Cross Modification Attention Based Deliberation Model for Image Captioning

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Abstract—The conventional encoder-decoder framework for image captioning generally adopts a single-pass decoding process, which predicts the target descriptive sentence word by word in temporal order. Despite the great success of this framework, it still suffers from two serious disadvantages. Firstly, it is unable to correct the mistakes in the predicted words, which may mislead the subsequent prediction and result in error accumulation problem. Secondly, such a framework can only leverage the already generated words but not the possible future words, and thus lacks the ability of global planning on linguistic information. To overcome these limitations, we explore a universal two-pass decoding framework, where a single-pass decoding based model serving as the Drafting Model first generates a draft caption according to an input image, and a Deliberation Model then performs the polishing process to refine the draft caption to a better image description. Furthermore, inspired from the complementarity between different modalities, we propose a novel Cross Modification Attention (CMA) module to enhance the semantic expression of the image features and filter out error information from the draft captions. We integrate CMA with the decoder of our Deliberation Model and name it as Cross Modification Attention based Deliberation Model (CMA-DM). We train our proposed framework by jointly optimizing all trainable components from scratch with a trade-off coefficient. Experiments on MS COCO dataset demonstrate that our approach obtains significant improvements over single-pass decoding baselines and achieves competitive performances compared with other state-of-the-art two-pass decoding based methods.

Index Terms—Image captioning, deliberation, attention mechanism, cross modification.

I. INTRODUCTION

Image captioning is one of the quintessential sequence generation tasks, which aims to automatically generate natural-language descriptions for images [1]–[10]. This task is exceedingly challenging due to its strict requirements for exact recognition of salient objects, clear comprehension of their relationship and fluent expression describing the visual contents with human language. Image captioning is beneficial for a multitude of practical applications. For example, it can make it possible for visually impaired people to understand the rich visual world.

At present, the majority of image captioning models follow the conventional encoder-decoder framework [2]–[6], [11]–[14], where a Convolutional Neural Network (CNN) first encodes an input image into a sequence of regional features, and a Recurrent Neural Network (RNN) then decodes the visual features to a descriptive sentence. Despite the great success of this framework, it still suffers from two serious disadvantages. The first one is that such models adopt a regular single-pass decoding process, which results in their inability to correct the mistakes in predicted words. Furthermore, mistakes made in early steps may lead to error accumulation under the constraint of the language model. As shown in the first example of Fig. 1, the single-pass decoding based model generates a wrong word “two” at the beginning of caption generation, which leads the model to keep adding visual cues related to the “two polar bears”. Thus, another wrong word “water” is then generated to describe the surrounding, which is a typical example of error accumulation. The second weakness is that when the decoder performs to predict the \( w_{i+1} \) word \( w_i \), it can only leverage the already generated words \( w_{\leq i} \), but not the possible words \( w_{i+2} \) to be generated in the future. That is, the decoder in such a single-pass decoding framework lacks the ability of global planning on linguistic information, which may degrade the semantic consistency and fluency of generated captions. For the second example in Fig. 1 the single-pass decoding based model generates two consecutive prepositional phrases after the word “potatoes”. Although either of them can express reasonable semantics in their local contexts, it makes the sentence verbose and degrades its fluency to put them together for describing the image.

Deliberation is a rewarding behavior in human’s daily life. It plays a predominant role in improving the quality of reading and writing. When someone intends to produce high-level
writings, they will always make rough drafts first, and then refine their works by modifying the details. To overcome the limitations of single-pass decoding based methods, in this paper, we explore a universal two-pass decoding framework for image captioning, which is composed of two interrelated models: a single-pass decoding based model serving as the Drafting Model first produces a draft caption according to an input image in the first-pass decoding process, and a Deliberation Model then performs the polishing process to refine the draft caption to a better descriptive sentence. In order to enhance the correlation between the two models, a refining encoder is designed to participate in both decoding processes. All trainable components are jointly optimized from scratch with a trade-off coefficient to balance the performances of these two models.

Technically, the draft captions are completely derived from the input images and expected to approach the ground truths as much as possible. That is, image features contain more original and reliable information, while the draft captions carry more high level semantic information directly related to human language. Inspired from the complementarity between visual and linguistic modalities, we propose a novel Cross Modification Attention (CMA) module to perform mutual correction between the features of input images and the draft captions. CMA first generates visual and textual context vectors by applying the multi-head attention mechanism [13] to both visual and linguistic features, and then distills the information beneficial to word generation from both context vectors with gated operation. In order to prevent the visual features from being misinformed by wrong drafts while cross modification, we further add a residual connection on the visual side of CMA. In this case, CMA can not only correct the mistakes in the drafts, but also ensure the accuracy of visual features while enhancing their semantic expression. Although CMA is designed as a structural extension of the multi-head attention mechanism in this paper, it is also available for other attention modules, like additive attention [3]. We integrate CMA with the decoder of our Deliberation Model and name it as Cross Modification Attention based Deliberation Model (CMA-DM).

Within our two-pass decoding framework, CMA-DM shows powerful capability of error correction and global planning. As described in the first example of Fig. 1, our CMA-DM realizes the only polar bear in the image and corrects the wrong word “two” to “a”, which helps to predict the accurate surrounding, “snow”. For the second example, our CMA-DM performs global planning based on the draft caption and refines it to a more semantic and readable description.

Main contributions of this paper are summarized as follows:

- We explore a universal two-pass decoding framework for image captioning, where a single-pass decoding based captioning model serves as the Drafting Model to produce a draft caption in the first-pass decoding process, and a Deliberation Model then performs the polishing process to refine the draft caption to a better image description.
- We integrate a well-designed Cross Modification Attention (CMA) module with the decoder of our Deliberation Model, denoted as CMA-DM, to perform mutual correction between the features of input images and corresponding draft captions.
- Experiments on MS COCO dataset [16] demonstrate that our approach obtains significant improvements over single-pass decoding baselines and achieves competitive performances compared with other state-of-the-art two-pass decoding based methods.

II. RELATED WORK

A. Single-Pass Decoding Based Image Captioning Models

To date, most of the image captioning models have employed the conventional encoder-decoder framework to generate the image descriptions through one-pass decoding process [2]–[6], [11]–[14]. Vinyals et al. [2] introduced an end-to-end captioning model (NIC), which adopts a CNN as the encoder and an LSTM [17] instead of a vanilla RNN as the decoder. Yao et al. [12] detected visual attributes from images by using Multiple Instance Learning (MIL) for better image representations. Afterward, [13] built semantic/spatial directed graph on the detected regions with Graph Convolutional Networks (GCNs) and integrated both semantic and spatial object relationships into the image encoder for visual feature refinement. [18] represented the complex structural layout of both image and sentence with the scene graph for generating more human-like captions. Gu et al. [19] designed a language CNN model to capture the long-range dependencies in sequences through multilayer convolutional networks. [20] developed a convolutional architecture for image captioning, where multiple layers of masked convolution substitute for RNNs to decode the image features. [21] proposed a Predict Forward (PF) approach to predict the next two words in one time step against the exposure bias.

B. Attention Mechanisms

Attention mechanisms constitute a significant extension of the conventional encoder-decoder framework, which allow the decoder to selectively focus on the most relevant features at each time step of sequence generation. Inspired by human intuition and the effective research in neural machine translation [22], Xu et al. [3] made the first attempt to incorporate the visual attention into image captioning to dynamically attend to salient regions of the image while caption generation. Anderson et al. [6] introduced a combined bottom-up and top-down attention mechanism, where the bottom-up attention leverages Faster R-CNN [23] to provide image representations at the level of objects and the top-down attention is responsible for predicting the weight distribution. Boosted Attention [24] combined the stimulus-based attention with top-down captioning attention to provide prior knowledge on salient regions. More recently, Huang et al. [14] designed an “Attention on Attention” (AoA) module to determine the relevance between attention results and queries. [21] proposed to take into account the previous attention result when predicting the attention weights at current time. Significantly, these attention-based models also adopt the single-pass decoding based framework and are able to work as the Drafting Model as well.
C. Deliberation Networks

Deliberation is aimed at polishing the existing results for further improvement [25]–[27]. Review Net [28] was a rudiment of the deliberation network for image captioning, which outputs a thought vector after each review step to capture the global properties in a compact vector representation. Motivated by the great progress on deliberation networks in neural machine translation [25], Gao et al. [29] presented a Deliberate Residual Attention Network (DA), which consists of two residual-based attention layers. The first-pass residual-based attention layer generates raw context vectors, and then the second-pass deliberate residual-based attention layer refines them for generating better captions. Although both methods involve the deliberation process, they still stagnate in the single-pass decoding captioning framework, where they can only leverage the generated words but not the future words at each time step of word generation.

Later on, Sammani et al. [30] introduced a Modification Network (MN) to modify existing captions from a given framework by modeling the residual information. MN uses a Deep Averaging Network (DAN) to encode features of the existing captions into a fixed size representation and two separate LSTMs for attention and language modeling. Latterly, [31] proposed a caption-editing model to perform iterative adaptive refinement of an existing caption. The main advantage of these two methods is that they take the complete raw caption into consideration when predicting each word. However, these two models are not jointly trained with the base captioning model.

Our work is related to ruminant decoder (RD) [7]. It performs multi-pass decoding process to produce a more comprehensive caption, which is derived by refining the raw caption generated from the base model. There are three significant differences between RD and our proposed framework. The first one is that the ability for RD to correct mistakes in the draft captions mainly comes from the supervision information in the training process, while we design a novel Cross Modification Attention (CMA) module for explicit mutual correction between visual and linguistic features. The second difference lies in the structure of captioning frameworks. RD takes the hidden states of base decoder as input to the ruminant decoder, while our framework leverages the features of the refining encoder to enhance the contact between Drafting Model and Deliberation Model. The third difference lies in the training algorithms. RD adopts separately training method for cross entropy loss, and performs reinforcement learning by alternately optimizing the base and ruminant decoders. We train our framework by jointly optimizing all trainable components from scratch with a trade-off coefficient, which is a fairly simple but effective training strategy to achieve better performance.

III. METHODOLOGY

In this section, we focus on discussing our two-pass decoding framework for image captioning. To achieve a clear explanation of the details, we first introduce the Cross Modification Attention (CMA) module and then make an elaborate introduction to the overall framework along with each of its components, especially the Cross Modification Attention-based Deliberation Model (CMA-DM). Finally, we describe our joint optimization algorithm for both training stages with cross entropy loss and reinforcement learning.

A. Cross Modification Attention

Multi-Head Attention $f_{mh-att}(Q, K, V)$ [15] integrates several parallel Scaled Dot-Product Attention layers to jointly attend to information from different representation subspaces. It first projects the queries, keys and values (denoted by $Q, K, V$ respectively) $h$ times with different learnable linear transformation layers, and then applies the Scaled Dot-Product Attention $f_{dot-att}(Q, K, V)$ to each group of the projected features concurrently. After that, the attended results are concatenated and projected by one more linear transformation layer to form the final context vector. Here, we assume that the channel dimensions of $Q, K, V$ are respectively $d_q, d_k, d_v$.

The Multi-Head Attention, as depicted in Fig. 2(a), can be formulated as follows:

$$f_{mh-att}(Q, K, V) = Concat(head_1, \ldots, head_h)W^O$$

$$head_i = f_{dot-att}(Q_i, K_i, V_i)$$

$$f_{dot-att}(Q_i, K_i, V_i) = softmax\left(\frac{Q_iK_i^T}{\sqrt{d_k}}\right)V_i$$

$$Q_i = QW_Q, K_i = KW_K, V_i = VW_V, \quad (1)$$

where $W_Q \in \mathbb{R}^{d_q \times d_k}$, $W_K \in \mathbb{R}^{d_k \times d_k}$, $W_V \in \mathbb{R}^{d_k \times d_v}$, $W^O \in \mathbb{R}^{hd_v \times d_o}$ are linear transformation matrices; $d_k$ is the common dimension of the projected queries and keys; $d_v$ and $d_o$ are the dimensions of the attended results and the final context vector.

Such an attention module can only capture the query-related information from a single set of key-value pairs. As it is necessary for our framework to leverage both visual and linguistic features in the polishing process, we propose a Cross Modification Attention (CMA) module (as shown in Fig. 2(b)) to perform mutual correction between the features.

![Fig. 2. Multi-Head Attention and Cross Modification Attention. (a) Multi-head attention operates on a single set of key-value pairs and outputs the context vector by applying $h$ parallel scaled dot-product attention modules. (b) CMA operates on both visual and linguistic features and generates modified context vectors using gated operation and residual connection.](image-url)
of images and draft captions. CMA operates on some queries $Q \in \mathbb{R}^{k \times d_v}$, visual features $A \in \mathbb{R}^{n \times d_v}$ and linguistic features $B \in \mathbb{R}^{l \times d_v}$, where $k, n, l$ are the numbers of vectors in $Q, A, B$. It first produces visual and linguistic context vectors $A', B'$ by adopting two individual Multi-Head Attention modules:

$$
A' = f_{mha-att}(Q, A), \\
B' = f_{mha-att}(Q, B, B),
$$

where $A', B' \in \mathbb{R}^{k \times d_v}$. Then CMA filters out the information that is unrelated to the queries from both context features by using Gated Linear Units (GLU) $\text{[32]}$:

$$
\begin{align*}
A'' &= f_{glu}(Q, A') \\
&= ([Q; A']W^A_p + b^A_p) \odot \sigma((Q; A')W^A_g + b^A_g) \\
B'' &= f_{glu}(Q, B') \\
&= ([Q; B']W^B_p + b^B_p) \odot \sigma((Q; B')W^B_g + b^B_g),
\end{align*}
$$

where $[:]$ indicates concatenation, $W^A_p, W^A_g, W^B_p, W^B_g \in \mathbb{R}^{(d_v + d_o) \times d_v}$, $b^A_p, b^A_g, b^B_p, b^B_g \in \mathbb{R}^{d_v}$, $\sigma$ denotes the sigmoid activation function and $\odot$ is element-wise multiplication.

After that, the CMA makes mutual correction between the both gated features. This operation is also conditioned on the queries $Q$. As the draft captions sometimes carry error messages, they will make the visual context lose some valuable information during modifying. To alleviate this problem, we further add a residual connection between the modified and the original visual context vectors:

$$
\bar{A} = A'' \odot \sigma([Q; A''; B'']W^A_c + b^A_c) + A', \\
\bar{B} = B'' \odot \sigma([Q; A''; B'']W^B_c + b^B_c),
$$

where $W^A_c, W^B_c \in \mathbb{R}^{(d_v + 2d_o) \times d_v}$ and $b^A_c, b^B_c \in \mathbb{R}^{d_v}$. Above all, we obtain the modified visual and linguistic features by using the CMA $f_{cma}(Q, A, B)$:

$$
\bar{A}, \bar{B} = f_{cma}(Q, A, B).
$$

### B. Overall Framework

A complete overview of our two-pass decoding framework is shown in Fig. 3. It consists of two interrelated models: the Drafting Model and the Cross Modification Attention-based Deliberation Model (CMA-DM). The Drafting Model adopts the standard encoder-decoder framework and performs the first-pass decoding process. It first encodes an input image into a set of feature vectors, and then outputs a sequence of draft caption by decoding the visual representations. In the second-pass decoding process, the CMA module distills the information beneficial to current word generation from both the image and the draft caption and helps the Deliberation Model generate the refined caption with higher quality. With the help of CMA, the Deliberation Model can effectively filter out the error information in the draft captions and enhance the semantic expression of the image features. In general, our CMA-DM not only has access to the ability of global planning like other deliberation models, but also can correct mistakes in the draft captions through a powerful attention module. In the following sections, we will describe each of the two models in detail.

### C. Drafting Model

Within our proposed framework, any well-designed single-pass decoding based image captioning model can act as the Drafting Model to transform the given images into draft captions in the first-pass decoding process. In particular, the Drafting Model in our framework generally consists of three components: the basic encoder, the refining encoder and the drafting decoder.

**Basic Encoder:** Given an input image $I$, the basic encoder first extracts a set of feature vectors $V^B = \{v^B_1, v^B_2, \ldots, v^B_n\}$, $v^B_i \in \mathbb{R}^{d_v}$. More specifically, the Drafting Model mostly employs a pre-trained CNN $\text{[33], [34]}$ or R-CNN $\text{[23]}$ based network as the basic encoder, whose parameters are frozen during all the training process.

$$
V^B = f_{bs-enc}(I),
$$

Fig. 3. Overview of our two-pass decoding framework for image captioning. It consists of two interrelated models: the Drafting Model adopts the conventional encoder-decoder framework and generates a draft caption according to an given image in the first-pass decoding process; the Deliberation Model then performs the polishing process to refine the draft caption to a better image description. Note that as the refining encoder is not a necessary structure for every single-pass decoding based model, we will add one to it when necessary to adapt to the architecture of our framework.
where $f_{bs-enc}$ is the encoding function depending on the
network structure of the basic encoder.

**Refining Encoder:** Instead of directly feeding the fixed
features $V^B$ to the subsequent components, our Drafting
Model prefers to use an additional refining encoder to refine
the visual representations. As not all single-pass decoding
based models adopt this module, we will add one to it when
necessary to adapt to our framework.

\[
V^R = f_{r-f-enc}(V^B),
\]

where $V^R \in \mathbb{R}^{n \times d_R}$ is the refined features; $f_{r-f-enc}$ is the
refining function, which exists in various forms in different
drafting models, such as linear transformation layers and
attention functions. Significantly, the refined features not only
participate in the generation of draft captions, but also the
deliberation process.

**Drafting Decoder:** With the refined visual features $V^R$, the
drafting decoder generates a sequence of draft caption $W^D = \{w^D_1, w^D_2, \ldots, w^D_1\}$, where $l$ is the length of the draft caption.
At the $t$-th step, the drafting decoder outputs a probability
distribution $p^D_t$ to predict the next word $w^D_t$:

\[
w^D_t \sim p^D_t = f_{dra-dec}(V^R, w^D_{t-1}),
\]

where $f_{dra-dec}$ is the decoding function depending on the
network structure of the drafting decoder.

**D. Cross Modification Attention-Based Deliberation Model**

In the first-pass decoding process, the Drafting Model trans-
forms the given image $I$ into a sequence of draft caption $W^D$ word by word in temporal order. Therefore, it has no chance
to correct mistakes in the predicted words. That is, the
draft captions may contain some mistakes. Moreover, due to the lack of global planning ability, the Drafting Model cannot guarantee
the semantic consistency and fluency of the draft captions.
To address these problems, we propose a Cross Modification Attention-based Deliberation Model (CMA-DM) to polish the
draft captions in the second-pass decoding process.

As illustrated in Fig. 4, CMA-DM takes as input the refined
visual features $V^R$ and the draft caption $W^D$, and generates
the refined caption $W^R = \{w^R_1, w^R_2, \ldots, w^R_m\}$, where $m$ is
the length of the refined caption. Our CMA-DM is composed of
a deliberation encoder and a deliberation decoder.

**Deliberation Encoder:** To realize the strategy of global
planning, the deliberation encoder first projects the one-hot
encoding $\Pi^D$ of the input draft caption $W^D$ into dense vectors
$V^D = \{v^D_1, v^D_2, \ldots, v^D_l\}$, where $v^D \in \mathbb{R}^{d_D}$, by using a single
word embedding layer:

\[
V^D = \Pi^D W^D_e,
\]

where $W^D_e \in \mathbb{R}^{l \times d_D}$ is a word embedding matrix for a
vocabulary $\Sigma$, and $V^D \in \mathbb{R}^{l \times d_D}$ is the dense feature vectors
of the draft caption.

Rather than directly feeding the refined visual features $V^R$
and the dense word embeddings $V^D$ into the deliberation
decoder, we make a projection on both feature vectors with
two individual linear transformation layers followed by the
Rectified Linear Unit (ReLU) [35] activation function:

\[
A = \text{ReLU}(V^R W^A + b^A),
\]

\[
B = \text{ReLU}(V^D W^B + b^B),
\]

where $W^A \in \mathbb{R}^{d_R \times d_D}$, $W^B \in \mathbb{R}^{d_D \times d_D}$, and $b^A, b^B \in \mathbb{R}^{d_D}$.

**Deliberation Decoder:** We adopt the widely-used top-
down architecture from [6] as the general structure of our
deliberation decoder, as depicted in Fig. 4. It is composed of
an attention LSTM, a Cross Modification Attention module
and a language LSTM.

In order to provide a strong query with the knowledge of
global semantic information, we feed the mean-pooled features of $A$ and $B$ to the attention LSTM. Other input vectors
contains: the embedding vector of the input word at current
time step $x^1_t$ and the last hidden state of the language LSTM $h_{t-1}^2$. That is, the input of the attention LSTM at $t$-th step $x^1_t$
is given by:

\[
x^1_t = [\Pi x^1_e; \bar{A}; \bar{B}; h^2_{t-1}]
\]

\[
\bar{A} = \sum_{i=1}^n A_i,
\]

\[
\bar{B} = \sum_{i=1}^l B_i,
\]

where $\Pi x_e$ is the one-hot encoding vector of the input word and
$W^1 \in \mathbb{R}^{l \times d_D}$ is another word embedding matrix different
from $W^D_e$.

Then, we consider the current hidden state of the attention
LSTM as the query $Q$ to compute the context vectors from
both visual and linguistic features through CMA:

\[
h_t, c_t = LSTM^1(x^1_t, h^1_{t-1}, c^1_{t-1})
\]

\[
a_t, b_t = f_{ema}(h^1_t, \bar{A}, \bar{B}),
\]

where $a_t, b_t \in \mathbb{R}^{d_D}$ are respectively the visual context vectors
and the linguistic context vectors.

Finally, we feed the following inputs to the language LSTM
to get the probability distribution of each word in the refined

![Fig. 4. Main structure of our CMA-DM. It consists of two components: the deliberation encoder projects both visual and linguistic representations into a new feature space; the deliberation decoder takes the projected features as input and refines the draft caption to a better image description. Note that the basic encoder and the refining encoder are not illustrated in this figure for clarity.](image-url)
caption: both context vectors and the current hidden state of the attention LSTM:
\[
x^2_t = [h^1_t; a_t; b_t] \\
h^2_t, c^2_t = LSTM^2(x^2_t, h^2_{t-1}, c^2_{t-1}) \\
w^R_t \sim p^R_t = \text{softmax}(h^2_t).
\]

E. Joint Optimization Algorithm

During all the training process, the basic encoder is kept fixed, and the other components are jointly optimized from scratch with a trade-off coefficient. Denote the refining encoder as \(E_r(\theta_r)\), the drafting decoder as \(D_{d1}(\theta_{d1})\), the deliberation encoder as \(E_d(\theta_d)\) and the deliberation decoder \(D_2(\theta_{d2})\) parameterized with \(\theta_r, \theta_{d1}, \theta_d \) and \(\theta_{d2}\), respectively. Obviously, the Drafting Model \(M_1(\theta_1)\) is accompanied by the parameters \(\theta_1 = \theta_r \cup \theta_{d1}\), and the Deliberation Model \(M_2(\theta_2)\) appears with the parameter \(\theta_2 = \theta_r \cup \theta_d \cup \theta_{d2}\). Like previous methods, we first pre-train our framework with cross entropy (XE) loss and then directly optimize the non-differentiable metrics with Self-Critical Sequence Training (SCST) [56].

Given an input image \(I\) and a target ground-truth sequence \(W = w_1:T = (w_1, \ldots, w_T)\), we first optimize XE loss for both models in our framework with a trade-off coefficient \(\lambda_{XE}\):
\[
\mathcal{L}_{XE}(\theta_1) = - \sum_{t=1}^{T} \log(p_{\theta_1}(w_t|w_{1:(t-1)}, I)) \\
\mathcal{L}_{XE}(\theta_2) = - \sum_{t=1}^{T} \log(p_{\theta_2}(w_t|w_{1:(t-1)}, I, W^D)) \\
\mathcal{L}_{XE}(\theta_1, \theta_2) = \mathcal{L}_{XE}(\theta_1) + \lambda_{XE} \mathcal{L}_{XE}(\theta_2),
\]
where \(W^D\) is the draft caption generated by \(M_1\) in the first-pass decoding process.

Then we apply the standard SCST algorithm to each of the models. Similar to SCST training stage, we employ another trade-off coefficient \(\lambda_{RL}\) to realize joint optimization for our framework:
\[
\mathcal{L}_{RL}(\theta_1) = - \mathbb{E}_{w^D \sim p^D_{\theta_1}}[r(w^D)] \\
\mathcal{L}_{RL}(\theta_2) = - \mathbb{E}_{w^R \sim p^R_{\theta_2}}[r(w^R)] \\
\mathcal{L}_{RL}(\theta_1, \theta_2) = \mathcal{L}_{RL}(\theta_1) + \lambda_{RL} \mathcal{L}_{RL}(\theta_2),
\]
where \(w^D\) and \(w^R\) are sentences sampled from the predicted word distribution produced by \(M_1\) and \(M_2\), respectively; the reward \(r(\cdot)\) uses CIDEr score in this paper. The gradients of each model can be approximated using a single Monte-Carlo sample from \(p^D_{\theta_1}\) or \(p^R_{\theta_2}\):
\[
\nabla_{\theta_1} \mathcal{L}_{RL}(\theta_1) \approx - (r(w^D) - b_1) \nabla_{\theta_1} \log p^D_{\theta_1}(w^D) \\
\nabla_{\theta_2} \mathcal{L}_{RL}(\theta_2) \approx - (r(w^R) - b_2) \nabla_{\theta_2} \log p^R_{\theta_2}(w^R),
\]
where \(b_1\) and \(b_2\) are the baselines under the greedy decoding algorithm.

IV. EXPERIMENTAL SETUP

A. Datasets and Settings

Datasets: All of our experiments are conducted on the most popular MS COCO dataset [16]. MS COCO dataset contains a total of 123,287 images, including 82,783 training images, 40,504 validation images and 40,775 testing images. Each image is equipped with at least 5 human-annotated captions, and in this paper, we select 5 ground-truth sentences per image for performance evaluation like most studies. It is worth noting that the official testing set does not provide the annotations corresponding to the images, so we can only make the evaluation over the testing set through the online MS COCO testing server. Following previous work, we adopt the widely-used “Karpathy” split[37] from [36] for the offline evaluation, where 113,287 images are used for training, 5,000 images for validation and 5,000 images for testing.

Visual Genome [38] is a large-scale database containing over 108K images with dense annotations, where each image has an average of 35 objects, 26 attributes and 21 pairwise relationships between objects. To sufficiently describe all the contents and interactions in an image, Visual Genome provides on average 50 region descriptions per image, and each description consists of 1 to 16 words. In this paper, we adopt the Faster R-CNN [23] pre-trained on Visual Genome dataset as the basic encoder in the Drafting Model to detect the bottom-up image features.

Data Preprocessing: We first convert all sentences to lower case and count the occurrences of each word. In this paper, we only keep the words which appear more than 5 times, and replace the discarded words with the “UNK” token. Then we truncate the captions to no longer than 16 words, and those captions with less than 16 words are padded with the “PAD” token. Considering these two additional tokens, we obtain the final vocabulary of 10,369 unique words. We further add another two “PAD” tokens at both sides of each caption to symbolize the beginning and the end of it. By doing this, we finally obtain the processed captions with a fixed length of 18 for training.

Evaluation Metrics: We mainly make the performance evaluation of our proposed approach on 5 different metrics: BLEU (including BLEU-1,2,3,4) [39], METEOR [40], ROUGE_L [41], CIDEr [42] and SPICE [43], denoted as \(B_1,2,3,4, M, R, C\) and \(S\). These metrics measure n-gram overlap degree between generated sentences and reference sentences from different aspects. We also evaluate our CMA-DM with Word Mover’s Distance (WMD) [44] (denoted as \(W\)), which is first proposed to measure document distance by calculating Earth Mover’s Distance based on \(\text{word2vec}\) embeddings of the words. All these metrics are computed with the publicly released MS COCO caption evaluation tool[45]

B. Drafting Models

To convincingly demonstrate the powerful error-correcting capability of CMA-DM and the universality of our proposed two-pass end-to-end framework for image captioning, we conduct several experiments by employing three different single-pass decoding based models as the Drafting Model. We make a careful comparison between the following models and the corresponding CMA-DM in Section V.

a) Att2in: Att2in model is a slightly modified version of the soft attention model [8], which feeds the attention-derived image features only to the cell node of the LSTM.

[1] Online. Available: https://cs.stanford.edu/people/karpathy/deepimagesent/
[2] Online. Available: https://github.com/tylin/coco-caption/
Rather than using ResNet-101 in [36], we adopt the Faster R-CNN pre-trained on Visual Genome dataset as the basic encoder for better visual representations. To adapt to the structure of our proposed framework, we further employ a linear transformation layer followed by a ReLU activation function as the refining encoder to refine the detected image features.

b) Up-Down: Up-Down [6] model is a widely-used architecture for image captioning, on which many models are designed, including our CMA-DM. It first encodes the given images into object-level features by using a Faster R-CNN pre-trained on Visual Genome dataset, and then decodes the visual representations through two LSTMs with visual attention mechanism. Similar to Att2in model, we also project the object-level features with a linear transformation layer followed by ReLU before feeding them into the drafting decoder.

c) AoANet: AoANet [14] is the Base/Drafting Model of the current state-of-the-art two-pass decoding method [31]. It takes as input the detected features from Up-Down model, and then refines them by using an AoA module based encoder. As AoANet conforms to the architecture of our Drafting Model, we directly treat the pre-trained Faster R-CNN and the AoA encoder as the basic encoder and the refining encoder respectively, without further adding extra layers. In this paper, we adopt AoANet as our main Drafting Model and most of the experimental results reported in Section V are based on it.

C. Implement Details

We integrate each of the aforementioned drafting models with our CMA-DM to build the overall two-pass decoding framework.

Basic Encoder: As described in Section IV-B we adopt the Faster R-CNN pre-trained on Visual Genome dataset as the basic encoder in all experiments. We choose the “adaptive” version of the bottom-up features extracted by the pre-trained Faster R-CNN, which sets the class detection confidence threshold to 0.2 and detects 10’100 regions per image. More specifically, the dimension of the extracted features is 2,048.

Refining Encoder: For Att2in model and Up-Down model, the refining encoders of them project the extracted features to dimensions of 512 and 1,024, respectively. The refining module of AoANet integrates the self-attentive multi-head attention mechanism with the AoA module, which is stacked for 6 times and outputs the refined visual features with a dimension of 1,024.

Drafting Decoder: The original Att2in model and Up-Down model serve as the drafting decoder to perform the first-pass decoding process. For Att2in model, we set the dimensions of word embeddings and LSTM hidden states to 512. For Up-Down model, we set the dimensions of word embeddings and hidden states in each LSTM to 1,000, and the number of hidden units in the attention layer to 512. As for the decoder of AoANet, we set the dimensions of word embeddings and LSTM hidden states to 1,024. We employ 8 parallel attention heads in AoA module and set the dimension of the attended results for each head to 128. For all drafting models, we set the maximum length of the generated draft captions to 16.

CMA-DM: Before feeding the one-hot encodings of draft captions into the word embedding layer, we first pad the draft captions to 18 words with “PAD” tokens, which also contain the beginning and end symbols. We set the dimensions of both word embedding layers (one for draft captions, the other one for current input word) to 1,024. The deliberation encoder projects the refined visual features and the word embeddings of draft captions into the same dimension of 1,024, which is also the dimensions of the global visual/linguistic features and hidden states in each LSTM. Each multi-head attention in our CMA adopts the same settings as those in AoA. Outputs of other projection layers in CMA share the same dimension of 1024. Final captions generated by CMA-DM are also limited to no more than 16 words.

Training and Evaluation: All trainable components in our framework are jointly optimized from scratch with a
trade-off coefficient. We train all of our models by first optimizing the cross entropy loss and then optimizing the non-differentiable metrics with reinforcement learning. We use the Adam optimizer with batch size 50. To avoid gradient explosion, we use the gradient clipping strategy [45], which truncates the gradients to a range of [-0.1, 0.1]. As for the training process, we first train our models with cross entropy loss for 30 epochs. We adopt label smoothing [46] and set the confidence to 0.2. We use an initial learning rate of 2e-4 and anneal it by 0.8 every 3 epochs. We increase the scheduled sampling probability by 0.05 every 5 epochs until it reaches the probability of 0.5 [47]. In this training stage, we set the trade-off parameter $\lambda_{CE}$ to 0.2 to achieve the best performance. Then we optimize the CIDEr-D score with SCST [36] for another 15 epochs. The initial learning rate is set to 2e-5 and annealed by 0.5 when the CIDEr-D score shows no improvement for 3 consecutive evaluating steps. We set the trade-off parameter $\lambda_{RL}$ to 0.1 for sequence-level training. When training, we generate both draft captions and final captions by using greedy decoding to reduce the time cost. When testing, we employ beam search for better model performance and beam size is set to 3 for all models.

V. EXPERIMENTAL RESULTS
A. Comparing with Single-Pass Decoding Baselines

We conduct three groups of experiments by employing each of the single-pass decoding based models mentioned in Section IV-B as the Drafting Model. As shown in Table. [1] each group contains the experimental results produced by four different methods: (1) method is exactly the same as the model in the original paper. (2) method$^*$ and method$^\dagger$ implement the baseline models conforming to the structure setups of our Drafting Model. More specifically, compared to the baseline models, both Attr2in$^\dagger$ and Up-Down$^\dagger$ contain an additional refining encoder, which consists of a linear transformation layer followed by ReLU. As AoANet fully conforms to the structure of our Drafting Model, AoANet$^*$ reports the results obtained from the publicly available pre-trained AoANet. (3) method(Drafting) is the Drafting Model in our proposed framework, which performs the first-pass decoding process and generates the draft captions. (4) method + CMA-DM is our complete two-pass decoding based model, which uses method$^\dagger$ or method$^*$ as the Drafting Model. In this section, we first compare the model performances in different groups to show the effect of our CMA-DM, and then thoroughly analyze the characteristics of our proposed two-pass decoding framework by combining with all experiments.

Att2in Versus Att2in + CMA-DM: In the first group of experiments, we apply our CMA-DM to the baseline Att2in model. We report the results in Table. [1] Group 1. Compared to Att2in(Drafting), our Att2in + CMA-DM leads to significant improvements across all metrics after different training stages, especially increasing the CIDEr score from 111.7 to 118.7 with cross entropy loss and from 114.3 to 121.9 with reinforcement learning.

Up-Down Versus Up-Down + CMA-DM: For the second group, we apply our CMA-DM to the popular Up-Down model. As shown in Table. [1] Group 2, our Up-Down + CMA-DM also achieves better performances than its Drafting Model Up-Down(Drafting) across all metrics. Up-Down + CMA-DM increases the BLEU-4 / CIDEr scores from 35.9 / 113.0 to 37.5 / 115.1 with cross entropy loss and from 37.2 / 122.5 to 38.0 / 125.0 with reinforcement learning.

AoANet Versus AoANet + CMA-DM: We further apply our Deliberation Model to the widely-used Drafting Model AoANet. The model performances reported in Table. [1] Group 3 show that our AoANet + CMA-DM outperforms AoANet(Drafting) across most of the metrics, which substantially increases the BLEU-4 / CIDEr scores of 36.8 / 116.2 to 38.7 / 120.2 with cross entropy loss.

Framework Analysis: We make a careful analysis of our proposed framework from three aspects: (1) By comparing the performances between method(Drafting) and method$^\dagger$ / method$^*$, we discover that the former is often not as good as the latter. For example, considering the Up-Down model as the baseline, the Drafting Model Up-Down(Drafting) achieves BLEU-4 / CIDEr scores of 35.9 / 113.0 with cross entropy loss, while Up-Down$^\dagger$ obtains higher BLEU-4 / CIDEr scores of 36.2 / 113.7. This is because the refining encoder of the Drafting Model is also involved in the deliberation process. To ensure the high performance of the Deliberation Model, the refining encoder makes a compromise by sacrificing a little performance of the Drafting Model. (2) Comparison between method$^\dagger$ / method$^*$ and our complete framework method + CMA-DM demonstrates that the deliberation process is indeed effective at polishing the draft captions, and even taking as input the slightly worse draft captions generated by method(Drafting), our CMA-DM can still achieve definite improvement over the method$^\dagger$ / method$^*$. (3) The better the performance of the baseline model, the less the improvement brought by the Deliberation Model with reinforcement learning. As reported in Table. [1] Att2in$^\dagger$ achieves a CIDEr score of 118.4 and Att2in + CMA-DM shows an improvement of 3.0 percent on it. Up-Down$^\dagger$ obtains a higher CIDEr score of 124.1 and Up-Down + CMA-DM increases it by 0.7 percent. As for the AoANet$^*$, it achieves the performance of 128.9 CIDEr score and the deliberation process only provides little improvement of 0.07 percent.

B. Ablation Study on CMA

To clearly explain the performance improvement brought by each component in our CMA, we conduct ablation study by employing AoANet as the Drafting Model and the standard top-down architecture [4] as the deliberation decoder. We evaluate different methods by only changing the structure of the attention module. We design five variants of the CMA module, as illustrated in Fig. [5] and determine the best possible network structure by comparing their performances. We report the results after optimizing cross entropy loss with the trade-off parameter $\lambda_{XE} = 1.0$ in Table. [1]

We first make experiments (1 - 3) based on the conventional multi-head attention mechanism. Experiment 1 adopts the original structure of the top-down decoder, which contains a visual attention mechanism like the decoders of most single-pass
decoding based models to capture visual context features for each time step. Experiment 2 applies the multi-head attention function only to the features of draft captions to decide which parts of the linguistic features are the most relevant to the word currently to be generated. Experiment 3 simultaneously uses visual attention mechanism and textual attention mechanism to selectively focus on certain parts of both visual and linguistic features. The experimental results show that the model only equipped with textual attention mechanism in Experiment 2 reaches poor performances and gets a CIDEr score of 110.2. As expected, however, the performance of the model integrated with both visual and textual attention mechanisms in Experiment 3 performs slightly better than those reported in Experiment 1 and 2.

Considering the significance and synergy of both visual and textual attention mechanisms, we design five variants of the CMA module based on this parallel attention structure, as illustrated in Fig. 5. These modules perform mutual correction between visual and linguistic context features in different ways, which mainly depends on the sigmoid activation function. The comparison results are reported in the experiments (4 - 8). We weigh up the performances of different CMA modules and decide to adopt CMA-(d) as the main structure of our CMA, which achieves the best performances on most metrics.

We further test the performances of residual connections. We conduct experiments (9 - 11) by applying the residual connection to the visual side, textual side, or both sides of CMA-(d). Fig. 5(b) illustrates how the residual connection is added to CMA-(d) on its visual side, and it is a symmetrical structure for the residual connection on the textual side. The experimental results show that the residual connection on the visual side brings great improvements across all metrics, while the residual connection on the textual side leads to performance degradation.

C. Comparison of Different Complexity Refining Encoders

To gain insight into the influences of the refining encoder with different complexity, we conduct comparative experiments with the same setups, except the network structure of the refining encoder. This group of experiments are also based on the AoANet, and we use the CMA-(d) with a residual connection applied to the visual features as the deliberation decoder. We evaluate the performances of three different refining encoders: (1) The first kind of refining encoder is composed of a single linear transformation layer with ReLU as its activation function. (2) The second one consists of 3 layers of the AoA module. (3) The last one adopts the same structure as that in the original AoANet, which contains 6 layers of the AoA module. The comparison results are reported in Table. III after cross entropy training with $\lambda_{XE} = 1.0$. We find that the
TABLE III

PERFORMANCE COMPARISONS OF DIFFERENT COMPLEXITY REFINING ENCODERS WITH AoANet [14] AS OUR DRAFTING MODEL.

| Refining Encoder | Method                        | B@4 | R   | C   | S   |
|------------------|-------------------------------|-----|-----|-----|-----|
| FC + ReLU        | AoANet(Drafting)              | 36.2| 56.5| 114.1| 20.6|
|                  | AoANet + CMA-DM               | 37.7| 57.6| 117.2| 20.9|
| 3 × AoA          | AoANet(Drafting)              | 36.6| 56.8| 116.7| 20.8|
|                  | AoANet + CMA-DM               | 38.0| 57.6| 117.9| 21.0|
| 6 × AoA          | AoANet(Drafting)              | 36.9| 56.9| 117.2| 20.9|
|                  | AoANet + CMA-DM               | 38.3| 57.9| 119.7| 21.2|

TABLE IV

PERFORMANCE COMPARISONS OF OUR FRAMEWORK WITH DIFFERENT TRADE-OFF COEFFICIENT. BEST RESULTS OF THE DRAFTING MODEL AND THE DELIBERATION MODEL ARE HIGHLIGHTED IN RED AND BLUE, RESPECTIVELY.

| Trade-Off Coefficient | Cross Entropy Loss | SCST |
|------------------------|--------------------|------|
|                        | Method             | B@4  | R   | C   |
| \( \lambda = 0.1 \)    | Drafting           | 36.8 | 58.1| 119.7|
|                        | Deliberation       | 38.4 | 58.1| 119.7|
| \( \lambda = 0.2 \)    | Drafting           | 37.0 | 57.1| 116.7|
|                        | Deliberation       | 38.7 | 58.2| 120.2|
| \( \lambda = 0.5 \)    | Drafting           | 38.0 | 57.7| 118.5|
|                        | Deliberation       | 38.5 | 58.5| 127.5|
| \( \lambda = 1.0 \)    | Drafting           | 38.3 | 57.9| 119.7|
|                        | Deliberation       | 39.0 | 58.8| 128.3|

E. Comparing With State-of-The-Art Methods

We compare our models, including Up-Down + CMA-DM and AaANet + CMA-DM, with current state-of-the-art on the MS COCO “Karpathy” test split, especially other two-pass decoding based methods. These models include (1) NIC [2], which uses a vanilla CNN-LSTM encoder-decoder framework without attention mechanism; (2) Att2in [36], which applies visual attention mechanism and is optimized with non-differentiable metrics; (3) Up-Down [6], which first extracts object-level features using Faster R-CNN and then adopts a top-down decoder to decode the features; (4) DA [29], which refines the context vectors by a deliberate residual-based attention layer; (5) AoANet [14], which uses an attention gate to retain the expect useful knowledge from the attended results; (6) MN [30], which modifies the existing captions from a given framework; (7) RD [7], which polishes the captions generated from a base model by using a ruminant decoder; (8) ETN [31], which edits existing captions with iterative adaptive refinement.

As shown in Table. V our Up-Down + CMA-DM dramatically outperforms its baseline model, and our AoANet + CMA-DM achieves better performances than AoANet(*) on most of the metrics. Both results indicate that our framework can really refine the draft captions generated by single-pass decoding based models. With the same baseline model Up-Down, our CMA-DMS is superior to both MN and RD. Considering AoANet as the baseline, our approach achieves competitive performance compared to the current state-of-the-art two-pass decoding based model ETN. Furthermore, we report the model performances on the online COCO test server in Table. VI.

The performance of our single model AoANet + CMA-DM is slightly lower than that of its baseline, which is an ensemble of 4 models.

F. Qualitative Analysis

Attention Visualization: To qualitatively show the effect of our CMA-DM, we visualize both visual and textual attention weights in Fig. 6. As our CMA extends the multi-head attention mechanism, we only illustrate the attention maps at the time step of mistake correction for clarity. As shown in Fig. 6 the draft caption generated in the first-pass decoding process contains an obvious mistake, which is because the Drafting Model mistakenly considers the dog on the motorcycle as a “cat”. When our CMA-DM attempts to predict the correct word “dog” in the polishing process, the CMA pays more attention to the region of the dog in the image and assigns high weights to the related words in the draft caption, including “cat”, “seat” and “motorcycle”. In the correction process, the visual context provides more original and reliable information related to the animal and filters out the features related to “cat” from the linguistic context. As a result, our CMA-DM finally outputs “dog” for the next word instead of the “cat” and refines the draft caption to a better descriptive sentence.

Generated Captions: To further demonstrate the improvement of our CMA-DM on refining draft captions, we show some qualitative examples generated by our two-pass decoding based framework in Fig. 7. For each example, we show the...
TABLE V

| Method                  | B@1 | B@4  | M   | R   | C   | S   |
|------------------------|-----|------|-----|-----|-----|-----|
| NIC [2]                | 32.9| 25.5 | 52.6| 94.0| -   | -   |
| Att2in [36]            | 31.9| 25.5 | 54.3| 101.3| -   | -   |
| Up-Down [6]            | 33.3| 26.3 | 55.5| 111.4| -   | -   |
| DA [29]                | 37.2| 28.4 | 57.5| 119.8| -   | 21.3|
| AoANet [14]            | 30.9| 23.8 | 51.2| 99.9 | -   | -   |
| Up-Down + MN [30]      | 31.3| 23.5 | 51.8| 103.5| -   | -   |
| Up-Down + RD [7]       | 32.7| 24.7 | 53.7| 111.7| -   | -   |
| GCN-LSTM [21] + RD [7] | 35.7| 26.8 | 57.7| 119.7| -   | -   |
| Up-Down + CMA-DM       | 34.2| 26.1 | 54.5| 107.1| -   | -   |
| AoANet + CMA-DM        | 35.2| 27.3 | 56.0| 114.0| -   | -   |

Cross Entropy Loss Reinforcement Learning

| Model          | B@1 | B@4  | M   | R   | C   | S   |
|----------------|-----|------|-----|-----|-----|-----|
| NIC [2]        | 32.9| 25.5 | 52.6| 94.0| -   | -   |
| Att2in [36]    | 31.9| 25.5 | 54.3| 101.3| -   | -   |
| Up-Down [6]    | 33.3| 26.3 | 55.5| 111.4| -   | -   |
| DA [29]        | 37.2| 28.4 | 57.5| 119.8| -   | 21.3|
| AoANet [14]    | 30.9| 23.8 | 51.2| 99.9 | -   | -   |
| Up-Down + MN [30] | 31.3| 23.5 | 51.8| 103.5| -   | -   |
| Up-Down + RD [7] | 32.7| 24.7 | 53.7| 111.7| -   | -   |
| GCN-LSTM [21] + RD [7] | 35.7| 26.8 | 57.7| 119.7| -   | -   |
| Up-Down + CMA-DM | 34.2| 26.1 | 54.5| 107.1| -   | -   |
| AoANet + CMA-DM | 35.2| 27.3 | 56.0| 114.0| -   | -   |

TABLE VI

| Model          | BLEU-1 | BLEU-2 | BLEU-3 | BLEU-4 | METEOR | ROUGE | CIDEr |
|----------------|--------|--------|--------|--------|--------|-------|-------|
|                | c5     | c40    | c5     | c40    | c5     | c40   | c5     | c40    |
| SCST [36]      | 78.1   | 93.3   | 61.9   | 86.0   | 47.0   | 75.9  | 35.2   | 56.3   |
| Up-Down [6]    | 80.2   | 95.2   | 64.1   | 88.8   | 49.1   | 79.4  | 36.9   | 68.5   |
| AoANet [14]    | 81.0   | 95.0   | 65.8   | 89.6   | 51.4   | 81.3  | 39.4   | 71.2   |
| DA [29]        | 79.4   | 94.4   | 63.5   | 88.0   | 48.7   | 78.4  | 36.8   | 67.4   |
| Up-Down + RD [7] | 79.9  | 94.4   | 64.4   | 88.3   | 49.8   | 79.3  | 37.9   | 68.8   |
| GCN-LSTM [21] + RD [7] | 80.0  | 94.7   | 64.5   | 88.6   | 49.8   | 79.5  | 37.8   | 68.8   |
| AoANet + CMA-DM | 79.9  | 94.6   | 64.7   | 88.8   | 50.2   | 80.0  | 38.3   | 69.5   |

VI. Conclusion

In this paper, we explore a universal two-pass decoding based framework for image captioning to overcome the limitations of the single-pass decoding based models. To enhance the semantic expression of visual features and filter out the error information in the draft captions, we integrate a well-designed Cross Modification Attention (CMA) module with the decoder of the Deliberation Model to perform mutual correction between the features of input images and corresponding draft captions. Experiments on MS COCO dataset demonstrate the advantages and improvements of our CMA and the proposed framework.
Refined Caption: <start> a dog sitting in the seat of a motorcycle <end>
Draft Caption: <start> a cat sitting on the seat of a motorcycle <end>

Fig. 6. Visualization of both visual and textual attention matrices in our CMA of AoANet + CMA-DM model. For clarity, we show the attention maps of all 8 heads at the time step of generating the word, “dog”. For textual attention visualization, we only report the attention results with weights higher than 0.1.

Fig. 7. Examples of image captions generated by AoANet + CMA-DM model along with the corresponding ground truths. Mistakes or inappropriate words and phrases are highlighted in red. Red box indicates failure case.

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