

Gradient based optimization methods in Feedforward Neural Networks (topic presentation)

Julius Lind

14.06.2019

Advisor: Prof. *Harri Ehtamo*

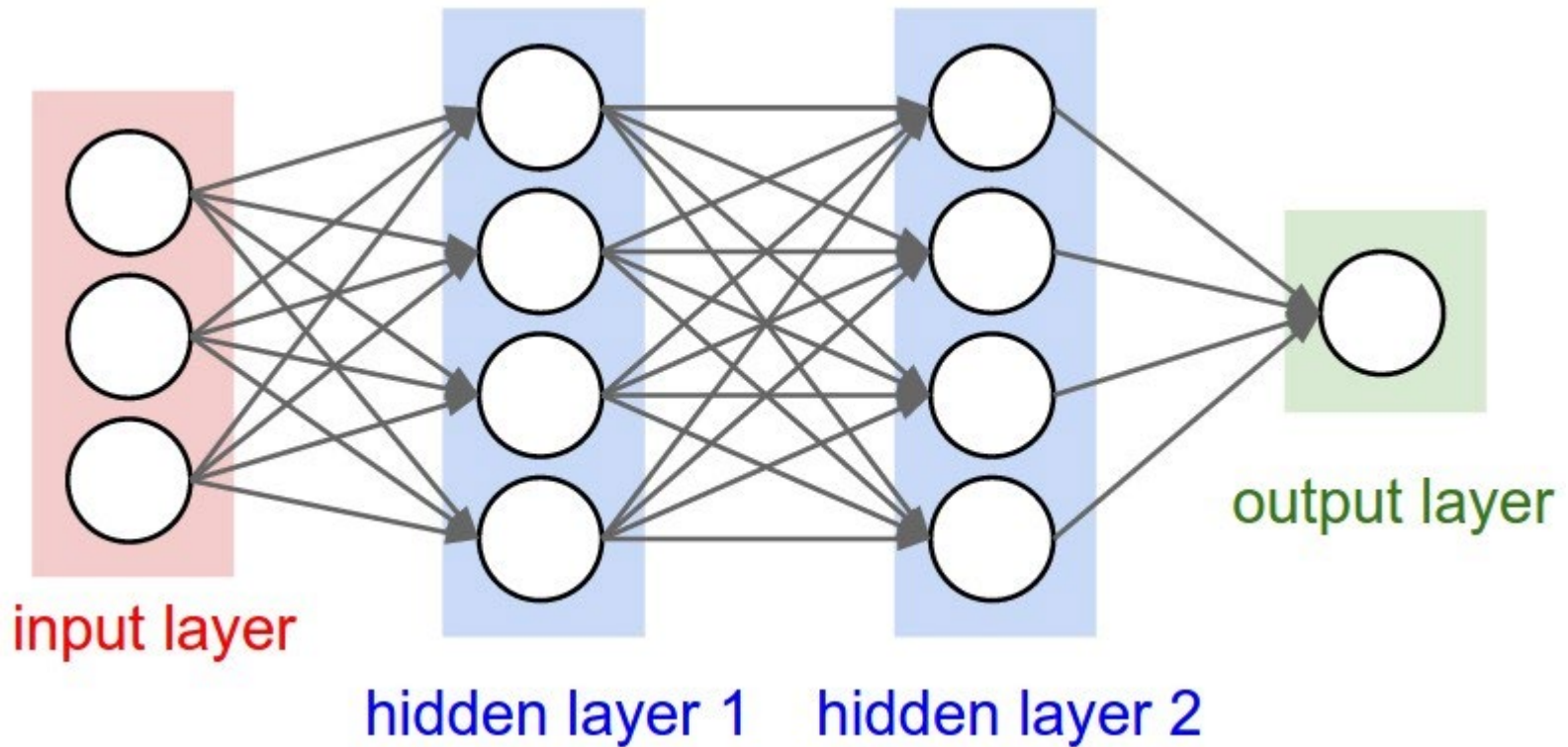
Supervisor: Prof. *Harri Ehtamo*

Työn saa tallentaa ja julkistaa Aalto-yliopiston avoimilla verkkosivuilla. Muilta osin kaikki oikeudet pidätetään.

Background

- Feedforward neural networks are a class of Artificial Neural Networks (ANN)
- ANNs can be used for:
 - Image classification
 - Machine translation
 - Regression tasks
- Feed forward neural networks consist of an input layer, an output layer, and optional hidden layers in between
- Input data (X, y)
- Each layer applies a transformation on its inputs, and feeds it to the next layer:

$$z = \sigma(AX + b)$$



Adapted from Stanford course CS231n Convolutional Neural Networks for Visual Recognition, [accessed 01.06.2019](#)

Background

- Output z compared to the target output y to compute loss:
 - $\text{MSE} = \frac{1}{n} \sum_{i=0}^n (y_i - z_i)^2$
- Optimization problem:
 - Minimize loss wrt. A, b
- Backpropagation
 - Use chain rule to calculate the gradient of the loss wrt. A, b
- Gradient can be used in gradient based methods to minimize loss
- Problems:
 - Large number of optimizable parameters
 - Large number of data points
 - Non-convex objective functions

Objectives

- Present training of feed forward neural networks as an optimization problem
- Present different gradient based optimization methods:
 - Gradient descent
 - Stochastic gradient descent
 - Momentum
 - Adaptive learning rates
 - Adam
- Test the performance of different gradient based methods on a large scale neural network
 - Final loss
 - Training time

Tools, Data and references

- PyTorch and Scikit-learn
 - Open source machine learning libraries for python
- MNIST dataset
 - Image classification dataset consisting of 60000 images of handwritten digits
- Ian Goodfellow, Yoshua Bengio, and Aaron Courville. Deep Learning. MIT Press, 2016.
- Sebastian Ruder. An overview of gradient descent optimization algorithms. arXiv e-prints, art. arXiv:1609.04747, Sep 2016

Schedule

- 14.06.2019: Topic presentation
- 06/2019: Literature review
- 07/2019: Performance tests
- 08/2019: Final presentation