

2.3

We can write the gradient $\nabla_{\theta} L(\theta)$ as

$$\nabla_{\theta} L(\theta) = \left[\frac{dL}{d\theta_0}, \frac{dL}{d\theta_1}, \dots, \frac{dL}{d\theta_{M-1}} \right]$$

where

$$\frac{dL}{d\theta_k} = \sum_{n=0}^{N-1} \left[-x_{nk} + \sum_{i=0}^{M-1} \left[x_{n,i} \frac{e^{\theta_k}}{\sum_{j=0}^{M-1} e^{\theta_j}} \right] \right] \quad k \in [0, M-1]$$

$$\frac{dL}{d\theta_k} = \sum_{n=0}^{N-1} \sum_{i=0}^{M-1} \left[-x_{n,i} \left[s(k-i) - \frac{e^{\theta_k}}{\sum_{j=0}^{M-1} e^{\theta_j}} \right] \right]$$

$$\frac{dL}{d\theta_k} = \sum_{i=0}^{M-1} \left[\underbrace{\sum_{n=0}^{N-1} -x_{n,i}}_{\text{From 2.1}} \left[s(k-i) - \frac{e^{\theta_k}}{\sum_{j=0}^{M-1} e^{\theta_j}} \right] \right]$$

$$\frac{dL}{d\theta_k} = \sum_{i=0}^{M-1} \left[-N_i \left[s(k-i) - \frac{e^{\theta_k}}{\sum_{j=0}^{M-1} e^{\theta_j}} \right] \right] \quad \left(\sum_t g(t) s(t-t_0) = g(t_0) \right)$$

$$\frac{dL}{d\theta_k} = -N_k + \left[\sum_{i=0}^{M-1} N_i \right] \frac{e^{\theta_k}}{\sum_{j=0}^{M-1} e^{\theta_j}}$$

- To obtain θ_k^* that minimizes Loss

$$\frac{dL}{d\theta_k} = 0$$

$$\frac{dL}{d\theta_k}$$

$$-N_k + \left[\sum_{i=0}^{M-1} N_i \right] \frac{e^{\theta_k^*}}{\sum_{j=0}^{M-1} e^{\theta_j^*}} = 0$$

$$e^{\theta_k^*} = \frac{\sum_{j=0}^{M-1} e^{\theta_j^*}}{\sum_{i=0}^{M-1} N_i} \cdot N_k$$

$$\Rightarrow e^{\theta_k^*} = \alpha N_k$$

$$\theta_k^* = \beta + \log N_k$$

$$(\beta = \log \alpha)$$

↓
For any constant β