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Sigsoftmax

Kanai et al's Sigsoftmax properties

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Abstract Sigsoftmax properties

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1 Introduction

Kamai et al, NIPS 2018: "Sigsoftmax: Reanalysis of the Softmax Bottleneck" It is different than having a set of multiple binary outputs and then normalizing them with softmax, as follows.

Sigsoftmax:

$$y_i = \frac{\exp(a_i)\sigma(a_i)}{\sum_{j=1}^K \exp(a_j)\sigma(a_j)}$$
(1)

Binary with softmax:

$$y_i = \frac{\exp(\sigma(a_i))}{\sum_{j=1}^K \exp(\sigma(a_j))}$$
 (2)

2 Desired properties

"As the alternative function to softmax, a new output function f(z) and its g(z) should have all of the following properties ..."

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Theorem 5. Sigsoftmax has the following properties:

- 1. Nonlinearity of $\log(g(a))$: $\log(g(a)) = 2a \log(1 + \exp(a))$.
- 2. Numerically stable:

$$\frac{\partial \log y_i}{\partial a_j} = \begin{cases} (1 - y_j) \cdot (2 - \sigma(a_j)) & i = j, \\ -y_j \cdot (2 - \sigma(a_j)) & i \neq j. \end{cases}$$
(3)

- 3. Non-negative: $g(a_i) = \exp(a_i)\sigma(a_i) \ge 0$
- 4. Monotonically increasing: $a_1 \leq a_2 \Rightarrow \exp(a_1)\sigma(a_1) \leq \exp(a_2)\sigma(a_2)$.

What we have. (1.) Kamai et al's sigsoftmax:

$$g(a) = \exp(a) \cdot \sigma(a) = \frac{\exp(a)}{1 + \exp(-a)} = \frac{\exp(2a)}{\exp(a) + 1}$$

$$\tag{4}$$

(2.) Sigmoid:

$$\sigma(a) = \frac{1}{1 + \exp(-a)} = \frac{\exp(a)}{\exp(a) + 1} \tag{5}$$

(3.) Property 1:

$$\log(g(a)) = 2a - \log(1 + \exp(a)) \tag{6}$$

(4.) Normalization:

$$y_i = \frac{g(a_i)}{\sum_k g(a_k)} \tag{7}$$

(5.) Analyse partial derivative of log output:

$$\frac{\partial \log(y_i)}{\partial z_j} = \frac{\partial \log(g(z_i))}{\partial z_j} - \frac{\partial \log(\sum_k g(z_k))}{\partial z_j} \\
= \frac{1}{g(z_i)} \frac{\partial g(z_i)}{\partial z_j} - \frac{1}{\sum_k g(z_k)} \frac{\partial g(z_j)}{\partial z_j} \\
= \begin{cases}
-\frac{1}{\sum_k g(z_k)} \frac{\partial g(z_j)}{\partial z_j} & , j \neq i, \\
\left(\frac{1}{g(z_j)} - \frac{1}{\sum_k g(z_k)}\right) \frac{\partial g(z_j)}{\partial z_j} & , j = i.
\end{cases} \\
= \begin{cases}
-\frac{g(z_j)}{\sum_k g(z_k)} \frac{1}{g(z_j)} \frac{\partial g(z_j)}{\partial z_j} & , j \neq i, \\
\left(\frac{g(z_j)}{g(z_j)} - \frac{g(z_j)}{\sum_k g(z_k)}\right) \frac{1}{g(z_j)} \frac{\partial g(z_j)}{\partial z_j} & , j = i.
\end{cases} \\
= \begin{cases}
-y_j \cdot \frac{\partial \log(g(z_j))}{\partial z_j} & , j \neq i, \\
(1 - y_j) \cdot \frac{\partial \log(g(z_j))}{\partial z_j} & , j \neq i, \\
(1 - y_j) \cdot \frac{\partial \log(g(z_j))}{\partial z_j} & , j = i
\end{cases} \tag{8}$$

From property 1 (Equation 6) and $\frac{d \log(1+\exp(a))}{da} = \frac{\exp(a)}{1+\exp(a)} = \sigma(a)$, we get:

$$\frac{\partial \log(y_i)}{\partial z_i} = \begin{cases} -y_j \cdot (2 - \sigma(a_j)) & , j \neq i, \\ (1 - y_j) \cdot (2 - \sigma(a_j)) & , j = i \end{cases}$$
(9)