

$$1. \quad P_i = \frac{e^{s_i}}{\sum_j e^{s_j}}, \quad i = 1, 2, \dots, C$$

$$\text{by } \left(\frac{f(x)}{h(x)} \right)' = \frac{f(x)'h(x) - f(x)h'(x)}{[h(x)]^2}$$

$$\boxed{\frac{\partial e^x}{\partial x} = e^x}$$

$$\textcircled{1} \quad \text{when } i = j \quad (s_i = s_j)$$

$$\begin{aligned} \frac{\partial P_i}{\partial s_j} &= \frac{e^{s_i} \cdot \sum_j e^{s_j} - e^{s_j} \cdot e^{s_i}}{[\sum_j e^{s_j}]^2} = \frac{e^{s_i} (\sum_j e^{s_j} - e^{s_j})}{[\sum_j e^{s_j}]^2} \\ &= \frac{e^{s_i}}{\sum_j e^{s_j}} \cdot \frac{\sum_j e^{s_j} - e^{s_j}}{\sum_j e^{s_j}} = P_i (1 - P_j) \end{aligned}$$

$$\textcircled{2} \quad \text{when } i \neq j$$

$$\begin{aligned} \frac{\partial P_i}{\partial s_j} &= \frac{0 \cdot \sum_j e^{s_j} - e^{s_j} \cdot e^{s_i}}{[\sum_j e^{s_j}]^2} \\ &= - \frac{e^{s_j}}{\sum_j e^{s_j}} \cdot \frac{e^{s_i}}{\sum_j e^{s_j}} = -P_j P_i \end{aligned}$$

$$2. \begin{cases} P_{y_i} = \frac{e^{s_{y_i}}}{\sum_j e^{s_j}} & \frac{\partial P_{y_i}}{\partial s_j} = \begin{cases} P_{y_i} (1 - P_j) & y_i = j \\ -P_{y_i} P_j & y_i \neq j \end{cases} \\ s_j = \underline{w}_j^T \underline{x}_j \end{cases}$$

$$\nabla_{\underline{w}_j} L_i = \frac{\partial L_i}{\partial s_j} \frac{\partial s_j}{\partial \underline{w}_j}$$

$$\textcircled{1} \quad \frac{\partial L_i}{\partial s_j} = \frac{\partial (-\log P_{y_i})}{\partial s_j} = -\frac{1}{P_{y_i}} \frac{\partial P_{y_i}}{\partial s_j} = \begin{cases} P_j - 1 \\ P_j \end{cases}$$

$$\textcircled{2} \quad \frac{\partial s_j}{\partial \underline{w}_j} = \frac{\partial (\underline{w}_j^T \underline{x}_j)}{\partial \underline{w}_j} = \underline{x}_j$$

$$\textcircled{1} \cdot \textcircled{2} \Rightarrow \nabla_{\underline{w}_j} L_i = \begin{cases} (P_j - 1) \underline{x}_j & y_i = j \\ P_j \underline{x}_i & y_i \neq j \end{cases}$$

3.

SVM:

$$\nabla_{\mathbf{w}_j} L_i = 1_{(\mathbf{w}_j^T \mathbf{x}_i - \mathbf{w}_{y_i}^T \mathbf{x}_i + 1 > 0)} \mathbf{x}_i,$$

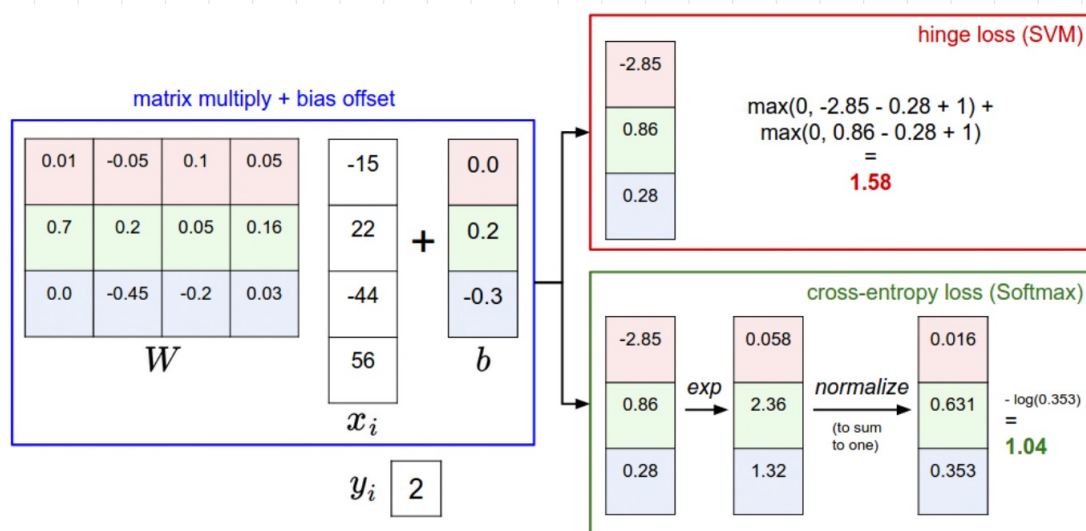
$$\nabla_{\mathbf{w}_{y_i}} L_i = - \left(\sum_{j \neq y_i} 1_{(\mathbf{w}_j^T \mathbf{x}_i - \mathbf{w}_{y_i}^T \mathbf{x}_i + 1 > 0)} \right) \mathbf{x}_i.$$

Softmax:

$$\nabla_{\mathbf{w}_j} L_i = P_j \mathbf{x}_i,$$

$$\nabla_{\mathbf{w}_{y_i}} L_i = (P_j - 1) \mathbf{x}_i.$$

Recall:



SVM: Scores.

Softmax: Scores \rightarrow Probability. (confidence)