

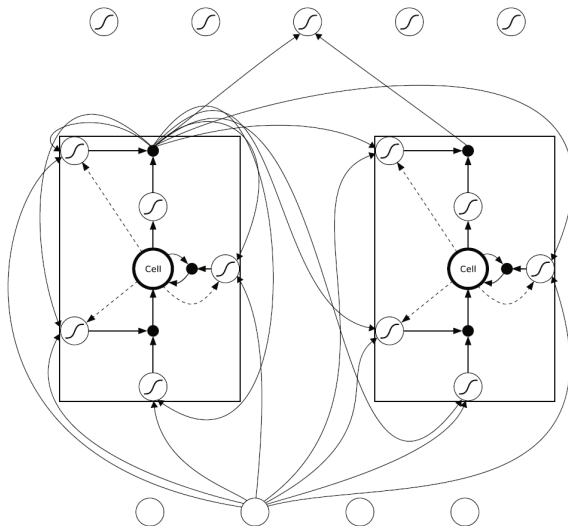
Deep Learning Technology and Application

Ge Li

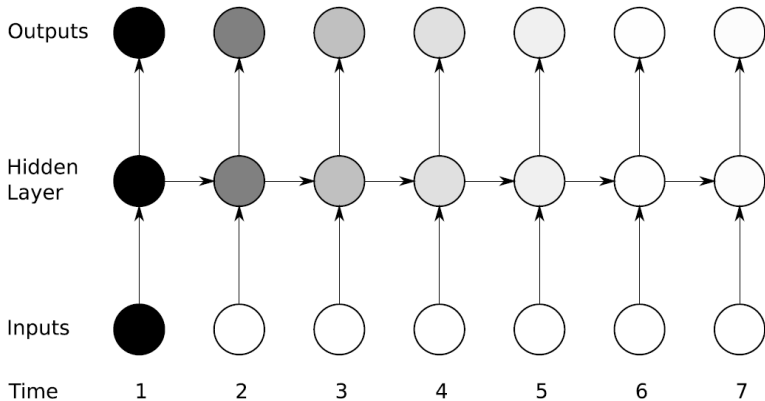
Peking University

LSTM Deduction

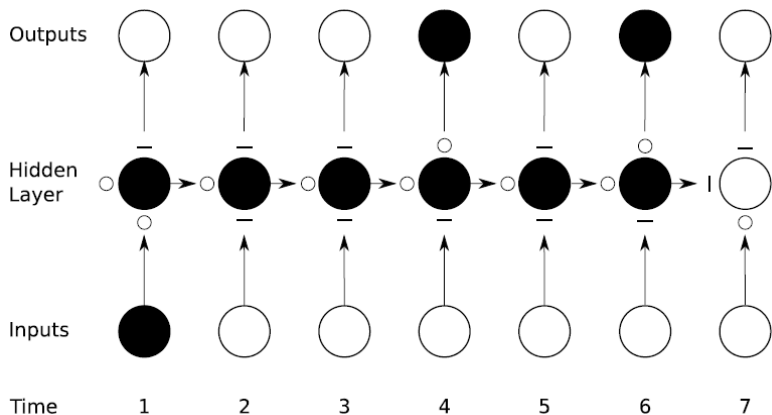
Recurrent Neural Network —LSTM



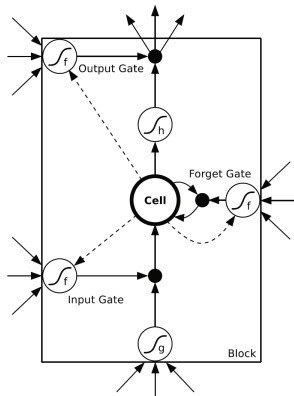
LSTM 的提出



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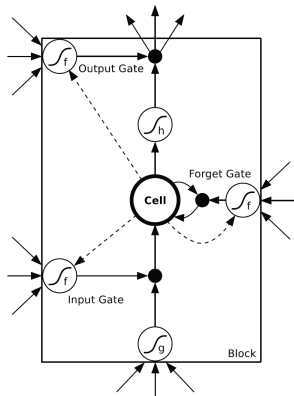


LSTM 单元



- 设 LSTM 隐藏层共包含 H 个神经元, 下标 h 表示其中之一;
- 设 LSTM 隐藏层共包含 C 个 Cell, 下标 c 表示某个 Cell;
- 当前的 LSTM 单元中 Input Gate, Forget Gate, Output Gate 分别用下标 α, β, γ 标识;
- LSTM 单元在 t 时刻的输入: z_h^t , t 时刻的输出: a_h^t ;
对于仅包含一个 Cell 的 LSTM 单元,
 $z_h^t = z_c^t, a_c^t = a_h^t$;

LSTM 单元



LSTM 单元的输入:

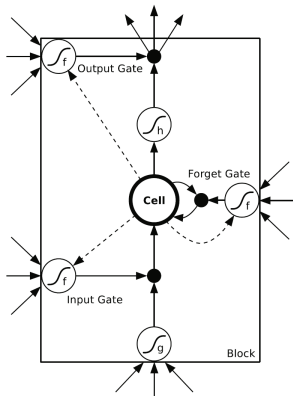
$$z_h^t = \sum_{i=1}^I w_{ci} x_i^t + \sum_{h=1}^H w_{ch} a_h^{t-1}$$

注意： a_h 表示来自于其他 LSTM 单元的输出 a_c ；

LSTM 单元的输出:

$$a_h^t = a_c^t$$

LSTM 单元



Input Gate:

$$z_{\alpha}^t = \sum_{i=1}^I w_{\alpha i} x_i^t + \sum_{h=1}^H w_{\alpha h} a_h^{t-1} + \sum_{c=1}^C w_{\alpha c} s_c^{t-1}$$

$$a_{\alpha}^t = f(z_{\alpha}^t)$$

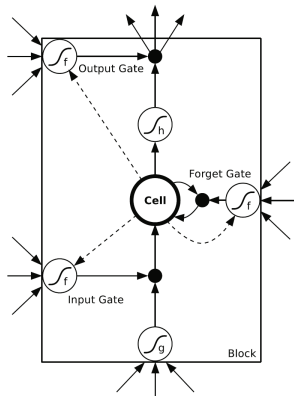
注意： a_h 表示来自于其他 LSTM 单元的输出 a_c ；

Forget Gate:

$$z_{\beta}^t = \sum_{i=1}^I w_{\beta i} x_i^t + \sum_{h=1}^H w_{\beta h} a_h^{t-1} + \sum_{c=1}^C w_{\beta c} s_c^{t-1}$$

$$a_{\beta}^t = f(z_{\beta}^t)$$

LSTM 单元



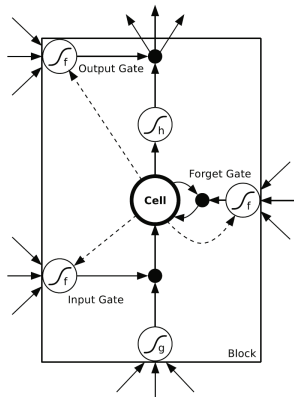
Cells:

$$z_c^t = \sum_{i=1}^I w_{ci} x_i^t + \sum_{h=1}^H w_{ch} a_h^{t-1}$$

注意： a_h 表示来自于其他 LSTM 单元的输出 a_c ；

$$s_c^t = a_\alpha^t g(z_c^t) + a_\beta^t s_c^{t-1}$$

LSTM 单元



Output Gate:

$$z_{\gamma}^t = \sum_{i=1}^I w_{\gamma i} x_i^t + \sum_{h=1}^H w_{\gamma h} a_h^{t-1} + \sum_{c=1}^C w_{\gamma c} s_c^{t-1}$$

$$a_{\gamma}^t = f(z_{\gamma}^t)$$

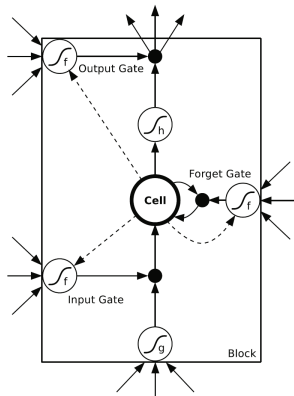
Cell Outputs:

$$a_c^t = a_{\gamma}^t h(s_c^t)$$

RNN Outputs:

$$z_k^t = \sum_{c=1}^C w_{kc} a_h^t$$

LSTM 单元



统计要计算的参数：

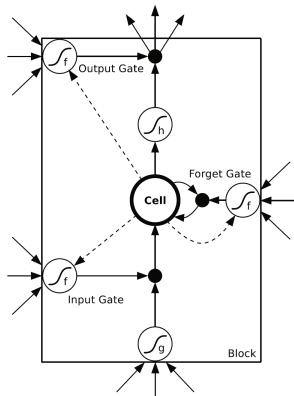
$$w_{\alpha i}, w_{\alpha h}, w_{\alpha c}$$

$$w_{\beta i}, w_{\beta h}, w_{\beta c}$$

$$w_{\gamma i}, w_{\gamma h}, w_{\gamma c}$$

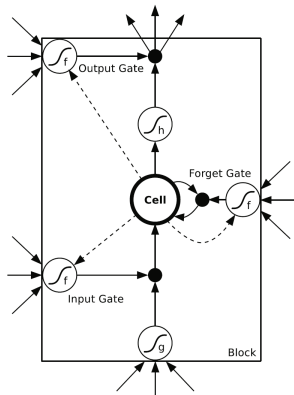
$$w_{ci}, w_{ch}, w_{kc}$$

LSTM 单元



$$\begin{aligned}
 w_{\alpha i}: \frac{\partial J(W, b)}{\partial w_{\alpha i}} &= \frac{\partial J(W, b)}{\partial z_{\alpha}^t} \frac{\partial z_{\alpha}^t}{\partial w_{\alpha i}} = \frac{\partial J(W, b)}{\partial z_{\alpha}^t} x_i^t \\
 w_{\alpha h}: \frac{\partial J(W, b)}{\partial w_{\alpha h}} &= \frac{\partial J(W, b)}{\partial z_{\alpha}^t} \frac{\partial z_{\alpha}^t}{\partial w_{\alpha h}} = \frac{\partial J(W, b)}{\partial z_{\alpha}^t} a_h^{t-1} \\
 w_{\alpha c}: \frac{\partial J(W, b)}{\partial w_{\alpha c}} &= \frac{\partial J(W, b)}{\partial z_{\alpha}^t} \frac{\partial z_{\alpha}^t}{\partial w_{\alpha c}} = \frac{\partial J(W, b)}{\partial z_{\alpha}^t} s_c^{t-1} \\
 w_{\beta i}: \frac{\partial J(W, b)}{\partial w_{\beta i}} &= \frac{\partial J(W, b)}{\partial z_{\beta}^t} \frac{\partial z_{\beta}^t}{\partial w_{\beta i}} = \frac{\partial J(W, b)}{\partial z_{\beta}^t} x_i^t \\
 w_{\beta h}: \frac{\partial J(W, b)}{\partial w_{\beta h}} &= \frac{\partial J(W, b)}{\partial z_{\beta}^t} \frac{\partial z_{\beta}^t}{\partial w_{\beta h}} = \frac{\partial J(W, b)}{\partial z_{\beta}^t} a_h^{t-1} \\
 w_{\beta c}: \frac{\partial J(W, b)}{\partial w_{\beta c}} &= \frac{\partial J(W, b)}{\partial z_{\beta}^t} \frac{\partial z_{\beta}^t}{\partial w_{\beta c}} = \frac{\partial J(W, b)}{\partial z_{\beta}^t} s_c^{t-1}
 \end{aligned}$$

LSTM 单元



$$w_{\gamma i}: \frac{\partial J(W, b)}{\partial w_{\gamma i}} = \frac{\partial J(W, b)}{\partial z_{\gamma}^t} \frac{\partial z_{\gamma}^t}{\partial w_{\gamma i}} = \frac{\partial J(W, b)}{\partial z_{\gamma}^t} x_i^t$$

$$w_{\gamma h}: \frac{\partial J(W, b)}{\partial w_{\gamma h}} = \frac{\partial J(W, b)}{\partial z_{\gamma}^t} \frac{\partial z_{\gamma}^t}{\partial w_{\gamma h}} = \frac{\partial J(W, b)}{\partial z_{\gamma}^t} a_h^{t-1}$$

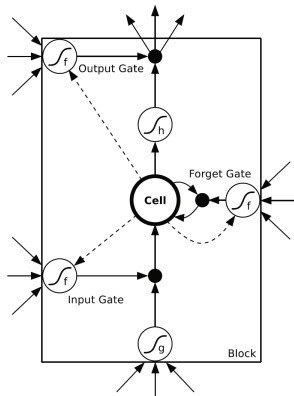
$$w_{\gamma c}: \frac{\partial J(W, b)}{\partial w_{\gamma c}} = \frac{\partial J(W, b)}{\partial z_{\gamma}^t} \frac{\partial z_{\gamma}^t}{\partial w_{\gamma c}} = \frac{\partial J(W, b)}{\partial z_{\gamma}^t} s_c^{t-1}$$

$$w_{ci}: \frac{\partial J(W, b)}{\partial w_{ci}} = \frac{\partial J(W, b)}{\partial z_h^t} \frac{\partial z_h^t}{\partial w_{ci}} = \frac{\partial J(W, b)}{\partial z_c^t} x_i^t$$

$$w_{ch}: \frac{\partial J(W, b)}{\partial w_{ch}} = \frac{\partial J(W, b)}{\partial z_h^t} \frac{\partial z_h^t}{\partial w_{ch}} = \frac{\partial J(W, b)}{\partial z_h^t} a_h^{t-1}$$

$$w_{kc}: \frac{\partial J(W, b)}{\partial w_{kc}} = \frac{\partial J(W, b)}{\partial z_k^t} \frac{\partial z_k^t}{\partial w_{kc}} = \frac{\partial J(W, b)}{\partial z_k^t} a_h^t$$

LSTM 单元

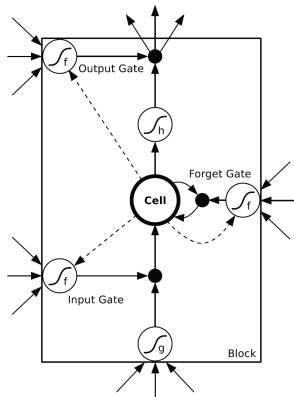


统计要计算的梯度：

$$\begin{array}{ccc} \frac{\partial J(W, b)}{\partial z_{\alpha}^t} & \frac{\partial J(W, b)}{\partial z_{\beta}^t} & \frac{\partial J(W, b)}{\partial z_{\gamma}^t} \\ \frac{\partial J(W, b)}{\partial z_c^t} & \frac{\partial J(W, b)}{\partial z_h^t} & \frac{\partial J(W, b)}{\partial z_k^t} \end{array}$$

LSTM 单元

梯度计算之一：

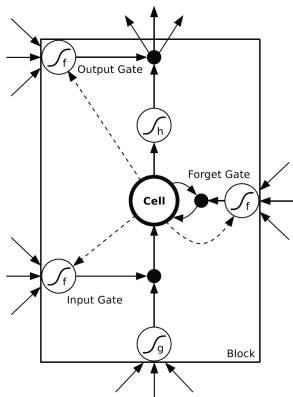


$$\text{若 } t=T, \text{ 则: } \frac{\partial J(W, b)}{\partial z_k^T} = \frac{\partial J(W, b)}{\partial a_k^T} \frac{\partial a_k^T}{\partial z_k^T} \\ = \frac{\partial J(W, b)}{\partial a_k^T} output'(\cdot)$$

$$\begin{aligned} \text{否则: } \frac{\partial J(W, b)}{\partial z_k^t} &= \frac{\partial J(W, b)}{\partial a_k^t} \frac{\partial a_k^t}{\partial z_k^t} \\ &= \sum_h^H \frac{\partial J(W, b)}{\partial z_h^{t+1}} \frac{\partial a_k^t}{\partial z_k^t} \\ &= \sum_h^H \frac{\partial J(W, b)}{\partial z_h^{t+1}} output'(\cdot) \end{aligned}$$

LSTM 单元

梯度计算之二：



$$\frac{\partial J(W, b)}{\partial z_{\gamma}^t} = \sum_{c=1}^C \frac{\partial J(W, b)}{\partial a_c^t} \frac{\partial a_c^t}{\partial a_{\gamma}^t} \frac{\partial a_{\gamma}^t}{\partial z_{\gamma}^t}$$

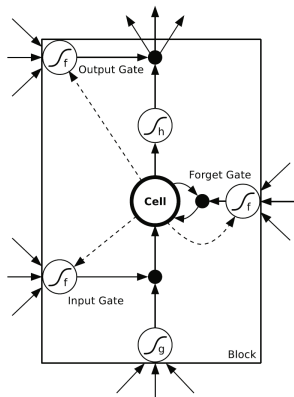
因为： $a_c^t = a_{\gamma}^t h(s_c^t)$

所以：

$$\begin{aligned} &= \sum_{c=1}^C \frac{\partial J(W, b)}{\partial a_c^t} h(s_c^t) f'(z_{\gamma}^t) \\ &= f'(z_{\gamma}^t) \sum_{c=1}^C \frac{\partial J(W, b)}{\partial a_c^t} h(s_c^t) \end{aligned}$$

LSTM 单元

梯度计算之三：



$$\frac{\partial J(W, b)}{\partial a_c^t} = \sum_k^K \frac{\partial J(W, b)}{\partial z_k^t} \frac{\partial z_k^t}{\partial a_c^t} + \sum_h^H \frac{\partial J(W, b)}{\partial z_h^{t+1}} \frac{\partial z_h^{t+1}}{\partial a_c^t}$$

因为：

$$z_h^{t+1} = \sum_{i=1}^I w_{ci} x_i^{t+1} + \sum_{h=1}^H w_{ch} a_h^t$$

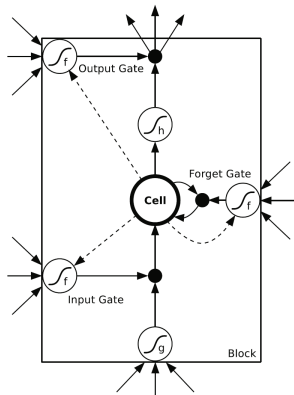
$$z_k^t = \sum_{k=1}^K w_{kc} a_h^t$$

所以：

$$\frac{\partial J(W, b)}{\partial a_c^t} = \sum_k^K \frac{\partial J(W, b)}{\partial z_k^t} w_{kc} + \sum_h^H \frac{\partial J(W, b)}{\partial z_h^{t+1}} w_{ch}$$

LSTM 单元

梯度计算之四：



$$\frac{\partial J(W, b)}{\partial z_h^t} = \sum_{c=1}^C \frac{\partial J(W, b)}{\partial s_c^t} \frac{\partial s_c^t}{\partial z_h^t}$$

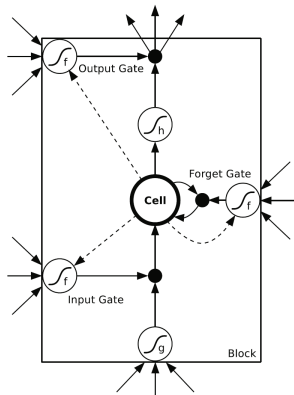
因为： $s_c^t = a_\alpha^t g(z_c^t) + a_\beta^t s_c^{t-1}$

所以：

$$\frac{\partial J(W, b)}{\partial z_h^t} = \sum_{c=1}^C \frac{\partial J(W, b)}{\partial s_c^t} a_\alpha^t g'(z_c^t)$$

LSTM 单元

梯度计算之五：



$$\frac{\partial J(W, b)}{\partial z_{\beta}^t} = \sum_{c=1}^C \frac{\partial J(W, b)}{\partial s_c^t} \frac{\partial s_c^t}{\partial z_{\beta}^t}$$

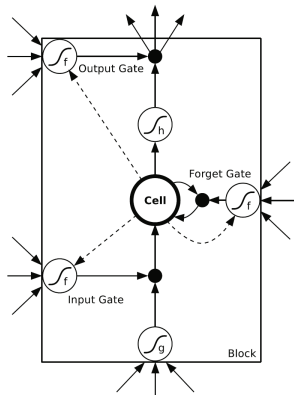
因为： $s_c^t = a_\alpha^t g(z_c^t) + a_\beta^t s_c^{t-1}$

所以：

$$\begin{aligned} \frac{\partial J(W, b)}{\partial z_h^t} &= \sum_{c=1}^C \frac{\partial J(W, b)}{\partial s_c^t} \frac{\partial a_\beta^t}{\partial z_\beta^t} s_c^{t-1} \\ &= f'(z_\beta^t) \sum_{c=1}^C \frac{\partial J(W, b)}{\partial s_c^t} s_c^{t-1} \end{aligned}$$

LSTM 单元

梯度计算之六：



$$\frac{\partial J(W, b)}{\partial z_{\alpha}^t} = \sum_{c=1}^C \frac{\partial J(W, b)}{\partial s_c^t} \frac{\partial s_c^t}{\partial z_{\alpha}^t}$$

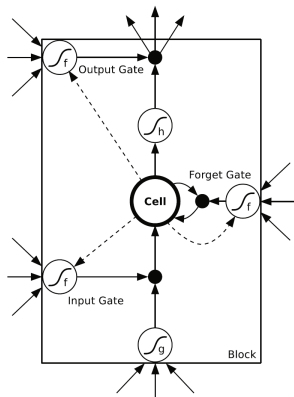
因为： $s_c^t = a_{\alpha}^t g(z_c^t) + a_{\beta}^t s_c^{t-1}$

所以：

$$\begin{aligned} \frac{\partial J(W, b)}{\partial z_h^t} &= \sum_{c=1}^C \frac{\partial J(W, b)}{\partial s_c^t} \frac{\partial a_{\alpha}^t}{\partial z_{\alpha}^t} g(z_c^t) \\ &= f'(z_{\alpha}^t) \sum_{c=1}^C \frac{\partial J(W, b)}{\partial s_c^t} g(z_c^t) \end{aligned}$$

LSTM 单元

梯度计算之七：



焦点集中在： $\frac{\partial J(W, b)}{\partial s_c^t}$

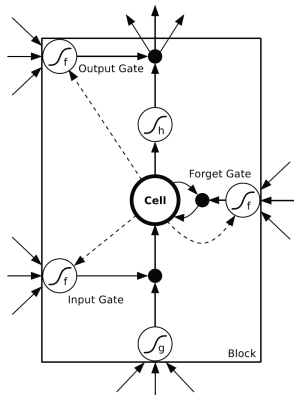
$$\begin{aligned} \text{因为：} \frac{\partial J(W, b)}{\partial s_c^t} &= \frac{\partial J(W, b)}{\partial a_c^t} \frac{\partial a_c^t}{\partial s_c^t} + \frac{\partial J(W, b)}{\partial s_c^{t+1}} \frac{\partial s_c^{t+1}}{\partial s_c^t} \\ &+ \frac{\partial J(W, b)}{\partial z_\alpha^{t+1}} \frac{\partial z_\alpha^{t+1}}{\partial s_c^t} + \frac{\partial J(W, b)}{\partial z_\beta^{t+1}} \frac{\partial z_\beta^{t+1}}{\partial s_c^t} \\ &+ \frac{\partial J(W, b)}{\partial z_\gamma^{t+1}} \frac{\partial z_\gamma^{t+1}}{\partial s_c^t} \end{aligned}$$

所以：

$$\begin{aligned} \frac{\partial J(W, b)}{\partial s_c^t} &= \frac{\partial J(W, b)}{\partial a_c^t} a_\gamma^t h'(s_c^t) + \frac{\partial J(W, b)}{\partial s_c^{t+1}} a_\beta^{t+1} \\ &+ \frac{\partial J(W, b)}{\partial z_\alpha^{t+1}} w_{\alpha c} + \frac{\partial J(W, b)}{\partial z_\alpha^{t+1}} w_{\alpha c} + \frac{\partial J(W, b)}{\partial z_\alpha^{t+1}} w_{\alpha c} \end{aligned}$$

LSTM 单元

最常见的表述：



$$\begin{aligned}
 i_t &= \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i) \\
 f_t &= \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f) \\
 c_t &= f_t c_{t-1} + i_t \tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \\
 o_t &= \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o) \\
 h_t &= o_t \tanh(c_t)
 \end{aligned}$$

Thanks.