TiGAN: Text-Based Interactive Image Generation and Manipulation

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Abstract

Using natural-language feedback to guide image generation and manipulation can greatly lower the required efforts and skills. This topic has received increased attention in recent years through refinement of Generative Adversarial Networks (GANs); however, most existing works are limited to single-round interaction, which is not reflective of real world interactive image editing workflows. Furthermore, previous works dealing with multi-round scenarios are limited to predefined feedback sequences, which is also impractical. In this paper, we propose a novel framework for Text-based interactive image generation and manipulation (TiGAN) that responds to users’ natural-language feedback. TiGAN utilizes the powerful pre-trained CLIP model to understand users’ natural-language feedback and exploits contrastive learning for a better text-to-image mapping. To maintain the image consistency during interactions, TiGAN generates intermediate feature vectors aligned with the feedback and selectively feeds these vectors to our proposed generative model. Empirical results on several datasets show that TiGAN improves both interaction efficiency and image quality while better avoids undesirable image manipulation during interactions.

Introduction

Text-to-image generation and text-guided image manipulation are important research topics, which have demonstrated great application potentials due to the flexibility and usability of natural language. Compared to traditional image editing software that require users to learn complex tools, language driven methods can be more intuitive for novice users. One main challenge of text-to-image generation/manipulation is that images are 2D arrays of pixels, while natural language expressions are sequences of words with no clear mapping between them. While existing works (Xu et al. 2018; Zhang et al. 2021; Xia et al. 2021; Patashnik et al. 2021) have proposed useful new models and loss functions, they share the limitation that they focus on single-round tasks, i.e., these methods generate or manipulate an image only in the context of a single natural language instruction. Such a restriction limits the applicability of the models for real-use cases, as a user may want to continually refine an image until satisfactory. While such models could be naively applied recursively, at each round, the model would be oblivious to previously given feedback leading to high likelihood that the model interferes with previous edits.

There also exist some works that sequentially generate images following different instructions (El-Nouby et al. 2019; Fu et al. 2020). However, these methods are not fully interactive and less practical. For example, models in (El-Nouby et al. 2019; Fu et al. 2020) are trained on predefined sequences of natural language instructions, while the instructions are independent of generated images and follow a predefined order. However, when a real user interacts with the model, the natural-language feedback is unpredictable and depends on generated image in each round. Thus, the use of predefined sequences is impractical for real-world interactive applications.

In this work, we focus on a new problem of interactive image generation, which generalizes text-to-image generation and text-guided image manipulation to the multiple round setting. It is a natural extension to existing single round methods, and our goal is to generate desired images with fewer interactions. Consequently, we address these two critical challenges: (i) how to learn a better text-to-image mapping; (ii) how to avoid undesirable image manipulations throughout the interaction session. A better text-to-image mapping would improve overall image quality and improve how well the image agrees with the text. An undesirable image manipulation would occur if the model accidentally changes an aspect of the image that the user already specified. For instance, assume the user requests the model to “generate a man’s face” and then issues the command “make the hair long”. We are expecting two generated images: an image of a man and an image of a man with long hair for this two-round example. Receiving an image of a man and an image of a woman with long hair is a failure case which also satisfies the user’s requirement at every round. Since user has requested the image to be of a man in the first round, the model should not change that aspect of the image in later manipulations unless the user explicitly says otherwise.

To handle the aforementioned challenges, we propose Text-based Interactive image generation and manipulation (TiGAN). Different from existing works that focus on complicated architecture designs, we tackle the problem by di-
Figure 1: Overview of our interactive image generation. A user starts a session and keeps giving natural-language feedback to the generative model until they are satisfied with the generated image. We propose TiGAN with specifically designed contrastive losses that encourage a better text-to-image mapping, which is used in both generation and manipulation. The pre-trained CLIP encoders help TiGAN to better understand images and texts semantically.

Directly adapting powerful unconditional generative models into our model for text-conditional generation. Specifically, TiGAN uses state-of-the-art (SOTA) StyleGAN2 (Karras et al. 2020) as its backbone and use Contrastive Language-Image Pre-training (CLIP) (Radford et al. 2021) to inject text information into StyleGAN2. CLIP is a multi-modal model pre-trained on 400 million text-image pairs and consists of one image encoder and one text encoder that respectively map images and text into a unified joint embedding space. Using CLIP, TiGAN can evaluate the semantic similarity of text with images inside the joint embedding space. We train TiGAN with various proposed contrastive losses that encourage the model to learn a better text-to-image mapping with disentangled intermediate features. On top of the trained model, we propose an image manipulation mechanism that manipulates an image according to text feedback and avoids undesirable visible changes. We achieve this by only updating the intermediate features of the generator that are relevant to the text.

To summarize, we propose a novel model for Text-based Interactive image generation (abbreviated TiGAN). Our main contributions are as follows:

- We propose a novel text-to-image generation model, which seamlessly integrates SOTA StyleGAN2 and CLIP model. To achieve a better text-to-image mapping with disentangled, semantically meaningful features, we also propose new contrastive losses to train the model;
- We further propose a new text-guided image manipulation mechanism, which can handle complex text information and maintain image consistency in the interaction;
- We conduct extensive experiments, demonstrating the advances of the proposed method over SOTA methods in both standard text-to-image generation and interactive image generation settings; Human evaluations in different scenarios further verify the effectiveness of the proposed method compared to existing works.

**Proposed Framework**

Based on generative adversarial networks (GANs) (Goodfellow et al. 2014) and contrastive language-image pre-training model (CLIP) (Radford et al. 2021), our framework consists of a text-to-image generation module and a text-guided image manipulation mechanism. Our proposed framework for interactive image generation is illustrated in Figure 1, with details described below. Different from the standard text-to-image generation task which is in a single-round setting, interactive image generation is naturally in a multi-round setting. At every round, the user will provide natural language to the proposed model, the model will generate or manipulate the images according to the requirements. The images will be fed to the user to obtain further feedback. The session will end when the user is satisfied with the results.

**Architecture of the Proposed TiGAN**

In this part, we present the detailed architecture designs for our proposed framework for text-based interactive image Generation. Throughout the paper, $z$ denotes standard Gaussian noise, $x$ denotes real image sample, $x'$ denotes generated image, $T$ denotes raw text description.

**Generator architecture**  
The generator is used to generate realistic and high-quality data samples. To achieve this, we build our generator based on the StyleGAN2 architecture (Karras et al. 2020). Our proposed generator architecture is illustrated in Figure 2, where $w$ denotes the intermediate latent vector, and $\{s_i\}_{i=1}^m$ denote vectors obtained by applying learned transformations on $w$. These transformations are affine transformations in original StyleGAN2. Throughout the paper, we use $s$ to denote the concatenation of vectors $\{s_i\}_{i=1}^m$, which is defined as the style vector following previous work (Wu, Lischinski, and Shechtman 2021).

Different from the original StyleGAN2, our proposed generator requires extra text features as inputs. Thus the main challenge is how to effectively extend the unconditional SOTA model to a conditional one by utilizing the text information. Existing works (Zhu et al. 2019; Xu et al. 2018; Zhang et al. 2021) inject text information either by directly concatenating the text feature with noise vector, or updating latent noise by learn-able scale and bias factors. Different from these methods that exploit different ways to update the noise vectors (initial input of the generator), we handle the problem by updating well-disentangled, intermediate features of the generator.
In standard unconditional settings, the discriminator should control a specific visible attribute of the generated images. Consequently, accurate text-to-image generation can be achieved if one can directly learn a mapping from text to the well-disentangled features.

To this end, let the *style space* $S$ be the space spanned by style vectors. As analyzed in some previous works (Wu, Lischinski, and Shechtman 2021; Liu et al. 2020), style space is shown to be well-disentangled. Inspired by these works, we propose to directly inject text information into this disentangled style space. We propose the following two modules to replace the affine transformations on $w$ in original StyleGAN2:

$$ s_i = \pi_i(\kappa_i(t), w), \quad \text{and} \quad (1) $$

$$ s_i = \phi_i(t) \odot \psi_i(w) + \chi_i(t), \quad (2) $$

where $\pi_i, \kappa_i, \phi_i, \psi_i, \chi_i$ denote different learnable functions constructed using 2-layer neural networks, $\odot$ denotes element-wise multiplication, $[\cdot, \cdot]$ denotes vector concatenation, $t$ denotes text feature extracted with pre-trained CLIP model. With the proposed module, the generator can generate images that match text descriptions. In practice, one can choose one of the modules, or use both modules in the generator. In experiments, we start from using (1) for all $s_i$, and gradually tune the model architecture by using (2) for some layers. Generally, using only (1) can lead to promising results, using (2) for the last few layers may further improve the results.

**Discriminator architecture**

In standard unconditional settings, the discriminator $D(\cdot)$ is trained to distinguish the real samples from fake samples. In our conditional setting, the discriminator should also consider text information to distinguish samples. To incorporate the text information, we propose to use the architecture in Figure 3, where $f_R(x)$ is a scalar that indicates the unconditional realness of the image as the standard discriminator output; and $f_D(x)$ is the semantic feature extracted by the discriminator. An image $x$ is classified as real when it has both high similarity with text $T$ and large unconditional realness $f_R(x)$. Thus we can define $D(x) = f_R(x) + \langle f_D(x), t \rangle$ as the realness of image $x$ given text feature $t$.

$$ L_{\text{CD}} = - \lambda \sum_{i=1}^{n} \log \frac{\exp(\tau \cos(f_D(x_i), t_i))}{\sum_{j=1}^{n} \exp(\tau \cos(f_D(x_j), t_j))} $$

where $\lambda$ and $\tau$ are hyper-parameters, and $\cos(\cdot, \cdot)$ denotes cosine similarity. Intuitively, minimizing $L_{\text{CLIP}}$ encourages the generator to generate image $x_i'$ that has high semantic similarity with the corresponding text description $T_i$. This also encourage $x_i'$ to have low semantic similarity with $\{T_j\}_{j \neq i}$, which are the text descriptions of other images.

In addition, we propose the following contrastive loss to regularize the discriminator.

$$ L_{\text{CD}} = - \lambda \sum_{i=1}^{n} \log \frac{\exp(\tau \cos(f_D(x_i), t_i))}{\sum_{j=1}^{n} \exp(\tau \cos(f_D(x_j), t_j))} $$

where $f_D(x_i)$ denotes the feature from the discriminator as illustrated in Figure 3. $L_{\text{CD}}$ encourages the discriminator to extract semantically meaningful features aligned with input text.
The final loss functions for the generator and the discriminator are defined respectively as:

\[ L'_G = L_G + \alpha L_{CLIP}(\{x'_i\}_{i=1}^n, \{T_i\}_{i=1}^n) + \beta L_{CD}(\{x'_i\}_{i=1}^n, \{T_i\}_{i=1}^n) \] (5)

\[ L'_D = L_D + \beta L_{CD}(\{x_i\}_{i=1}^n, \{T_i\}_{i=1}^n) \] (6)

During the training process, only the parameters of the generator and discriminator are updated. The parameters of the CLIP text and image encoders are fixed and loaded from the pre-trained checkpoint. In later section, we will discuss the difference between our work and other methods that also use contrastive loss (Xu et al. 2018; Zhang et al. 2021). We also performed an ablation study to help better understanding the impact of these contrastive losses.

**Interactive Image Generation**

Training with (5) and (6) results in a standard text-to-image generation model for a single-round interaction. To extend our model for interactive generation, we regard the problem as a combination of text-to-image generation and a sequence of text-guided image manipulation. Thus our next step is to design a method for image manipulation that only allows the model to manipulate target attributes of the image. With this, information from previous interactions can be maximally preserved, undesirable image changes can be maximally avoided.

Let \( z \) be a noise sampled from standard Gaussian distribution, \( f \) be a text feature from the dataset extracted with CLIP. The text-to-image generation process can be formulated as \( x = G_I(s), s = G_S(t, z) \), where \( s = [s_1, s_2, ..., s_m] \) denotes the generated style vector. As shown in Figure 2, \( G_S \) consists of a mapping network and a newly proposed module, which generates a style vector \( s \) given text \( t \). \( G_I \) denotes the synthesis network in Figure 2, which will generate an image based on the style vector \( s \). To manipulate an image \( x \) with style \( s \) according to a new text \( t' \), we first identify the most relevant dimensions of \( s \), denoted as \( \{c_i\}_{i=1}^k \). Then we generate new style \( s' \) via:

\[
[s'_i]_i = \begin{cases} [s_i]_i + \gamma ([G_S(z_i, t')]_i - [s_i]_i) & \text{if } i \in \{c_i\}_{i=1}^k \\ [s_i]_i & \text{otherwise} \end{cases}
\] (7)

where \([s_i]_i\) denotes the \( i^{th} \) element of \( s \), \( \gamma > 0 \) is the step size (we set \( \gamma = 1 \) in practice). With the updated style vector, a new image is generated via \( x' = G_I(s') \).

To obtain the relevant dimensions \( \{c_i\}_{i=1}^k \) of \( s \), we follow the same strategy as (Patashnik et al. 2021). Let \( s_i \in R^{\text{dim}(s)} \) be a vector with value \( \eta_i \) on its \( i^{th} \) dimension and 0 on other dimensions ( \( s_i \) has the same size as \( s \)). We use the following term to evaluate the effects of revising \( i^{th} \) dimension:

\[
\Delta r_i = \mathbb{E}_z [f_I(G_I(s + \tilde{s}_i)) - f_I(G_I(s)), s = G_S(z, t)]
\] (8)

where \( z \) is sampled from standard Gaussian distribution, \( \tilde{s}_i \) is randomly sampled text from the dataset. Intuitively, \( \Delta r_i \) evaluates the semantic feature change of revising \( i^{th} \) dimension of style vector. After obtaining \( \Delta r_i \) for all dimensions, we select all the dimension \( i \) satisfying:

\[
\cos(\Delta t, \Delta r_i) \geq a
\] (9)

where \( a > 0 \) is a threshold, \( \Delta t \) is the desired semantic change evaluated by CLIP. \( \Delta t \) can be estimated in different ways. For instance, let \( f_T \) be the text encoder of CLIP and we would like to edit the hair color of the human face in the image. \( \Delta t \) can be estimated using prompts: \( \Delta t = f_T(\text{a face with black hair}) - f_T(\text{a face with hair}) \). It can also be directly estimated by \( \Delta t = f_T(\text{this person should have black hair}) - t \), where \( t \) is the text feature of previous round’s instruction or the feature of an empty string (for the first round). In practice, we found both ways work equally well.

**Related Work**

Compared to existing works, our proposed framework is more general and can be applied in different scenarios.

**Text-to-Image Generation**

There are two major categories of text-to-image generation models. (Xu et al. 2018; Zhu et al. 2019; Zhang et al. 2021) propose to use GAN-based structures, (Ramesh et al. 2021; Ding et al. 2021) propose to combine discrete variational auto-encoder (VAE) (van den Oord, Vinyals, and Kavukcuoglu 2017) and transformer (Vaswani et al. 2017). Although (Ramesh et al. 2021; Ding et al. 2021) achieve better qualitative results compared to GAN-based models, they are large models trained on huge dataset, which is inaccessible to most researchers, e.g. DALL-E (Ramesh et al. 2021) has over 12 billion parameters and is trained on a dataset consists of 250 million image pairs.

Our proposed model follows the GAN-based structure. Although AttnGAN (Xu et al. 2018) propose DAMSM which also use contrastive loss, it only trains generator with the contrastive loss. XMC-GAN (Zhang et al. 2021) proposed to use contrastive loss for both generator and discriminator, and used a complicated architecture for SOTA models. Different from these works that directly design complex model architectures in a heuristical way, we focus on how to efficiently turn an existing SOTA unconditional GAN into a text-conditioned GAN. To this end, we propose to inject text information into the disentangled feature space of the generator, and train both generator and discriminator with the proposed contrastive loss. Pre-trained CLIP model is also incorporated to provide better semantic information for the training process. As a result, we obtains SOTA performance on text-to-image generation tasks.

**Text-guided Image Manipulation**

General idea on manipulating images consists of three steps: map images into some latent spaces, manipulate the obtained latent vectors, generate images with the manipulated latent vectors. Existing works (Wu, Lischinski, and Shechtman 2021; Liu et al. 2021; Li et al. 2020; Xi et al. 2021; Patashnik et al. 2021) handle the third step by directly using pre-trained GANs, and focus on the first or second step. Different from these works, we solve the challenge of the third step by training a better text-to-image generation model. Now we briefly discuss the SOTA methods for the second step, which is also the topic our manipulation mechanism focus on.

TediGAN (Xia et al. 2021) propose to train different encoders that map different modalities into the same latent
Interactive Multi-modal Learning  The classical multi-round manipulation problem considers the problem where a designer will sequentially generate images for the ultimate goal following a sequence of linguistic instructions (El-Nouby et al. 2019). The SOTA performance of this task is achieved by a self-supervised framework which incorporates counterfactual thinking to overcome data scarcity (Fu et al. 2020). These two methods are based on predefined sequences which are not practical for real interactive problems. Furthermore, they will suffer the exposure bias and error accumulation issues, i.e., the image quality becomes worse with more interactions. A POMDP formulation for conversational image editing was also developed to enable fully interaction (Lin et al. 2018), but the manipulation is based on predefined operations without any creation. The fully interactive image generation problem was explored in (Cheng et al. 2020), while the generation quality are miserably poor and can only handle relatively simple datasets. Interactive image retrieval was explored in (Guo et al. 2019, 2018; Tan et al. 2019; Zhang et al. 2019), which focus on learning a better recomender policy to handle user natural-language feedback. Compared to the aforementioned methods, our proposed method is fully interactive, does not have error accumulation, and can handle both image generation and manipulation problems on complex datasets.

Experiments

We conduct extensive experiments on three different datasets: UT Zappos50k (Yu and Grauman 2014), MS-COCO 2014 (Lin et al. 2014) and Multi-modal CelebA-HQ (Xia et al. 2021). The experiments are implemented under two settings: single-round image generation and interactive (multi-round) image generation. All experiments are conducted on 4 Nvidia Tesla V100 GPU and implemented with Pytorch. Details of the datasets, the experimental setup and hyper-parameters are provided in the Appendix.

Text-to-image Generation

To test the generation quality of our method for text-to-image generation, we first evaluate it on MS-COCO 2014, a dataset containing complex scenes and many kinds of objects and is commonly used in text-to-image generation tasks. Following previous work (Zhang et al. 2021), we report Fréchet Inception Distance (FID) (Heusel et al. 2017) and Inception Score (IS) (Salimans et al. 2016), which evaluate the quality and the diversity of generated images respectively. 30,000 generated images with randomly sampled text are used to compute the metrics. The main results are provided in Table 2. Our proposed method outperforms previous SOTA model XMC-GAN (Zhang et al. 2021). Compared to XMC-GAN that contains many attention modules, our proposed model has less parameters and smaller model size, while achieving better IS and FID scores. Some generated examples are shown in Figure 4, more results are provided in the Appendix.

In addition, (Xia et al. 2021) provides results of text-to-image generation on Multi-modal CelebA-HQ. We also have compared our method with it in Table 3. Note that the results in (Xia et al. 2021) are based on the generator pre-trained on FFHQ (Karras, Laine, and Aila 2019), which is directly used to calculate the FID score on Multi-modal CelebA-HQ. Since FID measures the distance between generated images and real images from a dataset, it is fairer to fine-tune the generator on Multi-modal CelebA-HQ before evaluating FID. Thus we report both the original results from (Xia et al. 2021) and the results of fine-tuning the model before applying their methods. Following (Xia et al. 2021), all the results
are evaluated by generating 6000 images using the descriptions from test set of Multi-modal Celeb-A-HQ. Note that we do not report LPIPS (Zhang et al. 2018) as (Xia et al. 2021), because we found that LPIPS can be easily hacked in this experiment, where one can easily obtain good LPIPS that does not represent a good model. More discussions can be found in the Appendix.

### Interactive Image Generation

We then test the proposed method on UT Zappos 50k and Multi-modal CelebA-HQ for the interactive image generation task. We choose these two datasets because each image has associated attributes in these datasets. Some examples are shown in the Appendix.

Some visualization results are illustrated in Figure 5. It is clear that the proposed method can manipulate the image correctly and maintain the manipulated attributes during the whole interaction. We also evaluate the proposed method quantitatively. To this end, we design a user simulator to give text feedback based on the generated images. In each test case, the user simulator has some target attributes in mind, which are randomly sampled from the dataset and unknown to the model. The model starts from generating a random image and feed the image to the user simulator. The user simulator will give feedback by randomly pointing out one of the target attributes that is not satisfied by the generation. The feedback will then be fed to the model for further image manipulation. The interaction process will stop when the user simulator finds the generated image matches all the target attributes. In the experiments, we use neural network based classifier as the user simulator, which classifies the attributes of the generated images, and output text feedback based on prompt engineering. The details of constructing user simulator can be found in Appendix.

The main results of averaging over 1000 test cases are reported in Table 1. Note that we set a maximal number of interaction rounds. Once the interaction exceed this number, the user simulator would directly treat current test as a failure case and start a new test case. The attributes used in this experiment are summarized in Table 6 in Appendix. We compare our proposed method with currently SOTA image manipulation methods: StyleCLIP-Global, TediGAN and existing SOTA interactive method SeqAttnGAN (Cheng et al. 2020). Note that for fair comparison, we re-implemented SeqAttnGAN using StyleGAN2 and CLIP model, which leads to a much more powerful variant than (Cheng et al. 2020). We also provide the results of our method without threshold during image manipulation, i.e., instead of using method in Eq. (7), we directly generate new method without threshold during image manipulation, (Cheng et al. 2020). We also provide the results of our method quantitatively. To this end, we design a user simulator to give text feedback based on the generated images. In each test case, the user simulator has some target attributes in mind, which are randomly sampled from the dataset and unknown to the model. The model starts from generating a random image and feed the image to the user simulator. The user simulator will give feedback by randomly pointing out one of the target attributes that is not satisfied by the generation. The feedback will then be fed to the model for further image manipulation. The interaction process will stop when the user simulator finds the generated image matches all the target attributes. In the experiments, we use neural network based classifier as the user simulator, which classifies the attributes of the generated images, and output text feedback based on prompt engineering. The details of constructing user simulator can be found in Appendix.

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### Human Evaluation

We also conducted human evaluation on Amazon Mechanical Turk (MTurk) for text-to-image generation, text-guided image manipulation and interactive image generation. In the evaluation, the workers were provided 100 images from each
method, which are generated or manipulated according to randomly sampled texts. The workers were asked to judge whether the generated or manipulated images match the text and how realistic the images are. Furthermore, the workers are also asked to judge whether the consistency is well maintained in manipulation, in the sense that there are no undesirable changes observed. The three metrics are denoted as Match, Realistic and Consistency respectively. The workers are all from the US and were required to have performed at least 10,000 assignments approved with an approval rate ≥ 98%. For each metric, the workers are asked to score the images at scale of 1 to 5, where 5 denotes the most realistic/best matching/most consistent. The main results are provided in Table 4 and more details of the human evaluation can be found in the Appendix.

**Ablation Study**

To better understand the proposed method, we conducted an ablation study to determine how each component of the loss function influence TiGAN. The main results are provided in Table 5. We observe that excluding either $L_{\text{CLIP}}$ or $L_{\text{CD}}$ leads to performance degeneration. Meanwhile, $L_{\text{CLIP}}$ seems to contribute more than $L_{\text{CD}}$, as the model trained without $L_{\text{CLIP}}$ has much poorer diversity according to IS.

**Conclusions**

In this paper, we proposed TiGAN for interactive image generation and manipulation from text. Using both human and automated evaluation, we showed that TiGAN is able to generate more realistic images that better match the text in fewer rounds than prior SOTA methods. Empirical results on several datasets show that TiGAN improves both interaction efficiency and image quality while better avoids undesirable image manipulations during interaction.
References

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