Deep Learning in Biological and Artificial Neuronal Networks
Assignment 2

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1 Part II: Feedback Alignment

1.1 Experiments with feedback alignment

1.1.1 Linear case

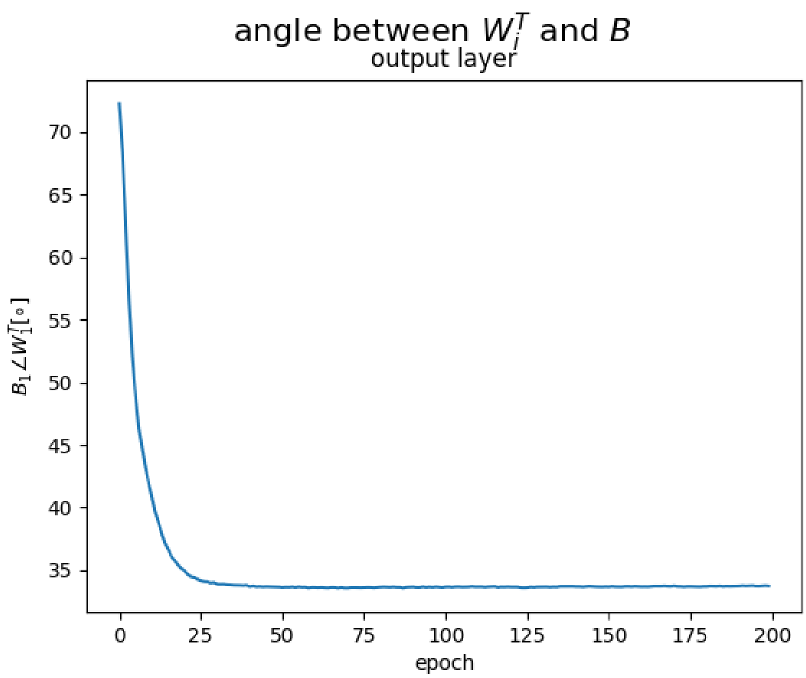
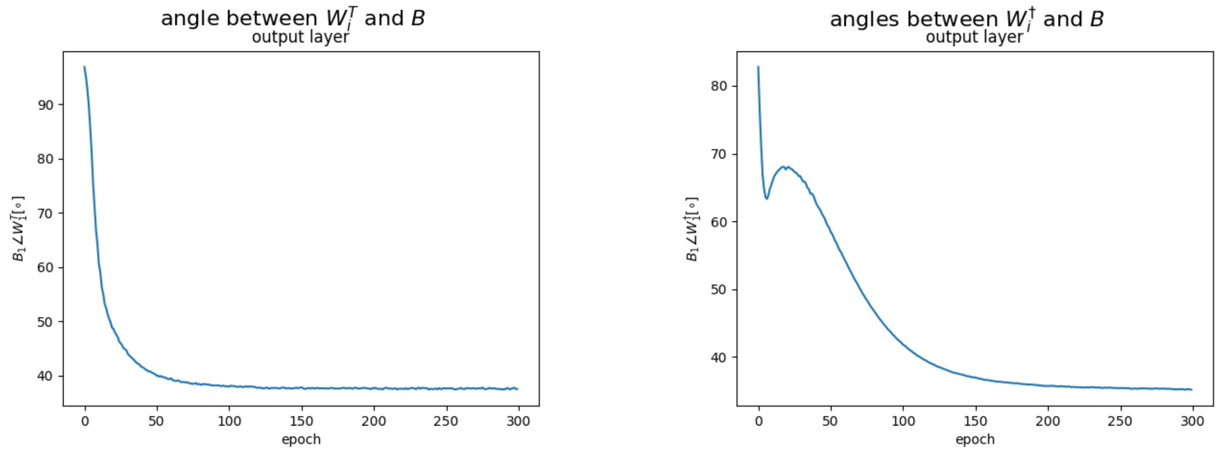


Figure 1: Plot of the Angle between B and W^T

From Figure 1, we know that the Feedback Alignment succeeds in diminishing the loss of the network by aligning the feedback weights B to be close to the transpose of the forward weight matrix W^T. Since the backward pass for backpropagation involves multiplying the backpropagated error term e by W^T, making B sufficiently close to W^T will allow the network to minimize its loss.

1.1.2 Non-linear case

From Figure 2, we can see that the Feedback Alignment also works in the non-linear case as the angles between the feedback weights B and the transpose of the forward weight W^T, as well as its pseudo-inverse, W^+, decrease over the training epochs.

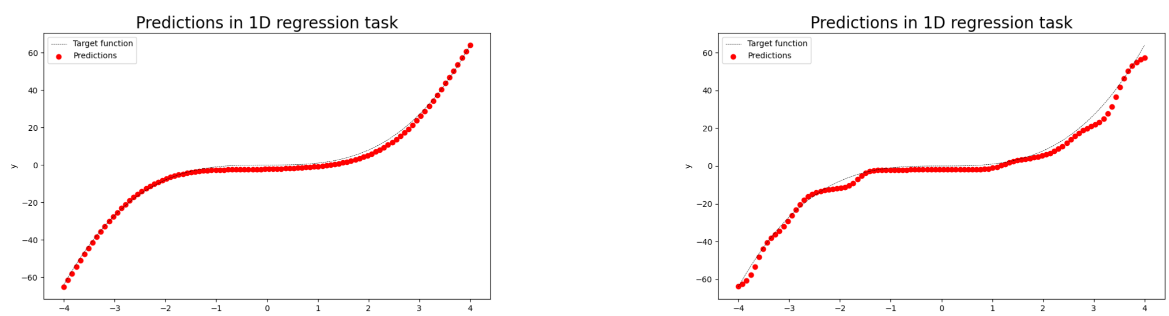


(a) Angle Between W^T and B (b) Angle between W^+ and B

Figure 2: Alignment of the forward weights W and the feedback weights B in non-linear case

When we train the same network for the non-linear student-teacher regression task with backpropagation, we observe that the network trained with backpropagation achieves a lower test Mean-Squared Error (MSE) of 0.00925 as compared to 0.0126 for Feedback Alignment. One possible reason for this is that in Feedback Alignment, the weights used during the backward pass, B, are not perfectly aligned with the transpose of the forward weights W^T.

1.2 Polynomial Fitting



(a) Feedback Alignment (b) Backpropagation

Figure 3: Polynomial fitting with Feedback Alignment and Backpropagation

Method	Mean-Squared Error	
	Train	Test
Feedback Alignment	2.769	**1.390**
Backpropagation	**1.958**	3.626

Table 1: Comparison of train and test MSE between feedback alignment and backpropagation

From Figure 3, we can observe that the predictions yielded by the Feedback Alignment is more accurate and closer to the target polynomial curve compared to the predictions from the network trained with backpropagation. We believe the network trained using backpropagation is overfitting to the training set compared to the network trained with feedback alignment. From Table 1, we can see that while backpropagation achieves a lower training MSE (1.958) than feedback alignment (2.769), it also yields a larger test MSE (3.626) than feedback alignment (1.390).

One possible explanation for why the network trained with backpropagation overfits more than the network trained with Feedback alignment could be that the addition of the random feedback weights B acts as a regularizer term for the neural network that reduces the 'capacity' of the model. This could in a way also explain why Feedback Alignment does not perform as well as Backpropagation on the non-linear regression task and generally does not scale with network size and task difficulty.