Artificial Neural Networks (Gerstner). Exercises for week 8

Convolutional neural networks

Exercise 1. Backprop in convnet

Consider a very simple convolutional neural network with 3 dimensional input (e.g. RGB image), one convolution layer with 5x5x3 filters, stride 1, non-linearity σ and one linear layer, i.e.

$$a_{ijk} = b_k + \sum_{x=1}^{5} \sum_{y=1}^{5} \sum_{c=1}^{3} I_{i+x-1,j+y-1,c} w_{xyck}^{(1)}$$
(1)

$$x_{ijk}^{(1)} = \sigma(a_{ijk}) \tag{2}$$

$$\hat{y}_o = \sum_{ijk} w_{ijko}^{(2)} x_{ijk}^{(1)} \tag{3}$$

- a. With loss $L = \frac{1}{2} \sum_{o} (t_o \hat{y}_o)^2$, compute $\partial L / \partial w_{1111}$.
- b. Compare your result to the one you obtain with a dense (fully-connected) layer, i.e. $a_k = b_k + \sum_x \sum_y \sum_c I_{xyc} w_{xyck}^{(1)}, x_k^{(1)} = \sigma(a_k)$ and $\hat{y}_o = \sum_k w_{ok}^{(2)} x_k^{(1)}$.
- c. How does the result for the convolutional network change, if you introduce a max pooling layer after the convolutional layer?

Exercise 2. Computing volume sizes

Given a volume of width n, height n and depth c.

a. Show that the convolution with k filters of size $f \times f \times c$ with stride s and padding p leads to a new volume of size

$$\left(\frac{n+2p-f}{s}+1\right) \times \left(\frac{n+2p-f}{s}+1\right) \times k.$$
(4)

b. What padding p do you have to choose such that the input and output volumes have the same width and depth for stride s = 1. Check you result for the special case of n = 4 and f = 3.

Exercise 3. Reverse-mode automatic differentiation

The backprop algorithm derived above is a special case of an algorithm called *Reverse-mode automatic differentation*. Modern deep learning software packages rely on this algorithm, as it allows flexible exploration of different architectures and cost functions without having to adapt the standard BackProp algorithm for each special case. To understand reverse-mode automatic differentiation we look at the function

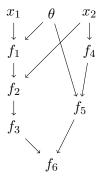
$$f(x_1, x_2, \theta) = \sin(\theta x_1 + x_2) + \theta x_2^2.$$
 (5)

Using the simple functions $f_1(x,y) = xy$, $f_2(x,y) = x + y$, $f_3(x) = \sin(x)$, $f_4(x) = x^2$, $f_5(x,y) = xy$ and $f_6(x,y) = x + y$, we can write the above function as

$$f(x_1, x_2, \theta) = f_6(f_3(f_2(f_1(x_1, \theta), x_2)), f_5(\theta, f_4(x_2))), \qquad (6)$$

that has the Abstract Syntax Tree (AST) or Computation Graph depicted on the right.

The reverse-mode Automatic Differentiation algorithm proceeds now as follows:



AutoDiff

- 1. Determine all children of the variable(s) of interest. In the example, using θ , this includes f_1, f_2, f_3, f_5, f_6 .
- 2. Find a reverse ancestral (backwards) schedule of nodes. All of the children of a node should be scheduled before the node itself. In the previous example with θ , the schedule could be $f_6, f_3, f_2, f_1, f_5, \theta$. For the full graph, this could be $f_6, f_3, f_2, f_1, x_1, f_5, \theta, f_4, x_2$.
- 3. Start with the first node n_1 in the reverse schedule and define $t_{n_1} = 1$, e.g. $t_{f_6} = 1$.
- 4. For the next node n in the reverse schedule, find the child nodes ch(n). Then define

$$t_n = \sum_{c \in ch(n)} \frac{\partial f_c}{\partial f_n} t_c \,. \tag{7}$$

- 5. The total derivative of f with respect to node n is given by t_n .
- a. Show that $t_{\theta} = \partial f / \partial \theta$ by following the steps of the algorithm, i.e. by computing t_6, t_3, \ldots , and comparing it to the result you get by differentiating Eq. 5 manually.
- b. Draw the AST of a fully connected network with 2 hidden layers and a single output, and convince yourself that the backpropagation algorithm is a special case of reverse-mode automatic differentiation.
- c. Draw the AST of a network with one 1D convolutional layer (with filter length 3 and stride 1), followed by one max-pooling layer (with k = 2), one dense layer, and a single output. For simplicity, assume only 1 filter is used in the convolutional layer.