

CIS4930 - Math for Machine Learning

## **Homework 6**

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### Question 1

You are given a set  $T = \{T_1, T_2, \dots, T_N\}$  of numbers. Given  $T$ , you compute a scalar quantity  $w \equiv \frac{1}{\beta} \log \sum_{k=1}^N \exp\{\beta T_k\}$  where  $\beta > 0$ . What is

$$\lim_{\beta \rightarrow \infty} w?$$

Use L'Hôpital's rule (or equivalent) to relate this limiting value to a property of the set  $T$ . You are allowed to assume that the elements  $T_k$  of the set are distinct numbers.

Next, you compute a scalar quantity  $z \equiv \sum_{k=1}^N T_k \frac{\exp\{\beta T_k\}}{\sum_{i=1}^N \exp\{\beta T_i\}}$  where  $\beta > 0$ . What is

$$\lim_{\beta \rightarrow \infty} z?$$

Relate this limiting value to a property of the set  $T$ . You are again allowed to assume that the elements  $T_k$  of the set are distinct numbers. Show all steps.

#### **Solution:**

Using the fact that  $\exp\{\beta T_k\}$  grows much faster than 1 as  $\beta \rightarrow \infty$ , we have that the only term in the sum that contributes to the limit is the one with the largest value of  $\beta T_k$ , say  $\beta T_M$ . Thus, we can rewrite the sum as

$$\sum_{k=1}^N \exp\{\beta T_k\} \approx \exp\{\beta T_M\}.$$

Substituting this approximation into the expression for  $w$ , we have

$$w \approx \frac{1}{\beta} \log(\exp\{\beta T_M\}) = \frac{1}{\beta} (\beta T_M) = T_M.$$

Therefore, the limiting value of  $w$  as  $\beta \rightarrow \infty$  is the maximum element of the set  $T$ , i.e.,

$$\lim_{\beta \rightarrow \infty} w = \max(T).$$

Next, we consider the second expression,

$$z \equiv \sum_{k=1}^N T_k \frac{\exp\{\beta T_k\}}{\sum_{i=1}^N \exp\{\beta T_i\}}.$$

We can rewrite the denominator as

$$\sum_{i=1}^N \exp\{\beta T_i\} \approx \exp\{\beta T_M\},$$

where  $\beta T_M$  is again the largest value in the set  $\beta T_k$ . This is because the exponentials with smaller values of  $\beta T_k$  will be negligible compared to the exponential with  $\beta T_M$  as  $\beta \rightarrow \infty$ . Substituting this approximation, we have

$$z \approx \frac{\sum_{k=1}^N T_k \exp\{\beta T_k\}}{\exp\{\beta T_M\}}.$$

Now we apply L'Hôpital's rule to the numerator and denominator to obtain

$$\begin{aligned} \lim_{\beta \rightarrow \infty} z &= \lim_{\beta \rightarrow \infty} \frac{\sum_{k=1}^N T_k \exp \beta T_k}{\exp \beta T_M} \\ &= \lim_{\beta \rightarrow \infty} \frac{T_M \exp \beta T_M}{\exp \beta T_M} \\ &= T_M \end{aligned}$$

Hence,  $\lim_{\beta \rightarrow \infty} \frac{\sum_{k=1}^N T_k \exp \beta T_k}{\exp \beta T_M} = T_M$ , where  $T_M = \max(T_k)$  and this limit is achieved when  $\beta$  approaches infinity.

## Question 2

For a sigmoid activation function  $z(u) = \sigma(u) = \frac{1}{1+\exp\{-u\}}$ , consider the following binary cross entropy (BCE) loss function:

$$\ell(y, z(u)) = y \log \frac{y}{z} + (1 - y) \log \frac{1 - y}{1 - z}.$$

(a) Show that  $\ell(y, z(u))$  can be written as

$$\ell(y, z(u)) = -yu + \log(1 + \exp\{u\}) + \text{terms independent of } u.$$

(b) Demonstrate this equivalence in PyTorch. Take the provided XOR code and show that a linear output with BCEWithLogitsLoss function gives the same results as a sigmoid output with BCELoss.

**Solution:**

(a) We have

$$\begin{aligned} \ell(y, z(u)) &= y \log \frac{y}{z} + (1 - y) \log \frac{1 - y}{1 - z} \\ &= -y \log z + (y - 1) \log(1 - z) + y \log y + (1 - y) \log(1 - y) \\ &= y \log\left(\frac{1 - z}{z}\right) - \log(1 - z) + y \log y + (1 - y) \log(1 - y) \\ &= y \log\left(\frac{\frac{1+\exp(-u)}{1+\exp(-u)} - \frac{1}{1+\exp(-u)}}{\frac{1}{1+\exp(-u)}}\right) - \log\left(\frac{1 + \exp(-u)}{1 + \exp(-u)} - \frac{1}{1 + \exp(-u)}\right) + y \log y + (1 - y) \log(1 - y) \\ &= y \log\left(\frac{\exp(-u)(1 + \exp(-u))}{1 + \exp(-u)}\right) - \log\left(\frac{\exp(-u)}{1 + \exp(-u)}\right) + y \log y + (1 - y) \log(1 - y) \\ &= y \log(\exp(-u)) + y \log(1 + \exp(-u)) - y \log(1 + \exp(-u)) - \log(\exp(-u)) + \\ &\quad \log(1 + \exp(-u)) + y \log y + (1 - y) \log(1 - y) \\ &= -yu + \log(1 + \exp(u)) + y \log y + (1 - y) \log(1 - y) \quad \odot \end{aligned}$$

(b) on Google Colab, Link:

<https://colab.research.google.com/drive/1tw9S-G2PdBg1cMDcl9RaU9kepfDSB8Um?usp=sharing>

## Question 3

Show, using the Schwarz inequality,

$$\left(\sum_{k=1}^N |x_k y_k|\right)^2 \leq \sum_{k=1}^N |x_k|^2 \sum_{k=1}^N |y_k|^2$$

that for  $c_n \geq 0$ ,  $\sum_{n=1}^N c_n = 1$  and a vector  $x \in \mathbb{R}^N$  with elements  $x_n \geq 0$ ,  $\sum_{n=1}^N c_n x_n^2 \geq (\sum_{n=1}^N c_n x_n)^2$ . Show all steps.

**Solution:**

Consider, since  $0 \leq c_n \leq 1$ , then  $c_n^2 \leq c_n$ .

$$\left(\sum_{n=1}^N c_n x_n\right)^2 \leq \sum_{n=1}^N |c_n|^2 \sum_{n=1}^N |x_n|^2$$

However,  $\sum_{n=1}^N c_n \geq \sum_{n=1}^N c_n^2$ . Therefore,

$$\begin{aligned} \sum_{n=1}^N c_n x_n^2 &\geq \sum_{n=1}^N c_n^2 x_n^2 \\ &\geq \left( \sum_{n=1}^N c_n x_n \right)^2 \quad \ominus \end{aligned}$$

F.S.
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**Note:-**

- Question 1: Almost Correct. Incorrect application of L'Hopital.
- Question 2: Correct
- Question 3: 10/25. Incorrect use of the Schwarz inequality.