Multi cell LSTM

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1 Introduction

In this document we formulate new modification of long short-term memory.

1.1 Conventional LSTM

Let $x_t \in \mathbb{R}^{D_x}$ be input vectors. LSTM state $(c_t, h_t)^T$ is defined by:

$$\begin{aligned} i_t &= \sigma(W^i x_t + U^i h_{t-1} + b^i) \\ f_t &= \sigma(W^f x_t + U^f h_{t-1} + b^f) \\ o_t &= \sigma(W^o x_t + U^o h_{t-1} + b^o) \\ \tilde{c}_t &= \tanh(W^c x_t + U^c h_{t-1} + b^c) \\ c_t &= f_t \bullet c_{t-1} + i_t \bullet \tilde{c}_t \\ h_t &= o_t \bullet \tanh(c_t), \end{aligned}, \tag{1}$$

Where i_t, f_t, o_t are calles input, forget and output gates, $\tilde{c}_t$ - candidate cell vector, c_t - cell vector, and h_t - hidden state vector. All aforementioned variables are D_h- dimensional.

1.2 Multi cell LSTM

We suggest variant of LSTM with D_p cells, assembled into $D_h \times D_p$ matrix C_t. Internal attention p_t controls importance weights of individual cells (columns of C_t).

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$$
\begin{aligned}
i_t &= \sigma(W^i x_t + U^i h_{t-1} + b^i) \in \mathbb{R}^{D_h} \\
f_t &= \sigma(W^f x_t + U^f h_{t-1} + b^f) \in \mathbb{R}^{D_h} \\
o_t &= \sigma(W^o x_t + U^o h_{t-1} + b^o) \in \mathbb{R}^{D_h} \\
p_t &= \mathrm{softmax}(W^p x_t + U^p h_{t-1} + b^p) \in \mathbb{R}^{D_p} \\
\tilde{C}_t &= \tanh(W^c x_t + U^c h_{t-1} + b^c) 1^T \in \mathbb{R}^{D_h \times D_p} \\
C_t &= (f_t p_t^T) \bullet C_{t-1} + (i_t p_t^T) \bullet \tilde{C}_t \in \mathbb{R}^{D_h \times D_p} \\
h_t &= \frac{1}{D_p} o_t \bullet (\tanh(C_t) 1) \in \mathbb{R}^{D_h}
\end{aligned}, \tag{2}
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