

MASK CAPTIONING NETWORK

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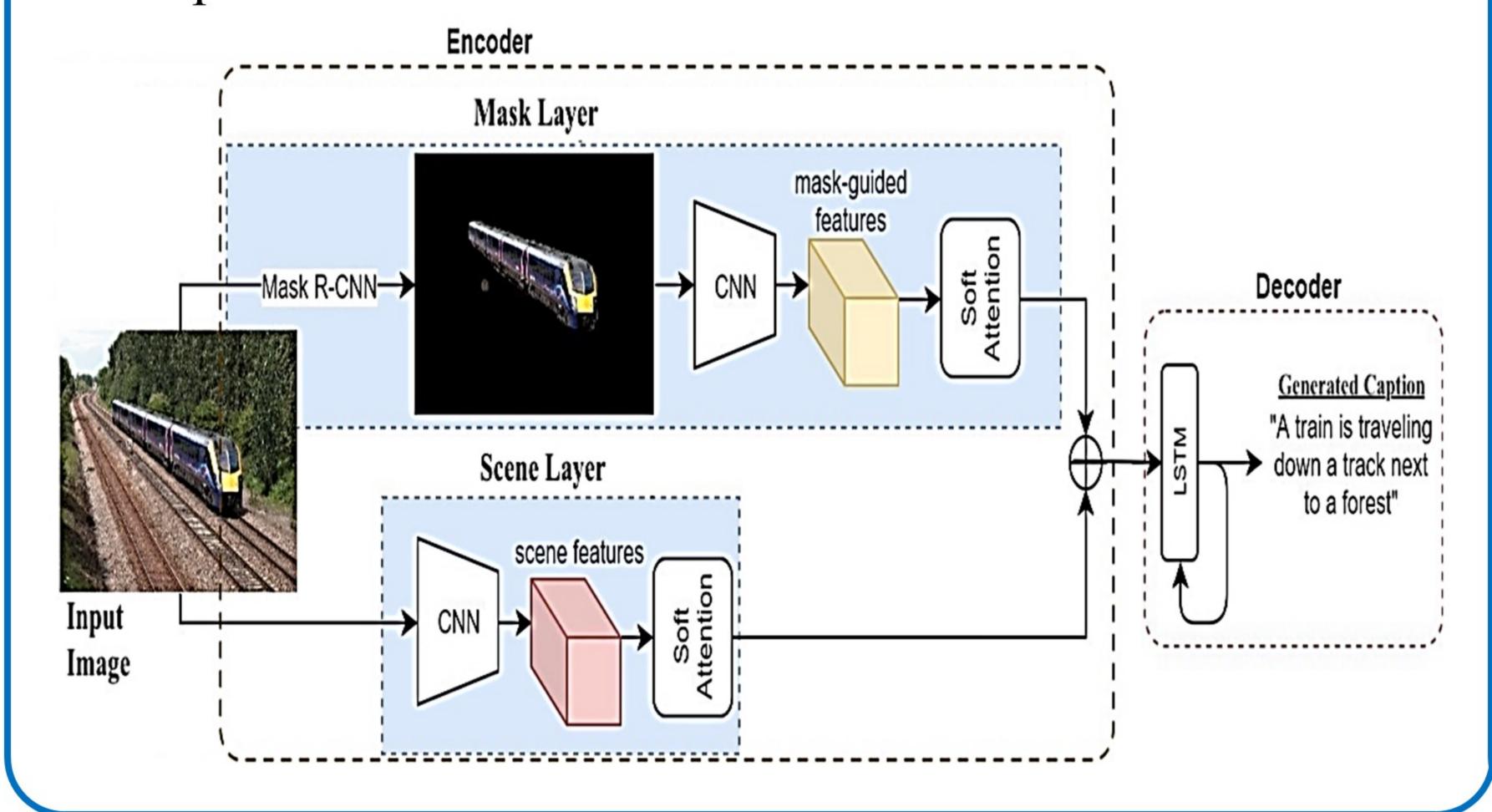
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Introduction

- Image captioning: generate a sentence to describe an image
- Visual attention: de facto solution in image captioning task to detect and attend salient image regions for a better . sentence generation.
- Will instance segmentation method improve the (encoder) performance in image captioning?

Main Contributions

- Propose a Mask Captioning Network (MaC) to detect salient regions in pixel level to eliminate the background information to focus on the image objects only
- Employ a much simpler solution to generate the scene features to ensure the overall meaning of the images are adapted into LSTM
- Our method outperforms baseline model and achieves comparable/better results with state-of-the-art methods



Methodology

- Leverage Mask R-CNN to produce a set of binary masks B and detection scores D
- Generate weighted mask B^W

$$B^w = \sum_{i=1}^N F_3(b_i) \odot d_i$$

 $\widehat{M} = \sum_{i} \alpha_i^m M_i$

• Attended mask features \widehat{M} :

$$M = f_m(B^w \odot I)$$

$$a^M = F_2((W_M M) \oplus (W_{M,h} h_{t-1}))$$

$$\alpha^m = softmax(W_{\alpha,m} a^M)$$

$$\beta^{s} = f_{CNN_s}(I)$$

$$\alpha^s = F_2((W_S S) \oplus (W_{S,h} h_{t-1}))$$

$$\alpha^s = softmax(W_{\alpha,s} a^S)$$

$$\beta^s = softmax(W_{\alpha,s} a^S)$$

• Attended scene features \hat{S} :

$$S = f_{CNN_s}(I)$$

$$a^S = F_2((W_S S) \oplus (W_{S,h} h_{t-1}))$$

$$\alpha^s = softmax(W_{\alpha,s} a^S)$$

$$\widehat{S} = \sum_{i=1}^k \alpha_i^s S_i$$

Concatenate \widehat{M} and \widehat{S} before feed into LSTM at each time step t as:

$$x_t = \widehat{M} \oplus \widehat{S}$$

$$h_t = LSTM(x_t, h_{t-1}, m_{t-1})$$

$$p(y_t | y_1, \dots, y_{t-1}, I) = F_1(h_t)$$

Implementation Details

- Mask R-CNN pretrained on MSCOCO dataset
- ResNet-50 pretrained on ImageNet as image encoder
- Train all models under cross entropy loss using ADAM optimizer with mini-batch size of 32 and dropout rate 0.5
- Train LSTM using learning rate of 1e-4 for 8 epochs and finetune CNN with learning rate of 1e-5 up to 20 epochs

Results

Table 1: Performance of the proposed MaC model and state ofthe-art methods on MSCOCO dataset

Methods	MSCOCO							
	B-1	B-2	B-3	B-4	M	R	С	
NIC [15]	66.6	45.1	30.4	20.3	-	-	-	
ATT-FCN [16]	70.9	53.7	40.2	30.4	24.3	-	-	
Hard-Attention [11]	71.8	50.4	35.7	25.0	23.04	-	-	
Soft-Attention [11]	70.7	49.2	34.4	24.3	23.9	-	-	
RA+SS [4]	72.4	55.5	41.8	31.3	24.8	53.2	95.5	
Baseline	70.2	53.8	40.4	30.3	23.8	52.1	89.3	
MaC _{mask}	69.8	53.1	39.7	30.0	23.6	51.7	89.6	
MaC (D=0.5)	72.3	56.0	42.6	32.4	25.0	53.7	96.8	
MaC (D=0.4)	72.3	55.9	42.3	32.0	24.8	53.6	95.9	
MaC (D=0.6)	72.2	55.9	42.5	32.4	25.0	53.6	96.7	

Table 2: Comparison on uniqueness of caption generated by proposed MaC model and baseline models.

Methods	MS	SCOCO	Flickr30k		
Iviculous	Unique	Avg. length	Unique	Avg. length	
Baseline	51.20%	8.92	89.50%	9.37	
MaC _{mask}	48.36%	9.07	87.90%	9.58	
MaC	53.74%	9.03	89.70%	9.37	



(a) two men playing frisbee in a field.

(b) a couple of men playing a game of frisbee.



(a) a young man throwing a frisbee on a beach.

(b) a group of people playing a game of

Comparison of captions generated by (a) MaC and (b) MaC_{mask} . Underline text indicates the scene in the sentence.