Iowa State University

Department of Electrical and Computer Engineering

Deep Machine Learning: Theory and Practice

EE 526X

Homework 2

Author:
Vishal Deep

Instructor:
Dr. Zhengdao Wang

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1 Problem 1

We have a softplus function,

$$f(z) = \log(1 + e^z) \tag{1}$$

Taking first derivative of the function:

$$f'(z) = \frac{1}{(1 + e^z)} e^z \tag{2}$$

multiplying and dividing by e^{-z},

$$f'(z) = \frac{e^z.e^{-z}}{(1.e^{-z} + e^z.e^{-z})} = \frac{1}{(1 + e^{-z})} \tag{3}$$

Now taking second derivative of softplus function,

$$f''(z) = \frac{(1 + e^{-z}).0 + e^{-z}}{(1 + e^{-z})^2} \tag{4}$$

$$f''(z) = \frac{e^{-z}}{(1 + e^{-z})^2} \tag{5}$$

From eq. (5), numerator is always positive because exponential is a positive number and any power to a positive is number is always a positive number. The denominator is always positive because is squared. Therefore we can say that second derivative of a softplus function is always positive for every value of z. This implies that a softplus function is convex in z.

2 Problem 2

We have a vector $z = [z1, z2, ..., zn]^T$ and $p = [p1, p2, ..., pn]^T$, where p is output after z is applied to a softmax function.

$$p_i = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}} \tag{6}$$

The jacobian matrix will have two types of elements diagonal and off-diagonal, we will calculate both and then generalize the result for all elements.

Diagonal row elements (i=j):

$$\frac{\partial p_i}{\partial z_i} = \frac{\sum_{j=1}^{n} e^{z_j}.e^{z_i} - e^{z_i}.e^{z_i}}{(\sum_{j=1}^{n} e^{z_j})^2}$$

$$\frac{\partial p_i}{\partial z_i} = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}} - \left(\frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}} \right)^2$$

$$\frac{\partial p_i}{\partial z_i} = p_i - p_i^2 \tag{7}$$

off-diagonal row elements (i≠j):

$$\frac{\partial p_i}{\partial z_j} = \frac{\sum_{j=1}^{n} e^{z_j}.0 - e^{z_i}.e^{z_j}}{(\sum_{j=1}^{n} e^{z_j})^2}$$

$$\frac{\partial p_i}{\partial z_j} = -\frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}} \times \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

$$\frac{\partial p_i}{\partial z_j} = -p_i p_j \tag{8}$$

The Jacobian matrix is given by

$$\frac{\partial p}{\partial z} = \begin{bmatrix} \frac{\partial p_0}{\partial z_0} & \frac{\partial p_0}{\partial z_1} & \cdots & \frac{\partial p_0}{\partial z_n} \\ \frac{\partial p_1}{\partial z_0} & \frac{\partial p_1}{\partial z_1} & \cdots & \frac{\partial p_1}{\partial z_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial p_n}{\partial z_0} & \frac{\partial p_n}{\partial z_1} & \cdots & \frac{\partial p_n}{\partial z_n} \end{bmatrix} \tag{9}$$

using eq. (7) and eq. (8), we get

$$\frac{\partial p}{\partial z} = \begin{bmatrix} p_0 - p_0^2 & -p_0 p_1 & \cdots & -p_0 p_n \\ -p_1 p_0 & p_1 - p_1^2 & \cdots & -p_1 p_n \\ \vdots & \vdots & \ddots & \vdots \\ -p_n p_0 & -p_n p_1 & \cdots & p_n - p_n^2 \end{bmatrix} \tag{10}$$

3 Problem 3

We have $y = [y1, y2, ..., yn]^T$, a correct probability vector. And the cross entropy is given by

$$J(z) = -\sum_{i=1}^{n} y_i \log p_i \tag{11}$$

eq. (11) is a dot product or element-wise product of y_i and $\log p_i$. Taking derivative of eq. (11) w.r.t. p_i,

$$\frac{\partial J}{\partial p_i} = -\frac{\partial}{\partial p_i} y_i \log p_i = -y_i \frac{\partial \log p_i}{\partial p_i}$$

$$\frac{\partial J}{\partial p_i} = -\frac{y_i}{p_i} \tag{12}$$

Also from eqs. (7) and (8) we know $\frac{\partial p_i}{\partial z_j}$,

$$\frac{\partial p_i}{\partial z_j} = \begin{cases} p_i - p_i^2 & i = j \\ -p_i p_j & i \neq j \end{cases} \tag{13}$$

from eqs. (12) and (13), we can find $\frac{\partial J}{\partial z_i}$

$$
\begin{aligned}
\frac{\partial J}{\partial z_i} &= \sum_{j=1}^{n} \frac{\partial J}{\partial p_j}\frac{\partial p_j}{\partial z_i} \\
&= \frac{\partial J}{\partial p_i}\frac{\partial p_i}{\partial z_i} + \sum_{i\neq j} \frac{\partial J}{\partial p_j}\frac{\partial p_j}{\partial z_i} \\
&= -\frac{y_i}{p_i}(p_i - p_i^2) + \sum_{i\neq j}(-\frac{y_j}{p_j})(-p_i p_j) \\
&= -y_i(1-p_i) + \sum_{i\neq j} y_j p_i \\
&= -y_i + y_i p_i + p_i \sum_j y_j
\end{aligned}
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