Adaptively Aligned Image Captioning via Adaptive Attention Time

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Abstract

Recent neural models for image captioning usually employ an encoder-decoder framework with an attention mechanism. However, the attention mechanism in such a framework aligns one single (attended) image feature vector to one caption word, assuming one-to-one mapping from source image regions and target caption words, which is never possible. In this paper, we propose a novel attention model, namely *Adaptive Attention Time* (AAT), to align the source and the target adaptively for image captioning. AAT allows the framework to learn how many attention steps to take to output a caption word at each decoding step. With AAT, an image region can be mapped to an arbitrary number of caption words while a caption word can also attend to an arbitrary number of image regions. AAT is deterministic and differentiable, and doesn't introduce any noise to the parameter gradients. In this paper, we empirically show that AAT improves over state-of-the-art methods on the task of image captioning. Code is available at `https://github.com/husthuaan/AAT`.

1 Introduction

Image captioning aims to automatically describe the content of an image using natural language [13, 29, 16, 6]. It is regarded as a kind of "translation" task that translates the content in an image to a sequence of words in some language.

Inspired by the development of neural machine translation [22], recent approaches to image captioning that adopt an encoder-decoder framework with an attention mechanism have achieved great success. In such a framework, a CNN-based image encoder is used to extract feature vectors for a given image, while an RNN-based caption decoder to generate caption words recurrently. The attention mechanism selects one attended feature vector for each one decoding step.

Despite the success that the existing approaches have achieved, there are still limitations in the encoder-decoder framework. The attention model generates one single image feature vector at each decoding step, which subsequently provides the decoder information for making the prediction about a caption word. Obviously, one-to-one mapping from image regions to caption words is assumed in the paradigm, which, however, is never possible and may involve the following issues: 1) unnecessary or even misleading visual information is forcibly given to all caption words, no matter whether they require visual clues or not [15]; 2) visual information in the decoder accumulates over time; however, words at earlier decoding steps require more knowledge about the image, but they are actually provided less; 3) it's hard to understand interactions between objects by analyzing one single

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attended weighted averaged feature vector. To conclude, a decoder requires a different number of attention steps in different situations, which is what one-to-one mapping can't provide.

To this end, we develop a novel attention model, namely *Adaptive Attention Time* (AAT), to realize adaptive alignment from image regions to caption words. At each decoding step, depending on its confidence, AAT decides whether to take an extra attention step, or directly output a caption word and move on to the next decoding step. If AAT does so, then at the subsequent attention step, AAT will take one more attended feature vector into the decoder, and again, AAT will make the decision. The attention process continues, until AAT is confident enough to output a word. With the techniques from *Adaptive Computation Time* (ACT) [8], we are able to make AAT deterministic and differentiable. Furthermore, we take advantage of the multi-head attention [23] to introduce fewer attention steps and make it easier to comprehend interactions among objects in an image.

We evaluate the effectiveness of AAT by comparing it with a *base* attention model, which takes one attending step as one decoding step, and a *recurrent* attention model, which takes a fixed number of attention steps for each decoding step. We show that those two models are special cases of AAT, and AAT is superior to them with empirical results. Experiments also show that the proposed AAT outperforms previously published image captioning models. And one single image captioning model can achieve a new state-of-the-art performance of 128.6 CIDEr-D [24] score on MS COCO dataset offline test split.

2 Related Work

Image Captioning. Early approaches to image captioning are rule/template-based [30, 21] which generate slotted caption templates and use the outputs of object detection, attribute prediction and scene recognition to fill in the slots. Recently, inspired by the great development of neural machine translation [22], neural-based encoder-decoder framework became the mainstream choice for image captioning. For instance, an end-to-end framework is proposed with a CNN encoding the image to feature vector and an LSTM decoding it to caption [25]. Further in [27], the spatial attention mechanisms on CNN feature map is used to incorporate visual context and is implicitly conditioned on the text generated so far. In [19], reinforcement learning algorithms are designed to directly optimize the non-differentiable evaluation metrics (*e.g.*, BLEU [17] and CIDEr [24]). Later, [15] introduces an adaptive attention mechanism to decide when to activate the visual attention. More recently, semantic information such as objects, attributes and relationships are integrated to generate better descriptions [32, 2, 31, 28, 9].

Adaptive Computation Time. Adaptive computation time (ACT) was proposed as an algorithm to allow recurrent neural networks to learn how many computational steps to take between receiving an input and emitting an output. Later, ACT is utilized to design neural networks of a dynamic number of layers or operations [26, 5]. In this paper, we implement our *Adaptive Attention Time* (AAT) model by using the techniques of ACT.

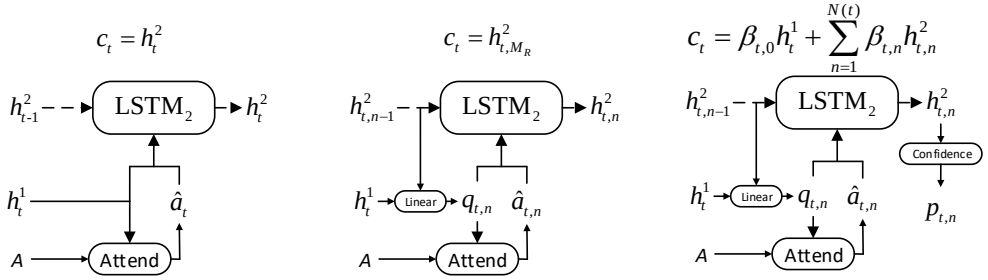
3 Method

Our image captioning model with *Adaptive Attention Time* (AAT) is developed upon the attention based encoder-decoder framework. In this section, we first describe the framework in Section 3.1, then show how we implement AAT to realize adaptive alignment in Section 3.2.

3.1 Model Framework

Image Encoder. The encoder in the attentive encoder-decoder framework is to extract a set of image feature vectors $A = \{\boldsymbol{a}_1, \boldsymbol{a}_2, \ldots, \boldsymbol{a}_k\}$ of different image regions for the given image, where k is the number of image regions. A typical choice is a pre-trained Faster-RCNN [18] model [2].

Caption Decoder. A two-layer LSTM decoder is popular in recent researches for image captioning [2]. We formalize a decoder with this kind of structure into three parts: an *input* module, an *attention* module and an *output* module.



(a) Attention Module: *Base* (b) Attention Module: *Recurrent* (c) Attention Module: *Adaptive*

Figure 1: Different attention models. For each decoding step, **(a)** *base* takes one attention step; **(b)** *recurrent* takes a fixed M_R steps; **(c)** *adaptive* takes adaptive steps.

The *input* module, which models the input word as well as the context information of the decoder, consists of an LSTM layer (LSTM$_1$). The process of this layer is:

$$(\boldsymbol{h}_t^1, \boldsymbol{m}_t^1) = \text{LSTM}_1([\Pi_t \boldsymbol{W}_e, \bar{\boldsymbol{a}} + \boldsymbol{c}_{t-1}], (\boldsymbol{h}_{t-1}^1, \boldsymbol{m}_{t-1}^1)) \tag{1}$$

where $\boldsymbol{h}_t^1, \boldsymbol{m}_t^1$ are the hidden state and memory cell of LSTM$_1$, W_e is a word embedding matrix, and Π_t is one-hot encoding of the input word at time step t, $\boldsymbol{c}_{t-1}$ is the previous context vector of the decoder, which is also the output of the *attention* module and input of the *output* module, and $\bar{\boldsymbol{a}} = \frac{1}{k}\sum_i \boldsymbol{a}_i$ is the mean-pooling of A and added to $\boldsymbol{c}_{t-1}$ to provide global information to the *input* module.

The *attention* module applies the proposed attention model on the image feature set A and generates a context vector $\boldsymbol{c}_t$, which is named as *Adaptive Attention Time* (AAT) and will be introduced in the following section together with other comparing attention models.

The *output* module passes $\boldsymbol{c}_t$ through a linear layer with softmax activation to predict the probability distribution of the vocabulary:

$$p(y_t \mid y_{1:t-1}) = \text{softmax}(\boldsymbol{c}_t \boldsymbol{W}_p + \boldsymbol{b}_p) \tag{2}$$

3.2 Adaptive Alignment via Adaptive Attention Time

To implement adaptive alignment, we allow the decoder to take arbitrary attention steps for every decoding step. We first introduce the *base* attention mechanism which takes one attention step for one decoding step, then the *recurrent* version which allows the decoder to take a fixed number of attention steps, finally the *adaptive* version *Adaptive Attention Time* (AAT), which adaptively adjusts the attending time.

3.2.1 Base Attention Model

Common practice of applying attention mechanism to image captioning framework is to measure and normalize the attention score α_i of every candidate feature vector $\boldsymbol{a}_i$ with the given query (i.e. h_t^1), resulting in one single weighted averaged vector $\hat{\boldsymbol{a}}_t = \sum_i^K \alpha_i \boldsymbol{a}_i$ over the whole feature vector set A.

By applying an attention mechanism to the image captioning framework, we obtain the attended feature vector:

$$\hat{\boldsymbol{a}}_t = \boldsymbol{f}_{att}(\boldsymbol{h}_t^1, A) \tag{3}$$

Next $\hat{\boldsymbol{a}}_t$ together with $\boldsymbol{h}_t^1$ is fed into another LSTM layer (LSTM$_2$):

$$(\boldsymbol{h}_t^2, \boldsymbol{m}_t^2) = \text{LSTM}_2\big([\hat{\boldsymbol{a}}_t, \boldsymbol{h}_t^1], (\boldsymbol{h}_{t-1}^2, \boldsymbol{m}_{t-1}^2)\big) \tag{4}$$

We let the context vector to be the output hidden state $\boldsymbol{c}_t = \boldsymbol{h}_t^2$.

3.2.2 Recurrent Attention Model

Rather than limiting the attention module to accessing the feature vectors only once for one decoding step. We allow attending for multiple times with *recurrent* attention.

First, we need to make the attention output vary with attention time, and we construct the attention query $\boldsymbol{q}_{t,n}$ at attention time step n of decoding time step t by transforming $\boldsymbol{h}_t^1$ and $\boldsymbol{h}_{t,n-1}^2$ through a linear layer:

$$\boldsymbol{q}_{t,n} = [\boldsymbol{h}_t^1, \boldsymbol{h}_{t,n-1}^2]\boldsymbol{W}_q + \boldsymbol{b}_q \tag{5}$$

where $\boldsymbol{h}_{t,0}^2 = \boldsymbol{h}_{t-1}^2$, and $\boldsymbol{h}_{t,n-1}^2$ is the output of LSTM_2 at attention time step $n-1$ of decoding time step t.

Then $\boldsymbol{q}_{t,n}$ is fed to the attention module and obtain $\hat{\boldsymbol{a}}_t = \boldsymbol{f}_{att}(\boldsymbol{q}_{t,n}, A)$, which is further fed to LSTM_2:

$$\boldsymbol{h}_{t,n}^2, \boldsymbol{m}_{t,n}^2 = \text{LSTM}_2\big([\hat{\boldsymbol{a}_{t,n}}, \boldsymbol{h}_t^1], (\boldsymbol{h}_{t-1,j}^2, \boldsymbol{m}_{t-1,j}^2)\big) \tag{6}$$

We set $\boldsymbol{h}_t^2 = \boldsymbol{h}_{t,M_r}^2, \boldsymbol{m}_t^2 = \boldsymbol{m}_{t,M_r}^2$, where $\boldsymbol{h}_{t,M_r}^2, \boldsymbol{m}_{t,M_r}^2$ are the hidden state and memory cell of the last attention step and M_r is the attention steps for each decoding step.

We let the context vector to be the output hidden state at the last attention step $\boldsymbol{c}_t = \boldsymbol{h}_{t,M_r}^2 = \boldsymbol{h}_t^2$.

3.2.3 Adaptive Attention Time

We further allow the decoder attending to the image for arbitrary times with *Adaptive Attention Time*.

To determine how many times to perform attention, an extra confidence network is added to the output of LSTM_2, since it's used to predict probability distribution. We design the confidence network as a two-layer feed forward translation:

$$p_{t,n} = \begin{cases} \sigma\big(\max\big(0, \boldsymbol{h}_t^1\boldsymbol{W}_1 + \boldsymbol{b}_1\big)\boldsymbol{W}_2 + \boldsymbol{b}_2\big) & n = 0 \\ \sigma\big(\max\big(0, \boldsymbol{h}_{t,n}^2\boldsymbol{W}_1 + \boldsymbol{b}_1\big)\boldsymbol{W}_2 + \boldsymbol{b}_2\big) & n > 0 \end{cases} \tag{7}$$

and the total attention steps is determined by:

$$N(t) = \min\{n' : \prod_{n=0}^{n'}(1 - p_{t,n}) < \epsilon\} \tag{8}$$

where ϵ is a threshold which is a small value and slightly greater than 0 (ϵ = 1e-4 in this paper).

The final hidden state and memory cell of LSTM_2 are computed as:

$$\begin{cases} \boldsymbol{h}_t^2 &= \beta_{t,0}\boldsymbol{h}_t^1 + \sum_{n=1}^{N(t)}\beta_{t,n}\boldsymbol{h}_{t,n}^2, \\ \boldsymbol{m}_t^2 &= \beta_{t,0}\boldsymbol{m}_{t-1}^2 + \sum_{n=1}^{N(t)}\beta_{t,n}\boldsymbol{m}_{t,n}^2 \end{cases} \tag{9}$$

where

$$\beta_{t,n} = \begin{cases} p_{t,0} & n = 0 \\ p_{t,n}\prod_{n'=0}^{n-1}(1 - p_{t,n'}) & n > 0 \end{cases} \tag{10}$$

and $\boldsymbol{h}_t^1$ is added to show that we can obtain context directly from the *input* module without attending to image feature vectors. and $\boldsymbol{c}_{t-1}^2$ is to show that when deciding not to attend image feature, the memory cell should maintain the previous state and not be updated.

Normalization. We normalize the hidden state and memory cell at each attention step: $\boldsymbol{h}_{t,n}^2 = \text{LayerNorm}_h(\boldsymbol{h}_{t,n}^2)$, and $\boldsymbol{m}_{t,n}^2 = \text{LayerNorm}_m(\boldsymbol{m}_{t,n}^2)$

We also normalize the weight of each attention step to make the sum of them to 1: $\beta_{t,n} \leftarrow \frac{\beta_{t,n}}{\sum_{n=0}^{N(t)}\beta_{t,n}}$.

Time Cost Penalty. We add a "attention time" loss to the training loss in order to penalize the time cost for attention steps:

$$L_t^a = \lambda\big(N(t) + \sum_{n=0}^{N(t)}(n+1)(1 - p_{t,n})\big) \tag{11}$$

where λ is a hyper-parameter, $(n+1)(1-p_{t,n})$ encourages $p_{t,n}$ to be larger so that the total attention steps can be reduced, and $N(t)$ is added to indicate the attention time steps and doesn't contribute to the parameter gradients.

Minimum and Maximum Attention Steps. We can set a minimum attention step M_{min} to make the attention module takes at least M_{min} attention steps for each decoding step, by simply setting $p_{t,n} = 0$ for $0 <= n <= M_{min} - 1$.

We can also set a maximum attention steps M_{max} to make sure the attention module takes at most M_{max} attention steps by modifying $N(t)$:

$$N(t) = \min\{M_{max}, \min\{n' : \prod_{n=0}^{n'}(1 - p_{t,n}) < \epsilon\}\} \tag{12}$$

As can be seen, the process of AAT is deterministic and can be optimized directly.

We let the context vector to be the weighted average over all hidden states at all attention steps $\boldsymbol{c}_t = \beta_{t,0}\boldsymbol{h}_t^1 + \sum_{n=1}^{N(t)} \beta_{t,n}\boldsymbol{h}_{t,n}^2 = \boldsymbol{h}_t^2$.

3.2.4 Connections between Different Attention Models

Base attention model is a special case of *recurrent* attention model when $M_r = 1$, and *recurrent* attention model is a special case of *adaptive* attention model when $M_{max} = M_{min} = M_r$.

4 Experiments

4.1 Dataset, Settings, and Metrics

Dataset. We evaluate our proposed method on the popular MS COCO dataset [14]. MS COCO dataset contains 123,287 images labeled with at least 5 captions, including 82,783 for training and 40,504 for validation. MS COCO also provides 40,775 images as the test set for online evaluation. We use the "Karpathy" data split [11] for the performance comparisons, where 5,000 images are used for validation, 5,000 images for testing, and the rest for training.

Settings. We convert all sentences to lower case, drop the words that occur less than 5 times, and trim each caption to a maximum of 16 words, which results in a vocabulary of 10,369 words.

Identical to [2], we employ Faster-RCNN [18] pre-trained on ImageNet and Visual Genome to extract bottom-up feature vectors of images. The dimension of the original vectors is 2048, and we project them to the dimension of $d = 1024$, which is also the hidden size of the LSTM of the decoder and the size of word embedding.

As for the training process, we train our model under cross-entropy loss for 20 epochs with a mini-batch size of 10, and ADAM [12] optimizer is used with a learning rate initialized with 1e-4 and annealed by 0.8 every 2 epochs. We increase the probability of feeding back a sample of the word posterior by 0.05 every 3 epochs [4]. Then we use self-critical sequence training (SCST) [19] to optimize the CIDEr-D score with REINFORCE for another 20 epochs with an initial learning rate of 1e-5 and annealed by 0.5 when the CIDEr-D score on the validation split has not improved for some training steps.

Metrics. We use different metrics, including BLEU [17], METEOR [20], ROUGE-L [7], CIDEr-D [24] and SPICE [1], to evaluate the proposed method and compare with others. All the metrics are computed with the publicly released code[2].

4.2 Ablative Studies

Attention Time Steps (Attention Model). To show the effectiveness of adaptive alignment for image captioning, we compare the results of different attention models with different attention time steps, including *base*, which uses the conventional attentive encoder-decoder framework and forces to align one (attended) image region to one caption word; *recurrent*, which at each decoding step attends to a fixed length of image regions recurrently; and *adaptive*, the proposed method in this paper, which attends to an adaptive length of image regions at each decoding step, allowing adaptive alignment from image regions to caption words.

[2]https://github.com/tylin/coco-caption

Table 1: Ablative studies of attention time steps. We show the results of different attention models with different attention time steps, which are reported after the cross-entropy loss training stage and the self-critical loss training stage. We obtain the mean score and the standard deviation of a metric for a model by training it for 3 times, each with a different seed for random parameter initialization.

Model	**Attention Time Steps**			**Cross-Entropy Loss**			**Self-Critical Loss**		
	min.	max.	avg.	METEOR	CIDEr-D	SPICE	METEOR	CIDEr-D	SPICE
Base	1	1	1	27.58 ± 0.03	113.37 ± 0.15	20.76 ± 0.03	27.96 ± 0.02	123.76 ± 0.41	21.35 ± 0.10
Recurrent	2	2	2	27.66 ± 0.06	114.21 ± 0.35	20.84 ± 0.05	28.06 ± 0.05	124.22 ± 0.24	21.54 ± 0.10
	4	4	4	27.79 ± 0.01	114.72 ± 0.17	20.93 ± 0.08	28.14 ± 0.05	124.96 ± 0.33	21.75 ± 0.03
	8	8	8	27.75 ± 0.05	114.74 ± 0.23	20.93 ± 0.05	28.16 ± 0.02	124.85 ± 0.30	21.76 ± 0.01
Adaptive	0	4	2.55 ± 0.01	$\mathbf{27.82 \pm 0.02}$	$\mathbf{115.12 \pm 0.38}$	$\mathbf{20.94 \pm 0.07}$	$\mathbf{28.25 \pm 0.05}$	$\mathbf{126.48 \pm 0.22}$	$\mathbf{21.84 \pm 0.05}$

Table 2: Tradeoff for time cost penalty. We show the average attention time steps as well as the performance with different values of λ. The results are reported by a single model after self-critical training stage.

λ	avg. steps	BLEU-1	BLEU-2	BLEU-3	BLEU-4	ROUGE	CIDEr-D	METEOR	SPICE
1e-1	0.35	78.1	62.1	47.4	35.8	56.9	118.7	27.2	20.5
1e-3	1.03	80.0	64.3	49.7	37.8	58.0	125.7	28.2	21.6
1e-4	2.54	**80.1**	**64.6**	**50.1**	**38.2**	**58.2**	**126.7**	**28.3**	**21.9**
1e-5	3.77	80.0	**64.6**	50.0	**38.2**	**58.2**	126.5	**28.3**	21.8
0	4.00	80.0	64.5	**50.1**	**38.2**	**58.2**	**126.7**	**28.3**	21.8

From Table 1, we observe that: 1) *recurrent* attention model (slightly) improves *base* attention model for all metrics, especially for those under self-critical loss training stage. 2) Focusing on the Cider-D score under self-critical loss, greatening the attention time steps for *recurrent* attention improves the performance. 3) *adaptive* attention model (AAT) further outperforms *recurrent* attention while requiring an average attention time steps of 2.2, which is quite small comparing to 4 and 8 attention time steps of the *recurrent* attention model. It shows that: firstly, incorporating more attention steps by adopting *recurrent* attention model helps to obtain better performance, however increasing the computation cost linearly with the number of the recurrent steps; secondly, adaptively aligning image feature vectors to caption words via *Adaptive Attention Time* requires less computation cost meanwhile leading to further better performance. This indicates *Adaptive Attention Time* to be a general solution to such sequence to sequence learning tasks as image captioning.

Tradeoff for Time Cost Penalty. We show the effect of λ, the penalty factor for attention time cost, in Table 2. We assign different values to λ and obtain the results of average attention time as well as performance for each value after the cross-entropy loss training stage. From Table 2, we observe that: 1) smaller value of λ leads to more attention time and relatively higher performance; 2) the increment of performance gain will stop at some value of λ but the attention time won't as λ decreases. We find 1e-4 to be a perfect value for λ with the best performance while involving relatively small attention time steps.

Number of Attention Heads. There are two kinds of commonly used attention functions: additive attention [3] and dot-product attention. The former is popular among image captioning models while the latter has also shown its success by employing multiple attention heads [23]. We compare the two attention functions and explore the impact of using different numbers of attention heads. From Table 3, we find that: 1) when using one single head, additive attention outperforms dot-product attention with higher scores for all metrics and fewer attention steps. 2) as the number of attention increases, the number of attention steps reduces and the performance first goes up then down. 4 and 8 bring better performance than other choices.

4.3 Comparisons with State-of-the-arts

Comparing Methods. The compared methods include: LSTM [25], which encodes the image using a CNN and decode it using an LSTM; ADP-ATT [15], which develops a visual sentinel to decide how much to attend to images; SCST [19], which employs a modified visual attention

Table 3: Ablation study of attention type and number of attention heads. For all models, we set λ =1e-4. The results are reported by a single model after self-critical training stage.

Type	Head(s)	avg. steps	BLEU-1	BLEU-2	BLEU-3	BLEU-4	ROUGE	CIDEr-D	METEOR	SPICE
Addictive	1	2.54	80.1	64.6	50.1	38.2	58.2	126.7	28.3	21.9
Dot-product	1	2.84	79.9	64.5	50.0	38.1	58.0	126.3	28.2	21.8
	2	2.78	80.0	64.6	50.1	38.3	58.2	126.8	28.2	21.9
	4	2.75	**80.3**	**65.0**	**50.5**	38.6	58.4	127.7	28.4	22.0
	8	2.66	80.1	64.9	**50.5**	**38.7**	**58.5**	**128.6**	**28.6**	**22.2**
	16	2.64	80.1	64.7	50.2	38.4	58.3	128.0	28.4	22.1

Table 4: Single model performance of other state-of-the-art methods as well as ours on the MS-COCO "Karpathy" test split. For our AAT model, we use multi-head attention [23] with the number of attention heads to be 8 and λ =1e-4.

Method	**Cross-Entropy Loss**					**Self-Critical Loss**				
	BLEU-4	ROUGE	CIDEr-D	METEOR	SPICE	BLEU-4	ROUGE	CIDEr-D	METEOR	SPICE
LSTM [25]	29.6	25.2	52.6	94.0	-	31.9	25.5	54.3	106.3	-
ADP-ATT [15]	33.2	26.6	-	108.5	-	-	-	-	-	-
SCST [19]	30.0	25.9	53.4	99.4	-	34.2	26.7	55.7	114.0	-
Up-Down [2]	36.2	27.0	56.4	113.5	20.3	36.3	27.7	56.9	120.1	21.4
RFNet [10]	35.8	27.4	56.8	112.5	20.5	36.5	27.7	57.3	121.9	21.2
GCN-LSTM [31]	36.8	27.9	57.0	116.3	20.9	38.2	28.5	58.3	127.6	22.0
SGAE [28]	-	-	-	-	-	38.4	28.4	**58.6**	127.8	22.1
AAT (Ours)	**37.0**	**28.1**	**57.3**	**117.2**	**21.2**	**38.7**	**28.6**	58.5	**128.6**	**22.2**

and is the first to use Self Critical Sequence Training(SCST) to directly optimize the evaluation metrics; Up-Down [2], which employs a two-layer LSTM model with bottom-up features extracted from Faster-RCNN; RFNet [10], which fused encoded results from multiple CNN networks; GCN-LSTM [31], which predicts visual relationships between any two entities in the image and encode the relationship information into feature vectors; and SGAE [28], which introduces language inductive bias into its model and applies auto-encoding scene graphs.

Analysis. We show the performance of one single model of these methods under both cross-entropy loss training stage and self-critical loss training stage. It can be seen that: for the cross-entropy stage, AAT achieves the highest score among all compared methods for all metrics (BLEU-4, METEOR, ROUGE-L, CIDEr-D, and SPICE); and for the self-critical stage, AAT reports the highest score for most metrics, with the METEOR score slightly lower than the highest (58.5 vs. 58.6).

Comparing to Up-Down [2], which is the previous state-of-the-art model and is the most similar to our AAT model in terms of the model framework, our single AAT model improves the scores on BLEU-4, METEOR, ROUGE-L, CIDEr-D, and SPICE by 2.2%, 4.1%, 1.6%, 3.3%, and 4.4% respectively for cross-entropy loss training stage by 6.6%, 3.2%, 2.8%, 7.1%, and 3.1% respectively for self-critical loss training stage, which indicates a significant margin and shows that AAT is superior to the vanilla attention model.

4.4 Qualitative Analysis

To gain a qualitative understanding of our proposed method, we use two examples and visualize the caption generation process of a model that employs AAT and a 4-head attention in Figure 2. For each example, we show the attention steps taken at each decoding step, with the visualized attention regions for all the 4 attention heads, the confidence for the output at the current attention step, and the corresponding weight. We also show the confidence/weight for the non-visual step (colored in orange and before the attention steps), which corresponds to $\boldsymbol{h}_t^1$ of the *input* module in the decoder and contains the previous decoding information and is used to avoid attention steps.

We observe that: 1) the attention regions of each attention heads are different from others, which indicates that every attention head has its own concern; 2) the confidence increases with the attention steps, which is like human attention: more observing leads to better comprehension and higher confidence; 3) the number of attention steps required at different decoding steps is different, more

steps are taken at the beginning of the caption or a phase, such as “on the side” and “at a ball”, which indicates that adaptive alignment is effective and has been realized by AAT.

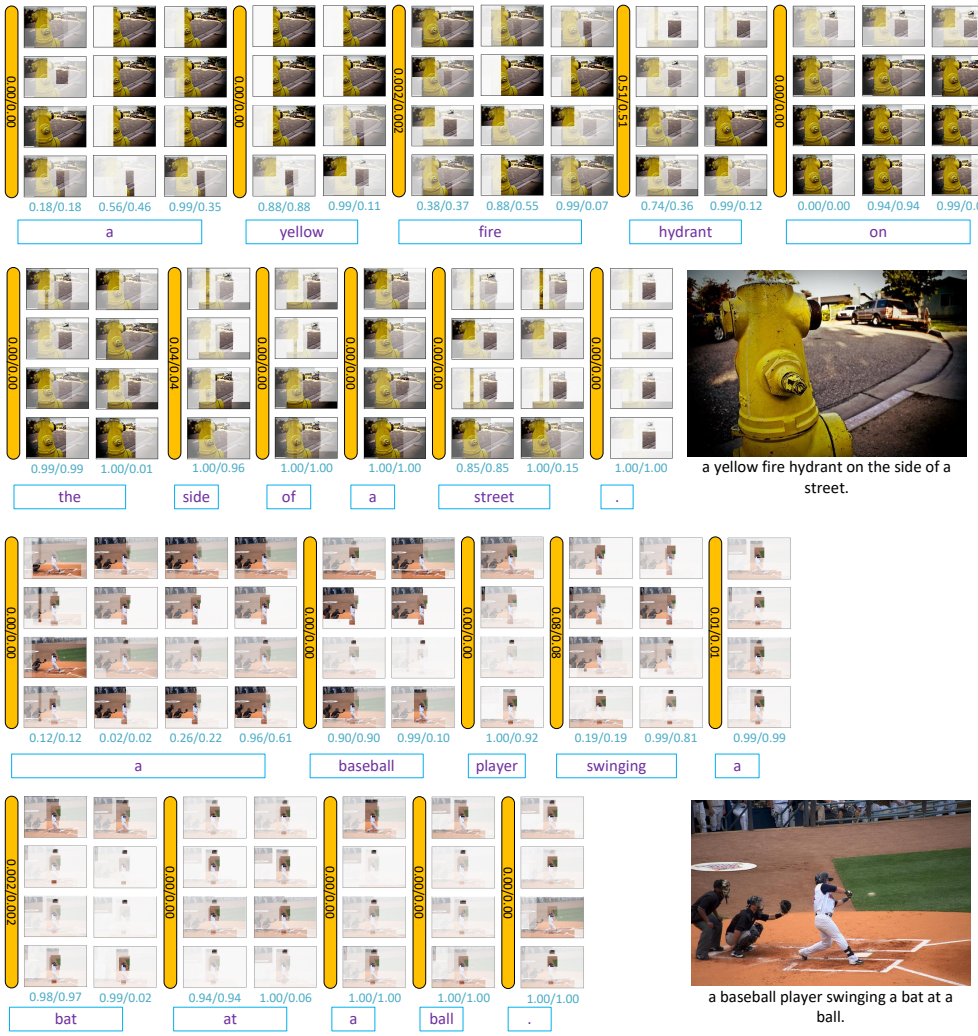


Figure 2: Qualitative examples for the caption generation process of AAT. We show the attention steps taken at each decoding step, with the visualized attention regions, the confidence and the weights of each attention step (*confidence/weight* is shown below the attention regions for each step).

5 Conclusion

In this paper, we propose a novel attention model, namely Adaptive Attention Time (**AAT**), which can adaptively align image regions to caption words for image captioning. AAT allows the framework to learn how many attention steps to take to output a caption word at each decoding step. AAT is also generic and can be employed by any sequence-to-sequence learning task. On the task of image captioning, we empirically show that AAT improves over state-of-the-art methods. In the future, it will be interesting to apply our model to more tasks in computer vision such as video captioning and those in natural language processing such as machine translation and text summarization, as well as any model that can be modeled under the encoder-decoder framework with an attention mechanism.

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References

[1] Peter Anderson, Basura Fernando, Mark Johnson, and Stephen Gould. Spice: Semantic propositional image caption evaluation. *European Conference on Computer Vision*, 11(4):382–398, 2016.

[2] Peter Anderson, Xiaodong He, Chris Buehler, Damien Teney, Mark Johnson, Stephen Gould, and Lei Zhang. Bottom-up and top-down attention for image captioning and visual question answering. 2018.

[3] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. *arXiv preprint arXiv:1409.0473*, 2014.

[4] Samy Bengio, Oriol Vinyals, Navdeep Jaitly, and Noam Shazeer. Scheduled sampling for sequence prediction with recurrent neural networks. In *International Conference on Neural Information Processing Systems*, pages 1171–1179, 2015.

[5] Mostafa Dehghani, Stephan Gouws, Oriol Vinyals, Jakob Uszkoreit, and Łukasz Kaiser. Universal transformers. 2018.

[6] Hao Fang, Saurabh Gupta, Forrest Iandola, Rupesh K Srivastava, Li Deng, Piotr Dollár, Jianfeng Gao, Xiaodong He, Margaret Mitchell, John C Platt, et al. From captions to visual concepts and back. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 1473–1482, 2015.

[7] Carlos Flick. Rouge: A package for automatic evaluation of summaries. In *The Workshop on Text Summarization Branches Out*, page 10, 2004.

[8] Alex Graves. Adaptive computation time for recurrent neural networks. *arXiv: Neural and Evolutionary Computing*, 2016.

[9] Lun Huang, Wenmin Wang, Jie Chen, and Xiao-Yong Wei. Attention on attention for image captioning. In *International Conference on Computer Vision*, 2019.

[10] Wenhao Jiang, Lin Ma, Yu-Gang Jiang, Wei Liu, and Tong Zhang. Recurrent fusion network for image captioning. In *The European Conference on Computer Vision (ECCV)*, September 2018.

[11] Andrej Karpathy and Fei Fei Li. Deep visual-semantic alignments for generating image descriptions. In *Computer Vision and Pattern Recognition*, pages 3128–3137, 2015.

[12] Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *International Conference on Learning Representations*, 2015.

[13] Girish Kulkarni, Visruth Premraj, Vicente Ordonez, Sagnik Dhar, Siming Li, Yejin Choi, Alexander C Berg, and Tamara L Berg. Babytalk: Understanding and generating simple image descriptions. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 35(12):2891–2903, 2013.

[14] Tsung Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C. Lawrence Zitnick. Microsoft coco: Common objects in context. *European Conference on Computer Vision*, 8693:740–755, 2014.

[15] Jiasen Lu, Caiming Xiong, Devi Parikh, and Richard Socher. Knowing when to look: Adaptive attention via a visual sentinel for image captioning. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 3242–3250, 2017.

[16] Margaret Mitchell, Xufeng Han, Jesse Dodge, Alyssa Mensch, Amit Goyal, Alex Berg, Kota Yamaguchi, Tamara Berg, Karl Stratos, and Hal Daumé III. Midge: Generating image descriptions from computer vision detections. In *Proceedings of the 13th Conference of the European Chapter of the Association for Computational Linguistics*, pages 747–756. Association for Computational Linguistics, 2012.

[17] Kishore Papineni, Salim Roukos, Todd Ward, and Weijing Zhu. Bleu: a method for automatic evaluation of machine translation. *Association for Computational Linguistics*, pages 311–318, 2002.

[18] S. Ren, K. He, R Girshick, and J. Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. *IEEE Trans Pattern Anal Mach Intell*, 39(6):1137–1149, 2015.

[19] Steven J Rennie, Etienne Marcheret, Youssef Mroueh, Jarret Ross, and Vaibhava Goel. Self-critical sequence training for image captioning. *Computer Vision and Pattern Recognition*, pages 1179–1195, 2017.

[20] Banerjee Satanjeev. Meteor : An automatic metric for mt evaluation with improved correlation with human judgments. *ACL-2005*, pages 228–231, 2005.

[21] Richard Socher and Li Fei-Fei. Connecting modalities: Semi-supervised segmentation and annotation of images using unaligned text corpora. In *Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on*, pages 966–973. IEEE, 2010.

[22] Ilya Sutskever, Oriol Vinyals, and Quoc V Le. Sequence to sequence learning with neural networks. In *Advances in neural information processing systems*, pages 3104–3112, 2014.

[23] Ashish Vaswani, Noam Shazeer, Niki Parmar, Llion Jones, Jakob Uszkoreit, Aidan N Gomez, and Łukasz Kaiser. Attention is all you need. *Neural Information Processing Systems*, pages 5998–6008, 2017.

[24] Ramakrishna Vedantam, C. Lawrence Zitnick, and Devi Parikh. Cider: Consensus-based image description evaluation. In *Computer Vision and Pattern Recognition*, pages 4566–4575, 2015.

[25] Oriol Vinyals, Alexander Toshev, Samy Bengio, and Dumitru Erhan. Show and tell: A neural image caption generator. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 3156–3164, 2015.

[26] Xin Wang, Fisher Yu, Zi-Yi Dou, Trevor Darrell, and Joseph Gonzalez. Skipnet: Learning dynamic routing in convolutional networks. In *ECCV*, 2018.

[27] Kelvin Xu, Jimmy Ba, Ryan Kiros, Kyunghyun Cho, Aaron Courville, Ruslan Salakhudinov, Rich Zemel, and Yoshua Bengio. Show, attend and tell: Neural image caption generation with visual attention. In *ICML*, 2015.

[28] Xu Yang, Kaihua Tang, Hanwang Zhang, and Jianfei Cai. Auto-encoding scene graphs for image captioning. *arXiv: Computer Vision and Pattern Recognition*, 2018.

[29] Yezhou Yang, Ching Lik Teo, Hal Daumé III, and Yiannis Aloimonos. Corpus-guided sentence generation of natural images. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*, pages 444–454. Association for Computational Linguistics, 2011.

[30] Benjamin Z Yao, Xiong Yang, Liang Lin, Mun Wai Lee, and Song-Chun Zhu. I2t: Image parsing to text description. *Proceedings of the IEEE*, 98(8):1485–1508, 2010.

[31] Ting Yao, Yingwei Pan, Yehao Li, and Tao Mei. Exploring visual relationship for image captioning. *arXiv: Computer Vision and Pattern Recognition*, pages 711–727, 2018.

[32] Ting Yao, Yingwei Pan, Yehao Li, Zhaofan Qiu, and Tao Mei. Boosting image captioning with attributes. *International Conference on Computer Vision*, pages 4904–4912, 2017.