BatchInhib

Rui Lu

Bigeye

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Inhibition via Mini-Batch Statistics 1

在一个 mini – batch 中,考虑某个 feature map $\{x_i^{(j)}\}(i=1,...,N$ 表示 feature 的维度, j = 1, ..., m 表示 batch size), 相互抑制的作用可以表示如下:

$$\mu_{x_i} = \frac{1}{m} \sum_{j=1}^{m} x_i^{(j)} \tag{1.1}$$

$$\sigma_{x_i} = \frac{1}{m} \sum_{j=1}^{m} (x_i^{(j)} - \mu_{x_i})^2$$
 (1.2)

$$r_{ik} = \frac{\frac{1}{m} \left[\sum_{j=1}^{m} (x_i^{(j)} - \mu_{x_i}) (x_k^{(j)} - \mu_{x_k}) \right]}{\sigma_{x_i} \sigma_{x_k}}$$

$$R_{ik} = \frac{g(\alpha_{ik}) r_{ik}}{\sum_{l \neq i} g(\alpha_{il}) r_{il}}$$
(1.3)

$$R_{ik} = \frac{g(\alpha_{ik})r_{ik}}{\sum_{l \neq i} g(\alpha_{il})r_{il}}$$
(1.4)

$$y_i^{(j)} = x_i^{(j)} - \sum_{l \neq i} R_{il} x_l^{(j)}$$
(1.5)

其中, $g(x) = \frac{1}{\rho} log(1 + e^{\rho x})$

对上面的式子求导:

$$\frac{\partial L}{\partial R_{ik}} = \sum_{j=1}^{m} \frac{\partial L}{\partial y_i^{(j)}} \frac{\partial y_i^{(j)}}{\partial R_{ik}} = \sum_{j=1}^{m} \frac{\partial L}{\partial y_i^{(j)}} (-x_k^{(j)})$$
(1.6)

$$\frac{\partial L}{\partial \alpha_{ik}} = \frac{\partial L}{\partial R_{ik}} \frac{\partial R_{ik}}{\partial \alpha_{ik}} = \frac{\partial L}{\partial R_{ik}} \frac{r_{ik} \left[\sum_{l \neq i} g(\alpha_{il}) r_{il} - g(\alpha_{ik}) r_{ik}\right]}{\left[\sum_{l \neq i} g(\alpha_{il}) r_{il}\right]^2} g'(\alpha_{ik})$$
(1.7)

$$\frac{\partial L}{\partial r_{ik}} = \frac{\partial L}{\partial R_{ik}} \frac{\partial R_{ik}}{\partial r_{ik}} = \frac{g(\alpha_{ik}) \left[\sum_{l \neq i} g(\alpha_{il}) r_{il} - g(\alpha_{ik}) r_{ik}\right]}{\left[\sum_{l \neq i} g(\alpha_{il}) r_{il}\right]^2}$$
(1.8)

$$\frac{\partial L}{\partial \sigma_{x_{i}}} = \frac{\partial L}{\partial r_{ik}} \frac{\partial r_{ik}}{\partial \sigma_{x_{i}}} = \frac{(-1)}{\sigma_{x_{i}}^{2}} \frac{\frac{1}{m} \left[\sum_{j=1}^{m} (x_{i}^{(j)} - \mu_{x_{i}})(x_{k}^{(j)} - \mu_{x_{k}})\right]}{\sigma_{x_{k}}} \\
\frac{\partial L}{\partial \mu_{x_{i}}} = \frac{\partial L}{\partial r_{ik}} \frac{\partial r_{ik}}{\partial \mu_{x_{i}}} + \frac{\partial L}{\partial \sigma_{x_{i}}} \frac{\partial \sigma_{x_{i}}}{\partial \mu_{x_{i}}} =$$
(1.9)

$$\frac{\partial L}{\partial \mu_{xi}} = \frac{\partial L}{\partial r_{ik}} \frac{\partial r_{ik}}{\partial \mu_{xi}} + \frac{\partial L}{\partial \sigma_{xi}} \frac{\partial \sigma_{x_i}}{\partial \mu_{xi}} = \frac{\partial L}{\partial \sigma_{xi}} \frac{\partial \sigma_{x_i}}{\partial \sigma_{x_i}} = \frac{\partial L}{\partial \sigma_{x_i}} \frac{\partial \sigma_{x_i}}{\partial \sigma_{x_i}} = \frac{\partial L}{$$

$$\frac{\partial L}{\partial r_{ik}} \frac{\frac{1}{m} \left[\sum_{j=1}^{m} (-1)(x_k^{(j)} - \mu_{x_k}) \right]}{\sigma_{x_i} \sigma_{x_k}} + \frac{\partial L}{\partial \sigma_{x_i}} \frac{(-1)}{2m} \sum_{j=1}^{m} (x_i^{(j)} - \mu_{x_i})$$
(1.10)

$$\frac{\partial L}{\partial x_i^{(j)}} = \frac{\partial L}{\partial \mu_{x_i}} \frac{\partial \mu_{x_i}}{\partial x_i^{(j)}} + \frac{\partial L}{\partial \sigma_{x_i}} \frac{\partial \sigma_{x_i}}{\partial x_i^{(j)}} + \frac{\partial L}{\partial r_{ik}} \frac{\partial r_{ik}}{\partial x_i^{(j)}} + \frac{\partial L}{\partial y_i^{(j)}} \frac{\partial y_i^{(j)}}{\partial x_i^{(j)}} =$$

$$\frac{\partial L}{\partial \mu_{x_i}} \frac{1}{m} + \frac{\partial L}{\partial \sigma_{x_i}} \frac{2}{m} (x_i^{(j)} - \mu_{x_i}) + \frac{\partial L}{\partial r_{ik}} \frac{1}{m} \frac{(x_k^{(j)} - \mu_{x_k})}{\sigma_{x_i} \sigma_{x_k}} + \frac{\partial L}{\partial y_i^{(j)}}$$
(1.11)