Authors:

- Mhd Jawad Al Rahwanji - 7038980 - mhal00002@stud.uni-saarland.de
- Christian Singer - 7039059 - chsi00002@stud.uni-saarland.de

Exercise 6.3 - Reading exercise (Bonus)

Hinton discussed a new learning approach, namely, the Forward-Forward algorithm (FFA) for neural networks replacing backpropagation (BP), and demonstrated that it works well on a few toy problems. As opposed to BP which pushes data through the network, computes the loss and updates the weights through a backward pass, FFA relies on two forward passes, one with positive data and the other with negative data. In the former, correct labels are encoded into the inputs, while in the latter, wrong labels are used instead. Then, a loss function (i.e. the sum of squared activities) is used which maximizes activation for good data and minimizes activation for bad data within one layer. It is necessary to normalize layer activity to stabilize the network. To sum up, during training, good and bad data pass through the network; weights are updated in each layer accordingly. As for inference, we pass new input multiple times each encoded with a different label and see which label achieves the highest activity. Benefits of FFA: a) Unlike BP, FFA doesn't require the forward pass to be differentiable which allows for fast-and-slow learning, b) FFA can be easily implemented with power-efficient circuits and c) FFA inherently leverages unsupervised learning as it learns about the task when fed corrupt data as bad data. Similar to BP, it was shown that FFA can take on sequence learning, and that it relates to Boltzmann machines, GANs and other contrastive learning techniques. We end with this… How dependent is FFA on the nature of bad data in various tasks, and how much overhead does that introduce from a practical standpoint?

References

1. Hinton, G. (2022). The Forward-Forward Algorithm: Some Preliminary Investigations.
2. Görner, M. (2022), *Thread*, Twitter, accessed 21 December 2022, <twitter.com/martin_gorner/status/1599755684941557761>