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# Supplementary Material

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## 1 The Basic Architecture of the Generator

2 As shown in Figure 2, the network has a multi-stage cascaded architecture that contains  $m$  generators  
3 ( $G_0, G_1, \dots, G_{m-1}$ ). Each stage takes a hidden state  $b_i$  generated from the previous stage as input,  
4 and produces images  $v_i$  of small to large scales. The first hidden state is the sentence embedding  $s$   
5 that is encoded by a pre-trained bidirectional RNN [7]. We also use the conditioning augmentation  
6 method (CA) [6] to smooth over text representation and to encourage robustness to small perturbation  
7 along the conditioning manifold:

$$\begin{aligned} b_0 &= F_0(z, F_{CA}(s)), \\ b_i &= F_i(b_{i-1}, F_{attn_i}(b_{i-1}, w, F_{CA}(s))), i = 1, 2, \dots, m - 1, \\ v_i &= G_i(b_i), \end{aligned} \quad (1)$$

8 where  $z \sim N(0, 1)$  denotes random noises,  $w$  is the word embeddings,  $F_{attn_i}$  is proposed word-level  
9 spatial and channel-wise attention model including two components: spatial attention model  $S_{Attn_{i-1}}$   
10 and channel-wise attention model  $C_{Attn_{i-1}}$ , and  $F_0, F_i, G_i$  are denoted as neural networks. Then,

$$F_{attn_i}(b_{i-1}, w, F_{CA}(s)) = \text{concat}(S_{Attn_{i-1}}, C_{Attn_{i-1}}). \quad (2)$$

## 11 Spatial Attention Model

12 The spatial attention model takes two inputs: the word embeddings  $w$  and the visual features  $v$  from  
13 the previous stage. Then, by using a perception layer  $F$ , the word embeddings  $w$  are converted into  
14 the common semantic space of the visual features denoted as  $\tilde{w} = Fw$ .

15 Next, we compute the dot product between  $\tilde{w}$  and visual features  $v$  to get a word-context vector,  
16 which is followed by the *Softmax* function to produce the attention weights. Thus, the spatial attentive  
17 word-context feature  $c$  is obtained by computing the dot-product between the attention weights and  
18  $\tilde{w}$ :

$$c_i = \sum_{j=0}^{T-1} \alpha_{i,j} \tilde{w}_j, \quad \text{where } \alpha_{i,j} = \frac{e^{s_{i,j}}}{\sum_{k=0}^{T-1} e^{s_{i,k}}}, s = \tilde{w}^T v. \quad (3)$$

19 Here,  $\alpha_{i,j}$  represents the correlation between the  $i^{th}$  sub-region of the image and the  $j^{th}$  word. Thus,  
20 the  $c_i$  indicates the correlation between the  $i^{th}$  sub-region of the image and the whole sentence.