GR-GAN: GRADUAL REFINEMENT TEXT-TO-IMAGE GENERATION

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ABSTRACT
A good Text-to-Image model should not only generate high quality images, but also ensure the consistency between the text and the generated image. Previous models failed to simultaneously fix both sides well. This paper proposes a Gradual Refinement Generative Adversarial Network (GR-GAN) to alleviates the problem efficiently. A GRG module is designed to generate images from low resolution to high resolution with the corresponding text constraints from coarse granularity (sentence) to fine granularity (word) stage by stage, a ITM module is designed to provide image-text matching losses at both sentence-image level and word-region level for corresponding stages. We also introduce a new metric Cross-Model Distance (CMD) for simultaneously evaluating image quality and image-text consistency. Experimental results show GR-GAN significant outperform previous models, and achieve new state-of-the-art on both FID and CMD. A detailed analysis demonstrates the efficiency of different generation stages in GR-GAN.

1. INTRODUCTION
Text-to-Image synthesis aims to automatically generate images conditioned on text descriptions, which is one of the most popular and challenging multi-modal task. The task requires the generator not only generates high-quality images, but also preserve the semantic consistency between the text and the generated image. Generative Adversarial Networks (GANs) [1] have shown promising results on text-to-image generation by using the sentence vector as a conditional information. Zhang et al. [2] proposes Stack-GAN++, which employed a multi-stage structure to improve image resolution stage by stage, and an unconditional loss besides a conditional loss at each stage. Xu et al. [3] proposes Attn-GAN with a module DAMSM to strengthen the consistency constraint on the generator. These models have achieved great improvements on the task, but the performances are still not satisfied, especially on complex scenes.

There are several important problems in previous models. (1) The current multi-stage networks generate images from low resolution to high resolution for better image quality without considering the language constraints in corresponding granularities. The correspondings between images in different resolutions and text descriptions in different granularities are normally specialized, images with low resolution are always described in coarse granularity, images with high resolution can be better described in fine granularity. The problem should be addressed for both better image quality and image-text consistency. (2) None of the current evaluation metrics could simultaneously evaluate image quality and image-text consistency, which are not suitable enough for this task. Meanwhile, previous works [4–6] have already observed that the evaluation metric IS [7] and R-precision [3] of some models have serious overfitting, which makes it impossible to accurately evaluate the Text-to-Image model.

To address the above problems, we propose a Gradual Refinement Generator Adversarial Network (GR-GAN) including a Gradual Refinement Generator (GRG) and a Image-Text Matcher (ITM). GRG is a multi-stage structure. As the increasing of the resolution of generated images, the text constraints are refined from sentences (coarse granularity) to words (fine granularity) stage by stage. The first discriminator uses only unconditional loss so that it focuses on image quality, and following two discriminators use conditional loss so that they focus more on text-image consistency. ITM computes image-text matching losses at both sentence-image level and word-region level. Those losses are used in corresponding stages of GRG, i.e. sentence-image level loss is used in second stage and word-region level loss is used in third stage. We also design a novel metric named CMD (Cross Model Distance) for evaluating image quality and image-text consistency simultaneously. Experimental results show GR-GAN significant outperform previous models, and achieve new state-of-the-art on both FID and CMD. A detailed analysis demonstrates the efficiency of different generation stages in GR-GAN.

The main contributions can be summarized as follows:

- We propose a GR-GAN model for progressively synthesizing images conditioned on text descriptions, where GRG module generates images from low reso-
olution to high resolution with the corresponding text constraints from coarse granularity to fine granularity stage by stage, ITM provides different level of image-text matching losses at each stage.

- We propose a new Text-to-Image measurement CMD which can simultaneously evaluate Image Quality and Image-Text Consistency. It is more suitable for evaluating Text-to-Image task.

- Experimental results on MS-COCO dataset show that the GR-GAN significantly outperforms previous models, and achieve new state-of-the-art on both FID and CMD.

2. RELATED WORK

Text-to-Image Synthesis. GAN-INT-CLS [1] first proposed the use of conditional GAN to solve text-to-image task, which became a standard paradigm for subsequent work. Zhang et al. [2] proposed a multi-stage network to improve the resolution of the generated image stage by stage, which has made significant progress compared with the single-stage model. In order to make better use of language information, Attn-GAN [3] and DM-GAN [8] respectively proposed the use of word granularity information based on Attention and Dynamic Memory. The word granularity information can be used to help the generation of image regions, which effectively strengthens the image quality. Others [4, 5, 9] further expand a object generation stage on the basis of multi-stage model. Compared to these multi-stage models, our proposed GR-GAN has a clearer division of work at each stage of the network by using a gradual refinement generator (see Sec.3.1).

Image-Text Consistency. Attn-GAN proposed a consistency constraint module DAMSM, which is pre-trained by image-text matching tasks on MS-COCO [10]. By adding an additional consistency loss in the training process, image-text consistency is significantly improved. Since DAMSM has poor consistency assessment ability, Mirror-GAN [11] adds a text generation model on DAMSM to strengthen the image-text consistency. CP-GAN [12] used a yoloV3 model to replace DAMSM, and used an object-level consistency constraint. These works enhanced the image-text consistency by strengthening the consistency constraint module. Our GR-GAN builds an ITM (see Sec.3.2) module that can calculate the similarity between images and text more accurately.

Evaluation Metrics. Evaluating Text-to-Image models need to consider both image quality and image-text consistency. Current methods use IS [7] and FID [13] to evaluate image quality, and R-precision [3] to evaluate the image-text consistency. However, [5, 6] turns out that IS always fails on COCO [10]. Our work also indicates a clear overfitting of IS metric (see Sec.4.2). Previous works [4, 14, 15] find that some report R-precision scores significantly higher than real images. Our work found that this is due to the use of DAMSM in both training and evaluation. Due to the huge shortcomings of the current metrics, we design a novel indicator CMD that can simultaneously evaluating image quality and image-text consistency.

3. PROPOSED METHOD

The overall architecture of our GR-GAN model is shown in Fig.1. The model mainly contains two core modules: ITM model and GRG model.

The GRG model includes three-level generators ($G_i, i = 1, 2, 3$) and corresponding three-level discriminators ($D_i, i = 1, 2, 3$). In all levels of networks, a neural network ($F_i, i = 1, 2, 3$) is used to obtain a hidden image feature representation ($h_i, i = 1, 2, 3$) which is as the input of the $G_i, i = 1, 2, 3$ for generating corresponding images ($I_i, I_2, I_3$). It generates images with better quality as well as higher image-text consistency gradually.

The ITM model includes two parts. One part is for encoding of text descriptions and generated images, the other provides similarities (image-text matching losses) in different granularities between images and texts.

3.1. Gradual Refinement Generator

The GRG model consists of three stages:

**Image Initialize Stage:** An unconditional adversarial network ($D_1, G_1$) is employed for generating a initial image. The stage focuses more on quality of generated images. A $F_{vca}$ module is used to convert the sentence vector $c_s$ encoded by the transformer in ITM to the condition vector $c$. $F_1$ fuse $c$ with a random initial Gaussian noise $z$ to obtain a new image feature $h_1$, and $G_1$ use $h_1$ to generate a 64*64 image. $D_1$ is designed to judges whether the image is a generated image or a real image. The unconditional loss function is defined as follows:

$$L^{uncon}_{D_1} = -\frac{1}{2}E_{x_1 \sim data}[log(D(x_1))] - \frac{1}{2}E_{x_1 \sim G_1}[1 - log(D(x_1))]$$

**Sentence-level Refinement Stage:** Sentence-level consistency constraints are introduced and enhanced in a conditional adversarial network ($D_2, G_2$) in this stage. The sentence encoding $c_s \in R^{1 \times N}$ is copied $L$ times to $c_s^{\ast} \in R^{L \times N}$ (L is the max number of words set in code). And then a Dynamic Memory [8] is used to fuse $c_s^{\ast}$ with the image feature $h_1$, as shown in Equ.2:

$$T_{R \rightarrow S} = F_{D^2}(h_1, c_s^{\ast})$$

$T_{R \rightarrow S}$ is then encoded by $F_2$ to obtain a new image feature $h_2$. $h_2$ is used by $G_2$ to generate a 128*128 image. At
this stage, $D_2$ is designed to judge whether the input image matches the sentence description $c_s$. The conditional loss function is as Equ.3:

$$L_{conD_2} = -\frac{1}{2}E_{x^2 \sim \text{data}}[\log(D(x^2, c_s))] - \frac{1}{2}E_{x^2 \sim G_2}[1 - \log(D(x^2, c_s))]$$

(3)

We add another loss $L_{ITM}$, for sentence-image level consistency on $G_2$ in order to strengthen the constraints on the overall consistency between the image and the sentence at this stage. The loss is provided by ITM model and will be defined in details in Sec.3.2. The total sentence-image loss in this stage is therefore shown as in Equ.4:

$$L_{G_2\text{~total}} = L_{G_2} + \lambda_2 L_{ITM}$$

(4)

**Word-level Refinement Stage:** Word-level consistency constraints are introduced and enhanced in a conditional adversarial network ($D_3, G_3$) in this stage to generate images with better image-text consistency in word-region level. Word embeddings $c_w$ encoded by the transformer in ITM model and $h_2$ generated in last stage are fused firstly by a Dynamic Memory [8] as shown in Equ.5:

$$T_{R-W} = F_{DM}(h_2, c_w)$$

(5)

A forward Neural network $F_3$ is then employed to map $T_{R-W}$ to a new representation $h_3$ as the input of $G_3$. At this stage, $D_3$ is designed to judge whether the input image is consistent with text description at the word level vector $c_w \in \mathbb{R}^{1 \times N}$ which is the average pooling of all word vectors $c_w$.

The conditional loss function at this stage is as follows:

$$L_{conD_3} = -\frac{1}{2}E_{x^3 \sim \text{data}}[\log(D(x^3, c_w))] - \frac{1}{2}E_{x^3 \sim G_3}[1 - \log(D(x^3, c_w))]$$

(6)

$$L_{conG_3} = -\frac{1}{2}E_{x^3 \sim G_3}[\log(D(x^3, c_w))]$$

We also add consistency loss on $G_3$. Besides sentence-image level loss as in second stage, a word-region level loss $L_{ITM_w}$ is added to further strengthen the constraints on the fine granularity consistency between the image and the description. $L_{ITM_w}$ is also provided by ITM model and will be given in Sec.3.2. The total text-image loss in this stage is therefore shown as in Equ.7:

$$L_{G_3\text{~total}} = L_{G_3} + \lambda_1 L_{ITM_s} + \lambda_2 L_{ITM_w}$$

(7)

**3.2. Image-Text Matcher**

The ITM model is a consistency constraint model constructed by a Transformer [16] and a ResNet101 [17], which is trained on the basis of CLIP [18] parameters. Different from CLIP,
distribution. CMD is defined as follows:

\[ \text{CMD} = \text{Dis}(f, r) + |\text{Dis}(f, l) - \text{Dis}(r, l)| \]  \tag{10} \]

We propose Cross Model Distance (CMD) for simultaneously evaluating image quality and image-text consistency by mapping image and text information into a multi-modal semantic distribution. CMD is defined as follows:

\[ \text{CMD} = \text{Dis}(f, r) + |\text{Dis}(f, l) - \text{Dis}(r, l)| \]  \tag{10} \]

Table 1. Results on MS-COCO dataset (**†** means the result is from the original paper)

|         | IS↑ | FID↓ | ITDis↓ | CMD↓ |
|---------|-----|------|--------|------|
| Attn-GAN [3] | 23.61 | 34.90 | 1.07 | 15.97 |
| Obj-GAN† [5] | 24.07 | 36.52 | - | - |
| DM-GAN [8] | 32.32 | 27.42 | 0.98 | 12.68 |
| OP-GAN [4] | 27.88 | 24.70 | 0.83 | 11.99 |
| CP-GAN [12] | 52.73 | 47.91 | 1.27 | 16.05 |
| DALL-E† [20] | 17.90 | 27.50 | - | - |
| GR-GAN | 25.60 | **22.58** | **0.80** | 8.04 |

Where, \( f \) is the feature of the generated image, \( r \) is the feature of the real image, \( l \) is the feature of the text description. All Dis() are the Fréchet Inception Distance [19] between two distributions. Details can be seen in appendix.

In the CMD, \( |\text{Dis}(f, l) - \text{Dis}(r, l)| \) measures the image-text consistency, denoted as ITDis for short, the smaller the ITDis is, the better the image-text consistency is. \( \text{Dis}(f, r) \) measures the image quality, the smaller \( \text{Dis}(f, r) \) is, the better the image quality is.

4. EXPERIMENTS

4.1. Experimental settings

Following previous work, we report validation results by generating images for 30,000 random captions on MS-COCO.

Evaluation metrics: As previous work did, Inception Score (IS) [7] and Fréchet Inception Distance (FID) [13] are used to evaluate image quality. Our work further proves that since the calculation method of IS evaluation is relatively simple, it is not suitable for datasets with complex scenes such as MS-COCO. Since R-Precision [3] has huge drawbacks as Sec.2 report, but ITDis defined in Sec.3.3 is direct and intuitive, we use ITDis for image-text consistency evaluation. CMD defined in Sec.3.3 is used for evaluating image quality and image-text consistency as a whole. To ensure the fairness of evaluation, CMD and ITDis use a off-the-shelf CLIP-ViT network for evaluation, which is different from our CLIP-Res101 used in ITM.

Parameter settings: Our work refers to Xu et al. [3] and set \( \gamma \) in Equ.8 to 10. For \( \lambda_1 \) and \( \lambda_2 \) in Equ.9, we set them between 1 and 5 for parameter adjustment experiments. Finally, it is determined that \( \lambda_1 = 4 \) and \( \lambda_2 = 1 \). The model learning rate and training epochs are set to 0.0002 and 300.

4.2. Experimental results

Table 1 gives the experimental results of our GR-GAN model and multiple current mainstream models on MS-COCO dataset. It’s easily to see that CP-GAN could get high IS
Table 2. Results of ablation studies. (DA means using DAMSM as the consistency constraint module, IT means using ITM. GRG refers to adding the GRG method)

| backbone | DA | IT | GRG | FID | ITDis | CMD |
|----------|----|----|-----|-----|-------|-----|
| Attn-GAN | ✓  | ✓  | ✓   | 43.88 | 1.31  | 17.65 |
|          | ✓  | ✓  | ✓   | 34.90 | 1.07  | 15.97 |
|          | ✓  | ✓  | ✓   | 29.69 | 1.05  | 14.89 |
|          | ✓  | ✓  | ✓   | 30.21 | 1.04  | 11.36 |
|          | ✓  | ✓  | ✓   | 28.72 | 0.87  | 10.57 |
| DM-GAN   | ✓  | ✓  | ✓   | 28.56 | 1.06  | 13.67 |
|          | ✓  | ✓  | ✓   | 27.42 | 0.98  | 12.68 |
|          | ✓  | ✓  | ✓   | 25.83 | 1.00  | 11.84 |
|          | ✓  | ✓  | ✓   | 25.33 | 0.96  | 9.01  |
|          | ✓  | ✓  | ✓   | 22.58 | 0.80  | 8.04  |

but perform poorly on the stronger FID, which indicates a clear overfitting of IS because of ignoring the real image distribution. Our model achieves best performance on three metrics. The FID metric of the GR-GAN model is increased by 8.58% (24.70 to 22.58) compared with the previous best OP-GAN model, increased by 17.65% (27.42 to 22.58) compared with DM-GAN. At the same time, GR-GAN is superior to the existing models in the consistency metric ITDis, and has a significant improvement in the comprehensive metric CMD compared with other models (11.99 to 8.04). These experimental results show that our GR-GAN is more effective than the previous SOTA model to generate high-quality images as well as with high image-text consistency.

Fig.2 gives some examples. As we can see, both the image quality and image-text consistency of our model are significantly better than those in previous models.

4.3. Ablation studies

We conducted some ablation experiments on the two core modules (GRG and ITM) on Attn-GAN and DM-GAN frame respectively.

**GRG:** As shown in Table 2, it can be seen that adding GRG not only effectively improve image quality (FID), but also generates images of better image-text consistency (ITDis), and achieves better performances on CMD. At the same time, we check the order of sentence and word constraints in the network, the experimental results and some examples are shown in Fig. 3. As the first row shows, by using our gradual sequence, the generation process has better performance. First, the overall image distribution is generated, then the sentence-level global semantics are enriched, and the detailed information (such as surf board, wave) is perfected finally. When the order of the constraints is changed, both the quality and consistency are worse. It shows that our coarse-to-fine order to refine the image gradually is important to the model. In addition, the effect of putting the I stage for image quality after the semantic stage (S, W) is much more worse than putting it before the semantic layer (the third rows). It shows that for the low-resolution generation stage, it is more reasonable to focus on quality of images.

**ITM:** In order to evaluate the role of our ITM module, we use ITM to replace DAMSM on Attn-GAN and DM-GAN respectively (the first and third rows of data in Table 2). The experimental results show that ITM brings significant improvement on image quality metric FID, as well as the comprehensive metric CMD.

Ablation results show that both GRG and ITM can significantly improve the performance of FID and CMD, and using them together could get the best results.

5. CONCLUSIONS

In this paper, we propose an Gradual Refinement Generative Adversarial Network (GR-GAN) for text-to-image synthesis. It generates images conditional on text descriptions gradually in three stages. Firstly, We build a novel GRG module to improve image quality by using language information from coarse-grained to fine-grained. Secondly, we propose a ITM model to compute image-text matching loss for training the generators of the GR-GAN, which is able to more accurately assess the image-text consistency than DAMSM. Finally, we propose an evaluation metric that is more suitable for Text-to-Image, which can simultaneously evaluate image quality and image-text consistency. Our GR-GAN significantly outperforms previous SOTA GAN models, boosting the best reported FID from 24.70 to 22.58 and CMD from 11.99 to 8.04 on MS-COCO. Extensive experimental results clearly demonstrate the effectiveness of our proposed methods.
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