Normalized and Geometry-Aware Self-Attention Network for Image Captioning

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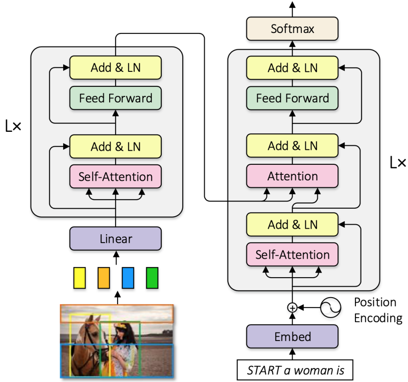

Normalization for an attention mechanism (N-SAN)

- Attention weights are calculated as:

$$\begin{aligned} S &= \text{Softmax}\left(QK^\top\right) \\ &= \text{Softmax}\left((XW_Q)\cdot\left(W_K^\top X^\top\right)\right) \end{aligned} \tag{1}$$

- The paper shows that it is beneficial to apply Instance Normalization to matrix Q:

$$\begin{gathered} \hat{x}_{btc} = \frac{x_{btc} - \mu_{bc}}{\sqrt{\sigma_{bc}^2 + \epsilon}} \\ \mu_{bc} = \frac{1}{T}\sum_{t=1}^{T} x_{btc}, \sigma_{bc}^2 = \frac{1}{T}\sum_{t=1}^{T}\left(x_{btc} - \mu_{bc}\right)^2 \end{gathered} \tag{2}$$

- i.e. we normalize each sample independently across time dimension;

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- We compute $G_{ij} = \text{ReLU}\left(\mathrm{FC}\left(\mathbf{f}^g_{ij}\right)\right)$ from $\mathbf{f}^g_{ij}$ which is a 4-dimensional vector of:

$$\mathbf{f}^g_{ij} = \left(\log\left(\frac{|x_i - x_j|}{w_i}\right), \log\left(\frac{|y_i - y_j|}{h_i}\right), \log\left(\frac{w_i}{w_j}\right), \log\left(\frac{h_i}{h_j}\right)\right)^{T-} \tag{4}$$

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- Authors do not provide stds of the runs which would be very helpful.