Adma-GAN: Attribute-Driven Memory Augmented GANs for Text-to-Image Generation.

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ABSTRACT
As a challenging task, text-to-image generation aims to generate photo-realistic and semantically consistent images according to the given text descriptions. Existing methods mainly extract the text information from only one sentence to represent an image and the text representation effects the quality of the generated image well. However, directly utilizing the limited information in one sentence misses some key attribute descriptions, which are the crucial factors to describe an image accurately. To alleviate the above problem, we propose an effective text representation method with the complements of attribute information. Firstly, we construct an attribute memory to jointly control the text-to-image generation with sentence input. Secondly, we explore two update mechanisms, sample-aware and sample-joint mechanisms, to dynamically optimize a generalized attribute memory. Furthermore, we design an attribute-sentence-joint conditional generator learning scheme to align the feature embeddings among multiple representations, which promotes the cross-modal network training. Experimental results illustrate that the proposed method obtains substantial performance improvements on both the CUB (FID from 14.81 to 8.57) and COCO (FID from 21.42 to 12.39) datasets.

CCS CONCEPTS
• Computing methodologies → Computer vision.

KEYWORDS

text-to-image generation, attribute memory, sample-aware, sample-joint, cross-modal alignment

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1 INTRODUCTION
Multimodal data [38, 48] has been widely used in numerous cross-modal tasks [1, 4, 50, 53, 57]. Among them, text-to-image generation is a research hotspot, which aims to generate photo-realistic images according to the text description and has great potential for applications e.g., image editing [46, 47], computer-aided design, entertainment interaction [29]. Due to the large gap of modal structure between text and image data, the optimization of the cross-modal text-to-image generative models is prone to overfitting or collapse, resulting in generating irregular object shape.

In the literature, most of the methods formulate the task with a conditional GAN formulation [28]. They usually first embedded the text description, and then set it as the conditional input of the generator for image generation. Typically, the text representation effects the quality of the generated image well. Existing sentence embedding methods only utilize the limited information in one sentence to model the text representation, resulting in the following obstacle: it misses some key attribute descriptions, which are the
crucial factors to describe an image accurately. To alleviate it, we propose an effective text representation method with the complements of attribute information of the sentence. As shown in fig. 1, we design an attribute memory to jointly control the generator with sentence. Hence, the text-to-image generation task can be considered as an attribute-sentence-joint conditional generation problem. The key points of this problem lie in two aspects: 1) how to construct an attribute memory, 2) how to learn the conditional image generator with the joint attribute and sentence conditions.

As for the attribute memory construction, we first collect all the possible attribute descriptions within a dataset as an attribute bank and convert them into an attribute memory. Then, we use the attribute label to extract the corresponding embeddings from the attribute memory and combine them into a common attribute embedding as the condition. Considering that attribute descriptions and images are two different modalities, a fixed memory is difficult to achieve cross-modal image generation. Therefore, we design a learnable memory update scheme to obtain an optimal attribute memory. Specifically, we explore two different mechanisms for optimization, the sample-aware and sample-joint update mechanisms. For the sample-aware one, we treat each sample in isolation and average all the sample-aware attribute embeddings together. In this way, only sample-related attribute embeddings will be optimized in one training session through gradient back-propagation. However, co-occurrence exists between attributes and attribute pairs are combined differently in different samples. The sample-aware mechanism only considers the co-occurrence inside an image while ignores the global correlation patterns within the entire dataset. Therefore, we further propose to model the sample-joint attribute relationship. Specifically, we construct a graph to represent the attribute correlation within a dataset and use GCNs [5, 21] to extract attribute features. Thus, the co-occurrence attribute embeddings will be updated with edge connections to get a more suitable one. Experimental results show that the improved sample-joint strategy maps multiple attributes to the images better.

After building the attribute memory, an attribute-sentence-joint conditional generator learning scheme is designed to handle the conversion among multiple representations (i.e., sentence, attribute, image). In our scheme, an image should strictly correspond to both the sentence and attribute. Therefore, we propose to align the image with sentence and attribute in a common space using contrastive learning. Attribute-image and sentence-image pairs belonging to the same sample are pulled closer, while pairs of different samples are pushed further.

Combining the above strategies, we improve DF-GAN [43] and obtain substantial performance improvements on the CUB [45] and COCO [27] datasets. Our contributions can be concluded as follow:

- We propose a novel attribute representation as an additional condition and construct an attribute memory to augment the text-to-image generation with richer information.
- We design a memory update scheme, including a sample-aware and a sample-joint update mechanism to obtain the optimal attribute memory for attribute-driven conditional generation.
- We introduce contrastive learning to enhance semantic consistency among multiple representations, which facilitates the training of cross-modal GAN well.

2 RELATED WORK

2.1 Text Representation

Generating an image from a single sentence is a process creating information from less to more, which is difficult to optimize the text-to-image generation model in practice. To alleviate such a problem, many works are devoted to enrich the text representation. 1) Providing additional descriptions. Cheng et al. [6] and Sun et al. [40] combined multiple captions together instead of one sentence input, and EI et al. [9] proposed a novel task of synthesizing images from long text. Sharma et al. [37] and Frolov et al. [11] introduced the dialog and questions. These additional descriptions provide richer content to reduce the gap across modalities. 2) Mining more representations from one sentence. Xu et al. [52] used word features to make the network pay attention to word-level image-text matching. Han et al. [13] disassembled the subject-predicate-object structure of the sentence to generate scene graph embedding. Ruan et al. [33] proposed to extract the aspect information from one sentence. Zhu et al. [61] modeled the instructions and ingredients of the dish description separately in the Recipe1M dataset [35]. In this paper, we propose a novel attribute representation, which complements the text information of a single sentence, and enables the network to focus more on the key descriptions.

2.2 Text-to-image Network Design

A powerful network architecture is also a key to the generation task. Several works focus on designing better network architecture for text-to-image generation. 1) Progressive generation. Zhang et al. [57] achieved cross-modal generation by first generating an initial image and then refining it to a larger resolution. There are many follow-up works [19, 58, 59] further optimized the structure based on such an idea. In addition, Li et al. [24] and Hong et al. [17] proposed to convert text into bounding box first, then into label map, and finally performed image-to-image translation to achieve transformation. 2) Cross-modal fusion. Most of the works introduce attention mechanism to fuse the cross-modal representations. Xu et al. [52] proposed AttnGAN, allowing attention-driven refinement for fine-grained text-to-image generation. Many follow-up works attempted to make improvement, including dual attention [3], segmentation attention [12], memory attention [23, 62] etc. Tao et al. [43] further proposed a simple but more efficient fusion method, named DF-GAN, to synthesize realistic and text-matching images. In this paper, we improve the network structure based on DF-GAN with a learnable attribute memory, and design an attribute-sentence-joint conditional framework for text-to-image generation.

2.3 Cross-modal Training Optimization

There exists another aspect to improve the model performance, i.e., optimizing the network training. The core optimization directions can be divided into the following three parts. 1) Large-scale pretrained model. Ramesh et al. [32] and Ding et al. [7] have proposed billion-parameter-level models and million-level datasets for training, both of which achieved amazing effect in society. Wu et al. [46] even extended this task to text-to-video generation with large-scale training strategies. 2) Cycle consistency. Qiao et al. [31]
proposed a text-to-image-to-text framework that utilizes bidirectional generation to maintain semantic consistency. Wang et al. [44] utilized GAN-inversion [49] technology to search the corresponding text embedding in reverse to optimize the text encoder. 3) Contrastive learning. Yin et al. [55] and Ye et al. [54] applied contrastive learning to constrain similar sentence for generating consistent images. Zhang et al. [56] constructed cross-modal pairs, achieving remarkable results. Furthermore, we apply contrastive learning to align multiple representations including attribute, sentence and image, and thus improves the model performance well.

3 METHOD

3.1 Overview

Traditional text-to-image generation approaches learn a mapping function $T_{\text{trad}}$ to transform a noise space $Z$ into an image space $X$ conditioned on the sentence space $S$, i.e., $T_{\text{trad}} : (Z|S) \rightarrow X$. However, utilizing the limited information in one sentence is not enough to accurately describe an image. Therefore, we introduce an attribute label space $Y$, and propose a framework to generate images from both attribute and sentence representations. It is thus an attribute-sentence-joint conditional GAN pipeline, learning a mapping function $T_{\text{adma}} : (Z|S,Y) \rightarrow X$. The proposed framework includes a memory augmented generator, and a conditional discriminator with auxiliary classification.

As shown in fig. 2, the generator is conditioned on the sentence embedding $e_s$ and attribute embedding $e_a$. We first convert the raw sentence into sentence embedding $e_s$ and construct an attribute memory $M_a$ from a pre-defined attribute bank. Then, attribute embedding $e_a$ is extracted from $M_a$ using a multi-attribute label $y$. After obtaining $e_a$ and $e_s$, we insert them into the low-level blocks and high-level blocks respectively to modulate features at different levels. Each block is a ResBlock [14] for text-image fusion and resolution enhancement.

The discriminator aims to determine the real probability and attribute probability of a real image $x$ or generated image $x_f$. It is composed of several down-sample ResBlocks followed by two fully connected branches. We first extract the input image into low-dimensional map, and then concatenate the sentence embedding on it as the joint map. Finally, the joint map is sent into two different layers, one for authenticity discrimination and the other one for multi-attribute classification. In this way, the discriminator is trained to obtain the discriminability and classification ability, and thus provides better optimization directions for the generator.

3.2 Attribute Memory Construction

In the previous text-to-image generation task, many works extract text embedding from only one sentence input, while ignore the attribute descriptions, which are critical factors for image-text matching. Therefore, we propose an attribute memory to assist the text-to-image generation task. In the following, we introduce the construction of the attribute memory and the read-and-write process of the proposed memory in detail.

We first collect all attribute descriptions and aggregate them together as an attribute bank. Then, we utilize a pre-trained text encoder [52] to extract all the descriptions as an attribute embedding memory $M_a$, in which each item represents the embedding of specific attribute description. Different from the previous memory modules [39, 60], the read-and-write process of the proposed memory is achieved through forward inference and backward propagation of the generator, which is illustrated in fig. 4.
where $y \in \mathbb{R}^{1 \times n}$, $M_a \in \mathbb{R}^{n \times d}$, $n$ represents the number of all attributes in a dataset, $d$ is the dimension of the embedding vector. The combined attribute embedding $e_a$ is then set as an additional condition with sentence embedding $e_s$ together to jointly modulate the image features.

In this way, through gradient back-propagation, only sample-related attribute embeddings are optimized when the network is updated. However, different attributes in the pre-defined attribute bank are inherently related. In fact, there exists an implicit knowledge graph between attributes beyond a single image. Combining the corresponding attributes with the way in eq. (1) only considers the co-occurrence of an image, while ignores the global correlation patterns within the entire dataset. In the following, we further propose a sample-joint memory update mechanism to model the global co-occurrence patterns.

**Sample-joint memory update mechanism:** Specifically, we introduce GCNs to model the relationship and propagate information between attributes based on the correlation matrix. In our GCN modeling, the attribute memory is set as the initial node features, and each embedding denotes a node. Given the initial node features $H^0 = M_a$ and the correlation matrix $C$, the GCN updates node features through stacked learnable transition matrix $W$. The forward of a GCN layer is denoted as:

$$H^{l+1} = \text{LeakyReLU}(C \cdot H^l \cdot W^l),$$

where $\text{LeakyReLU}(\cdot)$ is the Leaky ReLU activation function [51], $W^l$ is the learnable parameter in the $l$-th layer of GCN, $H^l$ and $H^{l+1}$ are the input and output node features, respectively.

In order to model the global correlation between attributes, we construct the correlation matrix $C$ by counting the occurrence of attribute pairs in the training set, which is denoted as:

$$C_{ij} = \begin{cases} 0, & \text{if } P_{ij} < \tau \\ 1, & \text{if } P_{ij} \geq \tau \end{cases},$$

where $P_{ij}$ represents the probability of $j$-th attribute when $i$-th appears in the whole dataset, $\tau$ is a threshold to filter noisy edges. As in [5], we also apply the re-weighted scheme to alleviate the

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**Figure 3:** Illustration of attribute embedding construction.

**Figure 4:** Illustration of the read-and-write process of the proposed memory.

Therefore, the attribute memory is first initialized by a set of attribute embeddings from the pre-trained text encoder, and then updated during the learning process. Several experiments are conducted to verify the importance of updated memory and attribute embedding initialization in section 4.3.

### 3.3 Attribute Memory Update

A fixed memory is difficult to be utilized for effective cross-modal image generation. Therefore, we design a learnable memory update scheme to update the attribute embedding memory dynamically in an effective way. In the following, we explore two different memory update mechanisms (sample-aware and sample-joint) to obtain suitable attribute embeddings from the attribute memory.

**Sample-aware memory update mechanism:** In order to update the attribute memory, we treat all the parameters of the memory as the optimizable parameters and add them to the parameter group of the entire generator. Thus, the update of memory can be achieved through the gradient back-propagation of the network.

As illustrated in fig. 3, an image sample is annotated with a multi-attribute binary label $y$, in which 1 denotes that the image has such an attribute while 0 means it does not. Given a sample, $y$ is used to extract the corresponding embeddings from attribute memory $M_a$ and combine them together as a common attribute embedding $e_a$, which has the same dimension as the sentence embedding $e_s$. The construction of $e_a$ is denoted as:

$$e_a = y \cdot M_a.$$  

(1)
over-smoothing problem in binary correlation matrix. Thus, a re-weighted correlation matrix $C'$ is denoted as:

$$C'_{ij} = \begin{cases} \frac{p}{\sum_{t=1, t\neq j}^n C_{ij}}, & \text{if } i \neq j \\ 1 - p, & \text{if } i = j \end{cases},$$  
where $p$ is a fixed weight assigned to a node itself and other correlated nodes to decide whether to consider neighbor information.

Therefore, initial node features $M_t$ are updated through stacked GCNs based on $C'$. The node features of the last layer $H^L$ is also pooled into an attribute embedding, which is denoted as:

$$e_a = y \cdot H^L.$$  
(5)

Thus, when updating the attribute embedding of the current sample, the co-occurrence attribute embeddings of other samples will also be optimized, leading to a more effective attribute memory.

### 3.4 Attribute-Image Alignment

With the introduction of attribute embedding, it is important to align the attribute-image during the cross-modal training. Therefore, we introduce a contrastive learning loss to align attribute and image embedding in a common space. Formally, we take the cosine similarity $\cos(\cdot, \cdot)$ as the distance metric:

$$\cos(u, v) = \frac{u^T \cdot v}{\|u\| \cdot \|v\|}.$$  
(6)

Thus, the contrastive loss takes a pair of input $(x^i, e^i_a)$ and minimizes the embedding distance when they are from the same pair (i.e., $i = j$) but maximizes the distance otherwise (i.e., $i \neq j$):

$$L_{cl}(u, v) = -\frac{1}{m} \sum_{i=1}^m \log \frac{\exp(\cos(u^i, v^i)/\eta)}{\sum_{j=1}^m \exp(\cos(u^i, v^j)/\eta)},$$  
(7)

$$L_{attr_real} = L_{cl}(D_{img}(x), e_a),$$  
$$L_{attr_fake} = L_{cl}(D_{img}(x_f), e_a),$$  
(8)

where $m$ is the mini-batch size of input samples, $u^i$ is the $i$-th sample in a mini-batch of $u$, and $v^j$ refers to the $j$-th one of $v$. $\eta$ is a temperature hyper-parameter, $D_{img}(\cdot)$ is the extraction process of image embedding in the discriminator, and projects the input image into image embedding.

Additionally, we apply contrastive learning to other modal pairs simultaneously, including image with sentence, fake image with real image of the same description.

$$L_{sent_real} = L_{cl}(D_{img}(x), e_s),$$  
(9)

$$L_{sent_fake} = L_{cl}(D_{img}(x_f), e_s),$$  
$$L_{img} = L_{cl}(D_{img}(x), D_{img}(x_f)).$$  
(10)

### 3.5 Overall Optimization

The proposed attribute-sentence joint conditional framework is optimized in an adversarial manner that the generator and discriminator are asynchronously updated. We improve the ability of the proposed cGAN through three types of constraints: 1) authenticity discrimination; 2) multi-attribute classification; 3) cross-modal alignment. All the loss functions are described in the following.

#### Authenticity discrimination

We employ the hinge loss [26] as the adversarial loss to stabilize the training process. The generator $G$ takes Gaussian noise $\epsilon_z$, attribute and sentence joint conditional embeddings $e_a, e_s$ as input, while the discriminator $D$ is required to distinguish between $x$ and $x_f = G(\epsilon_z, e_a, e_s)$. The corresponding adversarial loss functions for the generator $L_{adv, G}$ and discriminator $L_{adv, D}$ can be represented as follows:

$$L_{adv, D} = \mathbb{E}[\max(0, 1 - D(x))] + \mathbb{E}[\max(0, 1 + D(x_f))],$$  
$$L_{adv, G} = -\mathbb{E}[D(x_f)].$$  
(11)

#### Multi-attribute classification

The multi-attribute classification is set as an auxiliary task to let discriminator learn to recognize multiple attributes from a given image. In order to eliminate the bias in the learning process of two different tasks, we follow [18] to make the classifier capable of distinguishing real from fake while classifying attribute labels. The discriminative classifier maps $X \rightarrow \mathcal{Y} \times \{0, 1\}$ (n x 2 classes) that recognizes the attribute labels discriminatively. Specifically, when given real image $x$ (reps. fake image $x_f$), we convert it into logit $l_r$ (reps. $l_f$) through the discriminative classifier. Correspondingly, the label $y$ is extended twice that the odd positions denote fake label $y_f$ while the even ones refer to real label $y_r$. The above four items are $e \in \mathbb{R}^{1 \times 2n}$. We compute the BCE loss in generator $G$ and discriminator $D$ through:

$$L_{bce}(l, y) = -\frac{1}{2n} \sum_{i=1}^{2n} (y^i \log(l^i) + (1 - y^i) \log(1 - l^i)),$$  
(12)

$$L_{cls, D} = L_{bce}(l_r, y_r) + L_{bce}(l_f, y_f),$$  
$$L_{cls, G} = L_{bce}(l_f, y_r) - L_{bce}(l_f, y_f).$$  
(13)

where $n$ is the number of attributes, $y^i$ and $l^i$ are the $i$-th attribute of the attribute label and logit, respectively. $L_{cls, D}$ enables the discriminator to identify fake samples when doing multi-attribute classification, while $L_{cls, G}$ tries to fool $D$ without identification.

#### Cross-modal alignment

We combine all the contrastive loss functions between a real image $x$ and the corresponding text embeddings $\{e_z, e_a\}$ of $x$ to optimize the discriminator $D$. In addition, the contrastive loss functions between the fake image $x_f$ and $\{e_z, e_a\}$ are used to regularize the generator $G$. The corresponding alignment loss functions for $G$: $L_{align, G}$ and $D$: $L_{align, D}$ are denoted as:

$$L_{align, D} = L_{attr_real} + L_{sent_real},$$  
$$L_{align, G} = L_{attr_fake} + L_{sent_fake} + L_{img}.$$  
(14)

Overall, the full objective function of the generator $L_G$ and discriminator $L_D$ are obtained as a weighted combination of the corresponding individual loss functions defined above.

$$L_D = L_{adv, D} + \lambda_1 L_{align, D} + \lambda_2 L_{cls, D} + \lambda_3 L_{ma-gp},$$  
$$L_G = L_{adv, G} + \lambda_4 L_{align, G} + \lambda_5 L_{cls, G}.$$  
(15)

where $\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5$ are the coefficient weights. $L_{ma-gp}$ is the matching-aware gradient penalty in [43], which applies the gradient penalty on real images with the matching sentences.

### 4 EXPERIMENT

#### 4.1 Experimental Setup

In the following, we clearly introduce the datasets, evaluation metrics and implementation details.
Datasets: To evaluate the capability of our method, we conduct extensive experiments on both Caltech-UCSD Birds 200 (CUB) [45] and MS COCO [27] datasets. The CUB dataset contains 200 bird categories with 312 attributes description. It is divided into training set and testing set with 8855 and 2933 images, respectively. Each image is annotated with 10 text captions and a multi-attribute binary label. As for the COCO, it is a multi-object dataset with 80 categories with 312 attributes description. It is divided into training and testing set with 8855 and 2933 images, respectively. Each image is annotated with 10 text captions and a multi-object label.

Evaluation Metrics: Following other text-to-image generation tasks [43, 52], we introduce Fréchet Inception Distance (FID) [15] and Inception Score (IS) [34] for image quality evaluation. Both of them utilize a pre-trained Inception-v3 network [41] to extract the image features. Finally, in order to estimate the semantic consistency between the generated images and text inputs, we introduce two additional metrics. One is the top-1 image-sentence retrieval accuracy (Top-1 Acc) using the image and text encoder from [52], and the other is the mean average precision (mAP) to evaluate the multi-attribute classification performance of generated images following [22].

Implementation Details: We evaluate our methods on two widely used dataset, CUB and COCO. As shown in fig. 6, CUB is a single-object dataset, in which each image contains a single bird with multiple part descriptions. We define attributes as these part descriptions such as red eyes, black wings etc. In addition, COCO is a multi-object dataset, in which each image contains multiple objects. We define attributes as the instance object description, such as human, train etc. For each dataset, we first collect all the attribute descriptions and aggregate them together as an attribute bank, as shown in the right part of fig. 6. Then, we utilize a pre-trained text encoder provided from AttnGAN [52] to embed the attribute descriptions and form an attribute memory. Next, the attribute embedding is obtained through eq. (1) or eq. (5), and set as the context with sentence embedding to jointly control the conditional text-to-image GAN.

We utilize DF-GAN [43] as the network backbone and design three effective strategies to improve the model performance. All the hyper-parameter settings are the same for both datasets, except for the total iteration steps. The model is optimized by the Adam optimizer [20] with exponential decay rates ($\beta_1 = 0.0, \beta_2 = 0.9$). The learning rates are set to 0.0001 and 0.0004 for the generator and discriminator, respectively. According to [5], r in eq. (3) is set to 0.4 and $p$ in eq. (4) is 0.25. In eq. (7), $\eta$ is set to 0.1 as [56]. In eq. (15), the coefficient weights are set to $\lambda_1 = \lambda_4 = 0.1, \lambda_2 = \lambda_5 = 0.5, \lambda_3 = 2$. 

![Figure 6: Datasets display. Attribute definitions are different referring to CUB and COCO datasets. Left: image examples; Right: attribute descriptions.](image)

![Figure 5: Qualitative comparisons between the proposed method and baseline DF-GAN.](image)
We compare our method with other previous state-of-the-art methods using the same pre-trained text encoder [52], and the results are demonstrated in table 1. Our method achieves the best performance on CUB-FID, CUB-IS, and COCO-FID. Especially for the FID metric, the proposed method is much ahead of previous works, and degrades FID from 14.81 to 8.57 on the CUB dataset and from 21.42 to 12.39 on the COCO dataset. How to design a better multi-object image generation, this does not objectively reflect the generated image quality. We utilize n random noises to initialize the learnable memory in row 2. Row 3-4 represent the methods that use attribute embeddings as memory initialization. Compared with row 3 and row 4, we found that using the updated memory instead of a fixed one facilitates model training and improves the performance well.

The sample-joint strategy achieves better result than the sample-aware ones since it models the global correlation and obtains a more suitable attribute memory. Furthermore, the combination of the sample-joint and alignment strategies gets the best result.

| Method       | Reference | CUB FID | IS ↑ | COCO FID | IS ↑ |
|--------------|-----------|---------|------|----------|------|
| AttnGAN [52] | CVPR18    | 23.98   | 4.36 | 35.49    | 25.89|
| DM-GAN [62]  | CVPR19    | 16.09   | 4.75 | 32.64    | 30.49|
| SD-GAN [55]  | CVPR19    | -       | 4.67 | -        | 35.69|
| SEGAN [42]   | ICCV19    | 18.17   | 4.67 | 32.28    | 27.86|
| VICTR [13]   | COLING20  | -       | -    | 32.37    | 32.37|
| CPGAN [25]   | ECCV20    | -       | -    | 50.68    | 52.73|
| OP-GAN [16]  | TPAMI20   | -       | -    | 25.80    | 27.90|
| DAE-GAN [43] | ICCV21    | 15.19   | 4.42 | 28.12    | 35.08|
| CL [54]      | BMVC21    | 14.38   | 4.77 | 20.79    | 33.34|
| MDD [10]     | TMM21     | 15.76   | 4.86 | 24.30    | 34.46|
| KD-GAN [30]  | TMM21     | 13.89   | 4.90 | 23.92    | 34.01|
| DF-GAN [43]  | CVPR22    | 14.81   | 5.10 | 21.42    | -    |
| Ours         |           | 8.57    | 5.28 | 12.39    | 29.07|

### 4.2 Comparison with SOTA

We compare our method with other previous text-to-image generation works in terms of both the qualitative and quantitative results. We conduct the ablation study to estimate the performance of each component in our method and demonstrate the experimental comparisons under different settings.

#### Qualitative Results

As shown in fig. 5, the proposed method generates more semantically consistent images compared with the baseline DF-GAN. As for the CUB dataset, DF-GAN even synthesizes irregular birds body while our method avoids it well in column 1-2. As for the COCO dataset, we produce more reasonable images with better details in column 5-8. Visually, the images generated by our method are generally more realistic. For more visualizations, please refer to the supplementary material.

#### Quantitative Results

For fairness, we compare our method with previous state-of-the-art methods using the same pre-trained text encoder [52], and the results are demonstrated in table 1. Our method achieves the best performance on CUB-FID, CUB-IS, and COCO-FID. Especially for the FID metric, the proposed method is much ahead of previous works, and degrades FID from 14.81 to 8.57 on the CUB dataset and from 21.42 to 12.39 on the COCO dataset. As for COCO-IS, our method achieves a comparable result. It is worth mentioning that COCO-IS utilizes a single-object pre-trained inception network to estimate a multi-object dataset, which will lead to inaccurate assessments [8]. Thus, relatively speaking, this does not objectively reflect the generated image quality on the COCO dataset. How to design a better multi-object image evaluation metric is a problem worth exploring.

### 4.3 Ablation Study

We conduct the ablation study to estimate the performance of each component in our method and demonstrate the experimental comparisons under different settings.

#### Component Evaluation

The proposed method is composed of three main components, including the sample-aware and sample-joint mechanisms, and attribute-sentence-image alignment. The ablation study of each component is shown in table 2, and the FID scores indicate the effectiveness of them compared to the baseline.

#### Importance of the attribute memory

We study the importance of the proposed attribute memory and report the comparison results in table 3. We utilize n random noises to initialize the learnable memory in row 2. Row 3-4 represent the methods that use attribute embeddings as memory initialization. Compared with row 3 and row 4, we found that using the updated memory instead of a fixed one facilitates model training and improves the performance well.

#### Where to plug the sentence and attribute embeddings

We use attribute embedding to help improve the representation of a text input. Therefore, how to apply the sentence and attribute embedding to the network is a problem that needs to be explored. We try different combinations of these two embeddings and demonstrate the results in table 4. The sentence embedding $e_s$ and attribute embedding $e_a$ are inserted into the up-fusion blocks, and each contains an up-sample operation with two affine transformation modules. The affine transformation manipulates visual feature maps conditioned on $e_s$ or $e_a$. Thus, we attempt to call one type (a.k.a. OB − OT) or two types (a.k.a. OB − TT) of embeddings in an up-fusion block. Overall, OB − OT outperforms OB − TT, and in OB − OT, plugging the attribute embedding in lower layers while sentence embedding in higher layers gets the better result.

#### Semantic consistency of cross modalities

Finally, we estimate the semantic consistency of the generated images between modalities, including sentence-image and attribute-image pairs. To
We make a discussion about the interesting experimental findings, and analyze potential causes and improvements as follows.

Multi-attribute conditional generation: In this paper, we introduce the attribute memory to augment text-to-image generation task and table 3 demonstrates that attribute memory plays an important role to improve the model performance. The generation thus is conditioned on sentence embedding and attribute embedding jointly. Then, a question arises, what about the image is generated using only attribute embedding as a condition? To this end, we make an experiment under the sample-aware setting using attribute embedding only and achieve the FID score of 14.74, which is comparable to DF-GAN. It shows that this task is feasible to some extent. Multiple attribute descriptions provide the general content of a sample, and the sentence provides the association between attributes. The combination of the two synthesizes more photo-realistic and semantic matching images.

Similar to this setting, there are a few methods [2, 36] studying multi-class conditional generation without sentence input. It takes a multi-class binary label as the condition input to generate the image that contains the given number of classes. In fact, this task is more challenging due to the lack of association descriptions among multiple classes.

Sentence-only and sentence-with-attribute input: The interface for practical application of the proposed method should be both sentence description and attribute label. However, in some cases, only sentence are provided. Surprisingly, our method is flexible for both the sentence-only and sentence-with-attribute input. Without additional labeling, the attribute label can be retrieved in the predefined attribute bank using the only sentence. In this paper, we use the sentence to receive top \( k \) attribute descriptions according to the cosine similarity between the sentence embedding and each attribute embedding in the attribute bank. On the CUB dataset, we set \( k = 10, 30, 50 \), and obtain the FID score of 9.91, 8.89 and 9.11, respectively. Note that all these models are trained without contrastive learning. The model \( (k=10) \) trained with contrastive learning can even achieve an FID score of 8.78, which is comparable with the one trained with sentence-with-attribute input (FID=8.57). The experimental results indicate that our method also works well using only sentence as input, and is still superior to other compared methods.

4.4 Discussion

We make a discussion about the interesting experimental findings, and analyze potential causes and improvements as follows.

Table 4: Ablation Study on the combination of sentence and attribute embeddings. We compare the FID scores on each experiment list as follows. \( OB - OT \) refers to one block contains one type of embedding, while \( OB - TT \) denotes one block has two types of embedding.

| Settings       | CUB-FID ↓ |
|----------------|-----------|
| \( e_s \)-low, \( e_a \)-high | 9.67      |
| \( e_s \)-low, \( e_a \)-high | 9.04      |
| \( e_s \)-front, \( e_a \)-behind | 9.63      |
| \( e_s \)-front, \( e_a \)-behind | 9.94      |

Table 7: Semantic consistency performance evaluation of the proposed method and DF-GAN. Left: CUB dataset; Right: COCO dataset.

5 CONCLUSION

In this paper, we have proposed Adma-GAN, an attribute-driven memory augmented GAN for the text-to-image generation task. It is able to synthesize photo-realistic and semantically consistent images. The main contribution is that we propose an effective text representation method with the complements of attribute information to assist in controlling image generation. Firstly, we construct an attribute memory to jointly control the text-to-image generation with sentence input. With the help of attribute memory, the input text representation is enriched, and the cross-modal gap is thus reduced. Secondly, we explore two memory update mechanisms, sample-aware and sample-joint mechanisms, to dynamically optimize a generalized attribute memory. The sample-joint mechanism outperforms the sample-aware one since it models the global correlation between attributes within a dataset. Thirdly, we employ the contrastive learning in attribute-to-image, sentence-to-image and image-to-image, to facilitate the cross-modal alignment. Combining all the above strategies, our method achieves substantial performance improvements on both the CUB and COCO datasets.

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