

## 1.2 Calculus-Q2

The softmax function  $S : \mathbb{R}^k \rightarrow [0, 1]^k$ , is defined as follows:

$$S(x)_j = \frac{e^{x_j}}{\sum_{l=1}^k e^{x_l}}$$

This function takes an input vector  $x \in \mathbb{R}^d$  and outputs a probability vector (non-negative entries that sum up to 1), corresponding to the weight of original entries of  $x$ .

CQ2: Calculate the Jacobian of the softmax function  $S$ .

$$S'(x) = \begin{bmatrix} \frac{\partial S_1}{\partial x_1} & \dots & \frac{\partial S_1}{\partial x_K} \\ \vdots & & \vdots \\ \frac{\partial S_K}{\partial x_1} & \dots & \frac{\partial S_K}{\partial x_K} \end{bmatrix}$$

$$\text{let } Z = \sum_{i=1}^K e^{x_i}.$$

$$\begin{aligned} \frac{\partial S_i}{\partial x_j} &:= \frac{1}{Z} \cdot \frac{\cancel{e^{x_i}}}{\cancel{e^{x_j}}} * \frac{\cancel{\frac{d(e^{x_i})}{dx_j}} \cdot Z - e^{x_i} \cdot \cancel{\frac{d(Z)}{dx_j}}}{Z^2} \\ &\stackrel{**}{=} \frac{S_{ij} e^{x_i} Z - e^{x_i} e^{x_j}}{Z^2} \\ &= \frac{e^{x_i}}{Z} \left( S_{ij} - \frac{e^{x_j}}{Z} \right) \end{aligned}$$

therefore

$$J_{ij} = \begin{cases} S(x)_i \cdot (1 - S(x)) & i=j \\ -\frac{e^{x_i} e^{x_j}}{Z^2} = -S(x)_i S(x)_j & i \neq j \end{cases}$$

$$\begin{aligned} * \frac{f(x)}{g(x)} &= \frac{f'(x)g(x) - f(x)g'(x)}{g(x)^2} \\ (\sum e^{x_i})' &= \sum (e^{x_i})' = \sum e^{x_i} \\ ** \frac{\frac{d}{dx_j} e^{x_i}}{Z} &= \begin{cases} e^{x_i} & i=j \\ 0 & i \neq j \end{cases} \\ S_{ij} &= \begin{cases} 1 & i=j \\ 0 & i \neq j \end{cases} \\ \frac{d}{dx_j}(Z) &= \frac{1}{Z} \sum e^{x_i} = \begin{cases} 1 & i=j \\ 0 & i \neq j \end{cases} \end{aligned}$$

$$f = \begin{bmatrix} S(x)_1 \cdot (1 - S(x)_1) & -S(x)_1 \cdot S(x)_2 & \dots & -S(x)_1 \cdot S(x_K) \\ \vdots & \ddots & S(x_2) \cdot (1 - S(x_2)) & \\ -S(x_K) \cdot S(x_1) & & \ddots & S(x_K) \cdot (1 - S(x_K)) \end{bmatrix}$$