

Pull back /v Jp rule for softmax

$$f(\underline{x}) = \underline{y}$$

$$\underline{x} \in \mathbb{R}^N \quad \dots \text{logit values } (x_i \in (-\infty, \infty))$$

$$\underline{y} \in \mathbb{R}^N \quad \dots \text{probabilities } (y_i \in [0, 1]) \quad \text{with } \sum_i y_i = 1$$

$$y_i = \frac{e^{x_i}}{\sum_j e^{x_j}}$$

task: backward propagate $\underline{\bar{y}} \in \mathbb{R}^N$ to $\underline{\bar{x}} \in \mathbb{R}^N$

$$\underline{\bar{x}}^T = \underline{\bar{y}}^T \frac{\partial \underline{y}}{\partial \underline{x}}$$

$$\bar{x}_k = \left(\frac{\partial y_i}{\partial x_k} \right) \bar{y}_i$$

$$= (y_i \delta_{ik} - y_i y_k)$$

see pushforward
video

$$\bar{x}_k = (y_i \delta_{ik} - y_i y_k) \bar{y}_i$$

$$= y_i \bar{y}_i \delta_{ik} - y_i \bar{y}_i y_k$$

$$= y_k \bar{y}_k - y_i \bar{y}_i y_k$$

in symbolic notation

$$\underline{\bar{x}} = \underline{y} \circ \underline{\bar{y}} - (\underline{y}^T \underline{\bar{y}}) \underline{y}$$

Full pullback rule

$$\mathcal{B}(\text{softmax}, (\underline{x}_i), (\underline{\bar{y}}_i)) = \left(\underbrace{(\text{softmax}(\underline{x}_i))}_\underline{y}, \underbrace{(\underline{y} \circ \underline{\bar{y}} - (\underline{y}^T \underline{\bar{y}}) \underline{y})}_\underline{\bar{x}} \right)$$