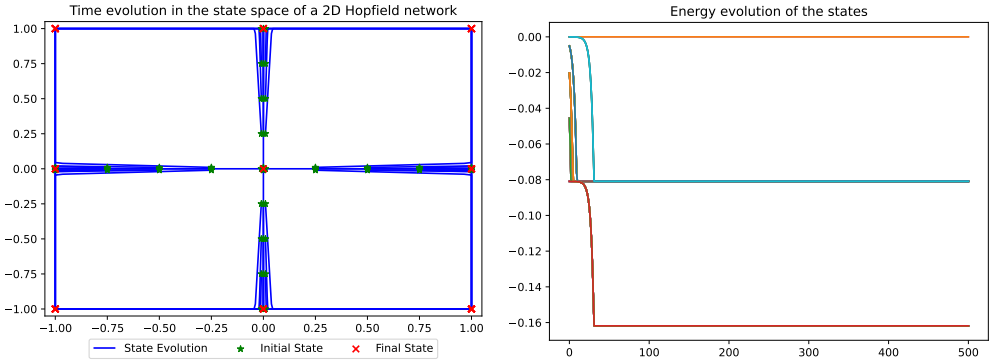


Figure 7: 2D network: inputs close to local minima

Task 2.1.2

For the 3D network, all the target patterns $[1, 1, 1]$, $[-1, -1, 1]$ and $[1, -1, -1]$ are reached, as shown in Figure 8. No additional attractors are found. The average number of iterations is 11.7. All of the attractors are stable, even if the initial points are placed exactly in the middle between two attractors, as shown in Figure 9. The simulated points first move

towards the plane that goes through all three attractors, and then moves along this plane to the closest attractor.

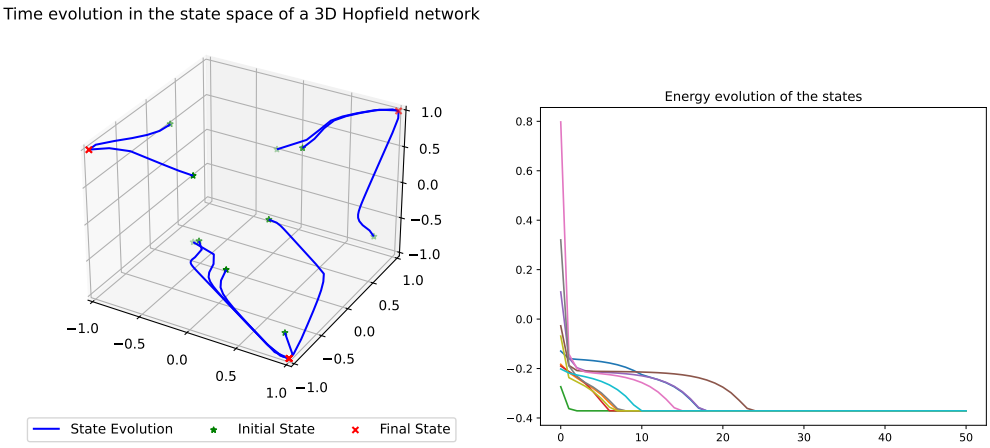


Figure 8: 3D network: random inputs

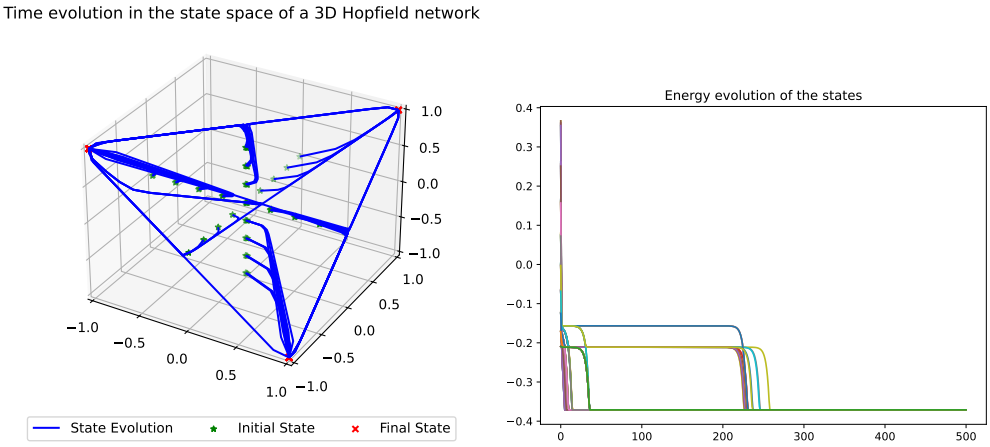


Figure 9: 3D network: inputs close to local minima

Task 2.1.3

For 100 iterations, the network is able to reconstruct the noisy digits for noise levels up to 5. Above this level, a few digits converge to the wrong attractor. Some digits are less robust to noise than others. For example, the digit 7 is often reconstructed as a 3. Also, with less iterations, the network often does not fully converge to an attractor. This leaves traces of the noisy input in the reconstructed digit. For a good reconstruction with a noise level of 5, the number of iterations should be at least 40. For a noise level of 1, the network is able to converge after only 4 iterations.

2.2 Timeseries Prediction

Task 2.2.1

Task 2.2.2

Task 2.2.3

[1]

References

[1] Adam Ries. *Rechenung auff der Linihen und Federn*. Hans Schönsperger, Annaberg, 1522.

A Benutzerdokumentation

B Introduction