

Machine Learning Exercise Sheet 09

Deep Learning

Homework

Problem 1: In machine learning you often come across problems which contain the following quantity

$$y = \log \sum_{i=1}^N e^{x_i}$$

For example if we want to calculate the log-likelihood of neural network with a softmax output we get this quantity due to the normalization constant. If you try to calculate it naively, you will quickly encounter underflows or overflows, depending on the scale of x_i . Despite working in log-space, the limited precision of computers is not enough and the result will be ∞ or $-\infty$.

To combat this issue we typically use the following identity:

$$y = \log \sum_{i=1}^N e^{x_i} = a + \log \sum_{i=1}^N e^{x_i - a}$$

for an arbitrary a . This means, you can shift the center of the exponential sum. A typical value is setting a to the maximum ($a = \max_i x_i$), which forces the greatest value to be zero and even if the other values would underflow, you get a reasonable result.

Your task is to show that the identity holds.

This is called the *log-sum-exp trick* and is often used in practice.

$$\begin{aligned}
 y &= \log \sum_{i=1}^N e^{x_i} \\
 e^y &= \sum_{i=1}^N e^{x_i} \\
 e^{-a} e^y &= e^{-a} \sum_{i=1}^N e^{x_i} \\
 e^{y-a} &= \sum_{i=1}^N e^{-a} e^{x_i} \\
 y - a &= \log \sum_{i=1}^N e^{x_i - a} \\
 y &= a + \log \sum_{i=1}^N e^{x_i - a}
 \end{aligned}$$

Problem 2: Similar to the previous exercise we can compute the output of the softmax function $\pi_i = \frac{e^{x_i}}{\sum_{i=1}^N e^{x_i}}$ in a numerically stable way by shifting by an arbitrary constant a :

$$\frac{e^{x_i}}{\sum_{i=1}^N e^{x_i}} = \frac{e^{x_i - a}}{\sum_{i=1}^N e^{x_i - a}}$$

often chosen $a = \max_i x_i$. Show that the above identity holds.

For some arbitrary constant C we have

$$\frac{e^{x_i}}{\sum_{i=1}^N e^{x_i}} = \frac{C e^{x_i}}{C \sum_{i=1}^N e^{x_i}} = \frac{e^{x_i + \log(C)}}{\sum_{i=1}^N e^{x_i + \log(C)}}$$

Since C is just an arbitrary constant, we can replace $\log(C) = -a$ and get $\frac{e^{x_i - a}}{\sum_{i=1}^N e^{x_i - a}}$.

Problem 3: Download the notebook `exercise_09_notebook.ipynb` from Piazza. Fill in the missing code and run the notebook. Convert the evaluated notebook to pdf and add it to the printout of your homework.

We have implemented several helper functions for checking the correctness of your code in a small library `nn_utils.py` that can be downloaded from Piazza as well.

Upload a single PDF file with your homework solution to Moodle by 15.12.2019, 23:59 CET. We recommend to typeset your solution (using L^AT_EX or Word), but handwritten solutions are also accepted. If your handwritten solution is illegible, it won't be graded and you waive your right to dispute that.

This week's programming assignment is closely connected to the contents of the in-class exercises. Make sure that you have a look at the in-class exercises before starting working on the homework task.

The solution notebook is uploaded on Piazza.

In-class Exercises

Problem 4: See notebook `inclass_09_vectorization_numerics.ipynb` on Piazza.

Problem 5: See notebook `inclass_09_backpropagation.ipynb` on Piazza.