Multimodal Image-to-Image Translation via a Single Generative Adversarial Network

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Abstract—Despite significant advances in image-to-image (I2I) translation with generative adversarial networks (GANs), it remains challenging to effectively translate an image to a set of diverse images in multiple target domains using a pair of generators and discriminators. Existing multimodal I2I translation methods adopt multiple domain-specific content encoders for different domains, where each domain-specific content encoder is trained with images from the same domain only. Nevertheless, we argue that the content (domain-invariance) features should be learned from images among all of the domains. Consequently, each domain-specific content encoder of existing schemes fails to extract the domain-invariant features efficiently. To address this issue, we present a flexible and general SoloGAN model for efficient multimodal I2I translation among multiple domains with unpaired data. In contrast to existing methods, the SoloGAN algorithm uses a single projection discriminator with an additional auxiliary classifier and shares the encoder and generator for all domains. As such, the SoloGAN model can be trained effectively with images from all domains so that the domain-invariance content representation can be efficiently extracted. Qualitative and quantitative results over a wide range of datasets against several counterparts and variants of the SoloGAN model demonstrate the merits of the method, especially for challenging I2I translation tasks, i.e., tasks that involve extreme shape variations or need to keep the complex backgrounds unchanged after translations. Furthermore, we demonstrate the contribution of each component using ablation studies.

Index Terms—Image-to-Image translation, generative adversarial network, image synthesis.

I. INTRODUCTION

IMAGE-TO-IMAGE (I2I) translation aims to learn a function that changes domain-specific part/style of given image to target while preserving its domain-invariance part/content [1], [2]. A variety of vision and graphics problems, e.g. semantic segmentation, object detection, and deblur, can be formulated as I2I problems (Fig. 1a). Generative adversarial networks (GANs) [3] have received extensive attention in recent years, and a number of GAN-based methods have been developed for vision tasks, including person reidentification [4], [5], superresolution [6], [7], text-to-image synthesis [8], [9], and facial attribute manipulation [10], [11]. Significant advances have been made in I2I translation tasks with the help of GANs [13]–[17]. Among them, Pix2Pix [13] trains a conditional GAN with paired training data for supervised I2I tasks. In contrast, some works attempt to learn I2I translation without supervision [18]–[21]. For instance, the CycleGAN [20] method introduces the cycle consistency loss for unsupervised I2I translation. To further enhance the capability of CycleGAN in identifying the most discriminative foregrounds, some attention-guided generators are proposed in [22], and a shared knowledge module along with absolute consistency loss is used in [23].

Although much progress has been made, those methods cannot translate a single image to a set of diverse images in a target domain, which is known as multimodal image translation [24]. Fig. 1(b) shows one example of the multimodal I2I translation task, where a horse is translated to a few zebras but with diverse appearances. To address this issue, a number of multimodal image translation algorithms have been proposed in recent years, including MUNIT [1] and DRIT [2], where the main idea is to employ a pair of content and style encoders to embed an image from a specific domain into a domain-invariant space and a domain-specific space and then use a generator to map the latent codes to diverse outputs in a target domain (Fig. 2(a)). However, those methods, including the improved GR-GAN [23], are less efficient since multiple pairs of content and style encoders and GANs are required for multimodal image translation among multiple domains.

An illustrative example to show the framework of existing methods for translating cat to dog and tiger is displayed in Fig. 2(a), where two independent cat content and style encoders, one dog and tiger generator, as well as one dog and tiger discriminators are involved. These approaches use different domain-specific content encoders to learn domain-invariant features for different domains and train the model of each domain using the images from the same domain independently.

These approaches need to decompose the cat twice with two totally independent encoders, aiming to extract the domain-invariance among the domains of cat, dog, and tiger. Nevertheless, the domain-invariance features should be learned from images from all domains. It is unlikely for these schemes to translate objects of different scales with complex backgrounds effectively. Consequently, existing methods can perform well in translating objects with simple backgrounds [as shown in Fig. 3(a)] but fail to translate objects with diverse appearances and complex backgrounds [e.g. translation from a horse in the wild to a zebra and vice versa, as shown in Fig. 3(b)], since the translation methods should be aware of the diverse
Unsupervised segmentation
Unsupervised detection
Blind deblur

(a) Unimodal I2I translations
(b) Multimodal I2I translations

Fig. 1: Image-to-image translation results synthesized by (a) unimodal variant of SoloGAN and (b) SoloGAN.

(a) Existing multimodal I2I translation methods
(b) Our method

Fig. 2: Workflows of (a) existing multimodal I2I translation methods and (b) our method. De, Cb, and Cd represent Decompose, Combine, and Condition, respectively. To translate an image from a source domain into a target domain, the latent space of the image is first decomposed into the content and style. A generator combines the content and different style vectors ($z$, the random samples from $N(0, 1)$) to generate different target images. Taking the translation from the same cat into dogs and tigers as an example, existing methods need to setup two independent pairs of translations: cat to dog and cat to tiger. In contrast, our method can obtain objects of different domains with the same encoder and generator when given different target domain labels.

backgrounds, which are also the domain-invariant components, among different domains. To summarize, there are three main challenges in the existing I2I methods:

- **Diverse outputs**: Existing multidomain I2I methods benefit from using a unified model to facilitate learning, but they fail to generate diverse outputs of the same domain when given one input.

- **Multiple GANs**: Multimodal I2I methods benefit from the disentangled representation of content and style, but they require multiple pairs of GANs for translation among multiple domains and need to train the content encoder independently with domain-specific images.

- **Ineffectiveness**: There are some common deficiencies in multidomain and multimodal methods. For instance, they are ineffective in dealing with translation tasks that require extreme shape variations or retain the complex background after translation.

To meet the above challenges, we propose SoloGAN for multimodal image translation among multiple domains. A single content encoder is used to encode the domain-invariant features of all the images from multiple domains; the style encoder and generator are shared among different domains in a conditional manner. In addition, a projection discriminator [25] with an additional auxiliary classifier is constructed instead of constructing multiple discriminators for different domains, e.g. IntersectGAN [26].

Specifically, we use an image and its label as input to the style encoder for domain-specific representation extraction and feed the latent codes along with the target labels to the generator to generate a set of diverse target images. The general framework of our proposed method, SoloGAN, is presented in Fig. 2(b). SoloGAN is able to learn multimodal mappings among multiple domains using a single pair of generators and discriminators. Since training samples from all domains are available to the single discriminator, its capability in discriminating real and generated samples is enhanced.

To better validate the performance of the proposed SoloGAN model, we modify existing datasets to be more challeng-
TABLE I: Comparisons of existing GAN-based image translation methods.

| Method        | Pix2Pix | CycleGAN | StarGAN | BicycleGAN | MUNIT | DRIT | SingleGAN | SoloGAN |
|---------------|---------|----------|---------|------------|-------|------|-----------|---------|
| Unsupervised  | ✓       | ✓        | ✓       | ✓          | ✓     | ✓    | ✓         | ✓       |
| MultiDomain   | ✓       | ✓        | ✓       | ✓          | ✓     | ✓    | ✓         | ✓       |
| MultiModal    | ✓       | ✓        | ✓       | ✓          | ✓     | ✓    | ✓         | ✓       |
| SinglePair    | ✓       | ✓        | ✓       | ✓          | ✓     | ✓    | ✓         | ✓       |

**A. Generative Adversarial Networks**

Generative adversarial networks (GANs) [3] have gained much attention in recent years. To improve the training process as well as the quality and diversity of generated samples, staple adversarial losses [29], [30] and regularization techniques [31], [32] have been proposed. In addition, conditional GANs [33] have been developed to help generate samples of desired classes. For instance, the ACGAN [34] method uses an auxiliary classifier to train the generator for generating samples of the desired classes. Image translation methods can also be formulated based on conditional GANs since the synthesized images belong to a specifically desired domain.

**B. Image-to-Image Translation**

The I2I translation task aims to learn a function to transfer the domain-specific part of a given image to the target domain [35]. In the Pix2Pix [13] method, a paired training dataset is used to train a cGAN [33] in a supervised manner. To alleviate the issue of collecting a large amount of paired training data, the CycleGAN [20] model uses a cycle consistency loss to preserve the key attributes between the input and the translated image.

CUT [36] argued that the cycle-consistency assumption is often too restrictive and proposes using contrastive learning to maintain correspondence in content by maximizing the mutual information between the corresponding input and output patches. In addition to explicit methods, LETIT [37] proposed applying energy-based models to perform implicit image translation by direct maximum likelihood estimation, which also achieves impressive results with less computational cost. To further alleviate the domain labels as supervision, TUNIT [38] proposed a truly unsupervised image-to-image translation mode. In addition, pSp [39] explored StyleGAN’s powerful ability to generate high-resolution images in the task of I2I. Despite their demonstrated success, these methods have limited scalability in handling I2I translation among multiple domains, since different generative models should be trained for each pair of source/target domains. Instead of training multiple GANs for multidomain I2I translation, e.g. ComboGAN [40], a number of methods explore multidomain translation using a single GAN, e.g. StarGAN [12] and GANimation [11].

Numerous I2I translation problems are inherently multimodal. The BicycleGAN [24] model explicitly encourages a bijection between two spaces in a supervised manner, which makes it possible to generate different images using different latent codes. The MUNIT [1] and DRIT [2] methods are developed based on partially shared latent space. These approaches use a content encoder as well as a style encoder to decompose the latent space of images into a domain-invariance part and a domain-specific part, respectively. DRIT++ [41] introduces the mode seeking regularization proposed in [42] to alleviate the mode-collapse problem in DRIT. StarGANv2 [43] also achieves promising results over face images without a complex background. As a result, these methods can translate images while preserving the domain-invariance properties without...
supervision. Closely related to this work is the recently proposed SingleGAN \cite{27} scheme, which shares the style encoder and generator using a conditional approach. Nevertheless, the SingleGAN model still requires multiple discriminators to determine the domain of each image. In addition, SingleGAN does not split the latent space into domain-invariant and domain-specific parts, which results in its poor performance over tasks involving extreme shape variations. Table \ref{tab} shows a comparison of existing I2I translation methods.

### III. SoloGAN

The goal of this work is to learn multimodal mappings among multiple domains using a single GAN. The overall network structure of our proposed SoloGAN is shown in Fig. 4(a) and consists of an encoder $E$ (including a content $E^c$, style $E^s$), generator $G$, and discriminator $D$. Fig. 4(b) shows a sample of multimodal image-to-image translation among multiple domains by SoloGAN. In addition, the Central Biasing Instance Normalization (CBIN) \cite{44} scheme is used for inductive bias.

#### A. Encoder

The encoder is used to map the input image into the latent space. As mentioned above, an image can be decomposed into the content and style in the latent space. Hence, we design a content encoder and a style encoder, respectively. The style is encoded using a conditional encoder design a content encoder and a style encoder, respectively. The style is encoded using a conditional encoder with the domain labels as the condition (i.e. domain labels are transferred to a one-hot vector). Furthermore, the style is distilled in a low-dimensional vector, where the length is set to 8 in this work.

#### B. Generator

Conditioned by a target domain label, the generator in the SoloGAN model maps the given content and style to the output directly. Specifically, the target domain label vector is concatenated with the given style vector, and then the obtained vector is fed into the generator network by using the CBIN scheme \cite{44}. The generator learns how to maximize the probability of the discriminator distinguishing outputs from it as real. By the end, the generator can produce samples with realistic details and correct global structure.

#### C. Discriminator

In contrast to existing I2I methods that separate multiple domains into individuals and use multiple domain-specific discriminators to distinguish the target translated images, we use a single discriminator as in conventional class-conditional image generation \cite{34, 45, 46}. Motivated by the classifier-based discriminator \cite{34} [Fig. 5(a)] and the projection discriminator (PD) \cite{25} [Fig. 5(b)], we propose a new discriminator [as shown in Fig. 5(c)] in this work. The classifier-based discriminator incorporates the label information into the objective function by augmenting the original discriminator objective with the likelihood score of the classifier on both the generated and training images. On the other hand, the projection operator incorporates the label into the discriminator by taking an inner product between the embedded one-hot vector domain label $y$ and the intermediate output feature vector. This significantly improves the quality of class conditional image generation. However, the classifier-based discriminator fails to generate samples with realistic details, while the projection discriminator is ineffective in punishing the generator for translating the input image into a target domain. In the proposed projection with a classification discriminator, part of the projection model structure is shared with an auxiliary classifier. This helps the projection discriminator classify the translated images into a target domain. Instead of using multiscale discriminators \cite{47} as in most I2I GAN-based models (e.g. MUNIT \cite{1} and DRIT \cite{2}), we use a single-scale discriminator in this work.

#### D. Loss Functions

Our loss is a weighted sum of the adversarial loss, domain classification loss, cycle consistency loss, and bidirectional reconstruction loss. These four losses aim to force the model to generate realistic samples, translate samples into the target domain, learn translation without ground truths, and decompose the content from style.

**Adversarial loss.** To make the images generated by our generator indistinguishable from the real images in the target domains, we use the least-square adversarial loss \cite{29}:

\[
L_{adv}^D = \mathbb{E}_{x,y,z \sim \mathcal{N}(0,1)}[D(\hat{x})^2] + \mathbb{E}_x[(1 - D(x))^2],
\]
\[
L_{adv}^G = \mathbb{E}_{x,y,z \sim \mathcal{N}(0,1)}[(1 - D(\hat{x}))^2],
\]

where $\hat{x}$ is an image in domain $y'$ translated from $x$ by $G(c, z, y')$, and $c$ denotes the content extracted from $x$ with $E^c$. Given an input pair $(x, y)$ and a target domain label $y'$, the goal is to translate image $x$ from domain $y$ into domain $y'$. The generator $G$ synthesizes an image $\hat{x}$ conditioned on both the content of $x$ (i.e. $c$) and target domain label $y'$, while the discriminator $D$ aims to classify and distinguish between real and fake. We refer to the term $D(x)$ as the probability that an input $x$ is a real sample in the domain $y$.

**Domain classification loss** To force the generator to translate an input image into a target domain when conditioned by a target label, we use the domain classification loss of both real and translated images when optimizing $D$, $G$, and $E$:

\[
L_{cls}' = \mathbb{E}_{x,y}[-\log D_{cls}(y|x)],
\]
\[
L_{cls} = \mathbb{E}_{x,y}[-\log D_{cls}(y'|\hat{x})],
\]

where $L_{cls}'$ and $L_{cls}$ are used to optimize $D$ and the joint of $G$ and $E$, respectively.

**Cycle consistency loss** When there is a lack of paired training samples for supervised learning, training $G$ with respect to the adversarial loss in \cite{1} does not guarantee that the translated images will preserve the content of the given image while only
changing the style. To alleviate this problem, we apply a cycle consistency loss [20] to the generator:

\[ L_{cyc} = \mathbb{E}_{x,y,\hat{x},y',s} \| x - G(E^s(\hat{x}), s, y) \|_1, \tag{5} \]

where \( s \) denotes the style extracted from \( x \) with \( E^s \). Note that \( c, \hat{x} \) [as given in (1)], and \( s \) are used as consistent denotations in the following unless otherwise specified. Specifically, an image \( x \) should be reconstructed after being translated to \( \hat{x} \) within the target domain \( y' \).

**Bidirectional reconstruction loss** To encourage a bijection between two spaces, we introduce a bidirectional reconstruction loss as proposed in the MUNIT [1] method. When the generator maps the latent code of an image to the output, the output should be the same as the given image (image reconstruction), and an encoder should learn the mapping from the output back to the same latent code (latent reconstruction) with the following losses:

- **Image reconstruction.** The image reconstruction loss requires that the translated image be reconstructed back to \( x \) by recombining its content and style:

\[ L_{img}^{rec} = \mathbb{E}_{x,y,c,s} \| x - G(c, s, y) \|_1. \tag{6} \]

- **Latent reconstruction** The latent reconstruction is presented in the BicycleGAN [24] scheme for style reconstruction to alleviate the mode collapse problem. The MUNIT [1] method adds the content reconstruction loss to encourage the preservation of the semantic content in the input image during the translation with

\[ L_{latent}^{rec} = \mathbb{E}_{x,y,z, s \sim N(0, 1)} \| z - E^s(\hat{x}, y') \|_1 + \mathbb{E}_{x,c} \| c - E^s(\hat{x}) \|_1. \tag{7} \]

**Full objective.** We jointly train the pair of style and content encoders and generators while the discriminator is trained independently, and the final objective functions for the joint \( (L_{GE}) \) and discriminator \( (L_D) \) are:

\[ L_{GE} = L_{adv}^G + \lambda_{cls} L_{cls}^G + \lambda_{cyc} L_{cyc} + \lambda_{img} L_{img}^{rec} + \lambda_{latent} L_{latent}^{rec}, \tag{9} \]

\[ L_D = L_{adv}^D + \lambda_{cls} L_{cls}^D, \tag{10} \]

\( \lambda_{cls}, \lambda_{cyc}, \lambda_{img}^{rec}, \) and \( \lambda_{latent}^{rec} \) are hyperparameters that control the relative importance of corresponding losses compared to the adversarial loss, which are set to 1, 10, 10, and 1, respectively, as suggested in [1], [2].

We also provide Algorithm 1 to present the training process of our SoloGAN.

### IV. Experiments

We describe implementation details (including network and training details) and then introduce evaluation metrics as well...
Algorithm 1: Training process of SoloGAN

Input: Training data \( \mathcal{D}_{train} \), max. # of training epochs \( T \), max. # of domains \( N \), Gaussian noise \( P_{\epsilon} \). \( x, y \) represent \( N \) images and corresponding domain labels in each batch.

Output: \( G, E^c, E^s, D \)

1. \( t \leftarrow 0 \) // initialize an epoch counter;
2. \( G, E^c, E^s, D \leftarrow Xavier \) // initialize weights with Xavier function;
3. while \( t < T \) do
   4.   \( \{x, y\} \in \mathcal{D}_{train} \) do
      5.     // Obtain target domain labels and style vectors randomly.
      6.     \( y', z \leftarrow N \) random numbers from \([1, \ldots, N]\) and samples from \( P_{\epsilon} \)
      7.     // Extract the content and style feature
      8.     \( c, s \leftarrow E^c(x), E^s(x, y) \)
      9.     // Generate fake images
      10.    \( \hat{x} \leftarrow G(c, z, y') \)
      11.    // ********** Update the discriminator ********** /
      12.    Update \( D \) according to Eq. 10
      13.    // ********** Update generator and encoder ********** /
      14.    Reconstruction of images, content and style features
      15.    Update \( G, E^c, \) and \( E^s \) according to Eq. 9.
      16.    \( t \leftarrow t + 1 \) // repeat above steps for \( T \) epochs.
5. return \( G, E^c, E^s, D \);

TABLE II: Structures of proposed style and content encoder.

| Input RBG image \( x \in \mathbb{R}^{256 \times 256 \times 3} \) | Output \( s \in \mathbb{R}^n \) |
|---------------------------------|-------------------------|
| **Style Encoder** | **Content Encoder** |
| CONV-(C64, K4x4, S2, P1), IN, ReLU | CBIN, ReLU |
| CD-ResBlock-(C256) | CD-ResBlock-(C256) |
| CONV-(C64, K4x4, S2, P1), IN, ReLU | GAP |
| CONV-(C64, K4x4, S2, P1), IN, ReLU | R-ResBlock-(C256) |
| GAP | GAP |
| Output \( s \in \mathbb{R}^n \) | Output \( c \in \mathbb{R}^{n \times n \times 256} \) |

TABLE III: Detailed structures of our proposed generator and discriminator.

| Input content \( c \in \mathbb{R}^{256 \times 256 \times 256} \), style \( s \in \mathbb{R}^n \) | Input RBG image \( x \in \mathbb{R}^{256 \times 256 \times 3} \) |
|---------------------------------|-------------------------|
| **Generator** | **Discriminator** |
| CONV-(C64, K7x7, S1, P3), Tanh | TrCONV-(C256, K4x4, S2, P1), CBIN, ReLU |
| CONV-(C64, K4x4, S2, P1), IN, ReLU | CONV-(C1024, K4x4, S2, P1), LReLU |
| C-ResBlock-(C256) | GAP |
| C-ResBlock-(C256) | C-ResBlock-(C256), CBIN, ReLU |
| C-ResBlock-(C256) | TrCONV-(C128, K4x4, S2, P1), CBIN, ReLU |
| C-ResBlock-(C256) | TrCONV-(C64, K4x4, S2, P1), CBIN, ReLU |
| C-ResBlock-(C256) | CONV-(C3, K7x7, S1, P3), Tanh |
| Output RBG image \( x \in \mathbb{R}^{256 \times 256 \times 3} \) | Output \( d_s = \text{Embed}(y) \cdot h + d \) |

### TABLE IV: Statistics of evaluated datasets.

| Dataset | Samples | Samples | Samples | Samples | Samples | Samples |
|---------|---------|---------|---------|---------|---------|---------|
| **cat ↔ dog ↔ tiger** | 771 100 1264 100 | 1173 100 5000 300 | 5000 300 5000 300 | 300 | 1231 309 963 238 | 2500 150 2500 150 |
| **horse ↔ zebra** | 1545 100 1070 100 | 620 200 1910 100 | 777 100 330 100 | 150 | 1000 1000 993 100 | 1231 309 400 400 |
| **summer ↔ winter** | 1000 100 1000 100 | 400 100 5 250 | 100 121 525 58 | 58 | 1000 1000 993 100 | 1231 309 400 400 |

Fig. 6: (a) Conditional downsampling residual block (CD-ResBlock) in our proposed style encoder, where “Avg 2, 2” denotes average pooling layer with both kernel and stride size set to 2. (b) Regular residual block (R-ResBlock) in our proposed content encoder. (c) Conditional residual block (C-ResBlock) used in our proposed generator.

### 1.6. Training Details

#### A. Network Details

The network structures of the style encoder and content encoder are given in Table II and the structures of the generator and discriminator are given in Table III. In the tables, \( C, K, S, \) and \( P \) are the number of output channels, kernel size, stride size, and padding size, respectively.

### B. Training Details

In this study, the spectral normalization (SN) method is applied to the weights of the discriminator, generator, and encoder in the training process, where the spectral norm of each layer is restricted. For all of the experiments, the input image is \( 256 \times 256 \) pixels, and the Adam optimizer with \( \beta_1 = 0.5, \beta_2 = 0.999 \) is used to train our model. Each minibatch consists of one image from each domain. Xavier initialization is used to assign the initial network weights of \( E, G, \) and \( D \). The initial learning rate of \( E, G, \) and \( D \) is 0.0002 for the first \( n \) epochs. The initial learning rate decays to zero linearly in the remaining \( n \) epochs, where \( n \) is set to 50 unless otherwise noted. The source code and trained models will be available to the public.

### C. Datasets

Table IV shows the datasets and statistics in the experiments. The properties of each dataset are given as follows.

- **Day ↔ Night**. The images are obtained from the Transient Attributes dataset with different cloud patterns and lighting conditions.
• *Summer ↔ winter*. This dataset is used for translation of landscapes in summer and winter [20].
• *Edges ↔ bags&shoes*. This dataset is used to translate images between edges and real content (i.e. handbags and shoes). A set of images are randomly sampled with equal probability from the edges2hangbags and edges2shoes sets [13], which contain thousands of images of shoes and handbags.
• *Horse ↔ zebra* and *leopard ↔ lion ↔ tiger ↔ bobcat*. The images are obtained from the Animals With Attributes dataset [50]. These images contain objects at different scales across different backgrounds.
• *Cat ↔ dog ↔ tiger*. The dog and cat images are from [2] and we collected the tiger pictures. The translation task among these domains needs to account for large shape changes.
• *Black ↔ blond ↔ brown*. This dataset is used to translate the color of human hair, which is randomly selected from the CelebA [51] dataset containing 202,599 face images with 40 attributes.
• *Photo ↔ VanGogh ↔ Monet ↔ Cezanne*. We extract images of the VanGogh, Monet, and Cezanne paintings from the photo2vangogh, photo2monet, and photo2cezanne datasets [20]. In addition, the “photo” shows the summer images from the summe2winter dataset [20].

D. Quantitative Evaluation Metrics

In this section, we present the metrics for quantitatively evaluating the translated images.

**Quality.** The inception score (IS) [52] and Fréchet inception distance (FID) [28] are two widely used metrics for measuring the quality of the images generated by GANs. For IS, we use an Inception-V3 classifier [53] fine-tuned on our specific dataset, and 10k translated images (100 input images and 100 translated samples per given input) are used to evaluate the IS. For FID, we use the ImageNet-pretrained Inception V3 [53] with 100 input images from each domain and 10 translated samples per given input. A lower FID value indicates a higher quality image, whereas a higher IS score indicates a better result.

**Diversity.** For diversity assessment, we introduce the LPIPS distance [54], which is computed by the weighted $L_2$ distance between deep features of 19 paired images per given input. There are 100 different input images per domain, and ImageNet-pretrained AlexNet [55] is used as the feature extractor. In addition, we introduce the conditional inception score (CIS) [1], which is modified from IS to measure the diversity of outputs conditioned on a single input image. It is calculated as the IS but with a different estimated equation as given in [1]. A higher value of either IS or CIS indicates an image with better diversity.

**Classification error.** Since the above evaluation metrics are not effective in explicitly reflecting whether a translation is successful, we propose to compute the classification error of translated images as an additional performance metric. We use the abovementioned fine-tuned Inception-V3 model, with a classification error of 0.50% on the test set, as a classifier. We then perform image translation on 100 test images for each domain, where 10 translated images given each test image are selected to make a new test set. Finally, we classify those images with annotated target domain labels. A lower classification error (Cls_error) indicates that the model has a higher success rate to translate input images into target domains.

**Human evaluation.** Human evaluation is much more persuasive than objective metrics for image-to-image translation. We conduct a user study to evaluate the realism of the translated images. We study $2 \times n$ input images for each translation task between two domains, e.g. $n$ images of the cat are input for translation from the cat to the dog, while $n$ images of the dog need to be translated to cats. In this work, we set $n$ to 50 and choose cat ↔ dog as well as horse ↔ zebra. We use these two datasets since they are representative translation tasks that need to account for large shape changes or maintain the complex background unchanged.

E. Evaluated Methods

Three variants of SoloGAN, i.e. w/o latent, w/o Cls, and w/o PD, are presented to validate the functionality of each component in the SoloGAN model. The first two variants ablate $I_{rec}^{\text{latent}}$ and the classifier, and the third variant replaces the projection model discriminator with a conventional discriminator.

We evaluate the proposed method against the StarGAN [12], MUNIT [1], DRIT [2], and SingleGAN [27] models. The StarGAN method is a unimodal model that addresses the issue of using multiple GANs for translation among multiple domains. The MUNIT and DRIT models focus on unsupervised multimodal image translation via disentangled representations. This consists of an encoder (i.e. style encoder and content encoder) and a GAN for each domain. Given a number of $n$ domains, both the MUNIT and DRIT models need to train $n$ encoders and GANs for image translation. The SingleGAN method shares the style encoder and generator using the domain labels as a condition, while multiple discriminators are required for distinguishing images in different domains. In contrast to the MUNIT, DRIT, and SingleGAN methods, which all employ multiscale discriminators, the proposed SoloGAN model adopts one single-scale discriminator.

F. Empirical Results

We first provide an ablation study to analyse each component in our SoloGAN. Then, we discuss the multimodal image translation results over four two-domain datasets achieved by the proposed SoloGAN, MUNIT, DRIT, and SingleGAN. Finally, we compare the proposed SoloGAN with StarGAN over three- and four-domain datasets. For fair comparison, we train all the evaluated methods for 100 epochs except the edges → bags&shoes dataset, which is trained with 60 epochs. Notably, the cat ↔ dog dataset is derived from the cat ↔ dog ↔ tiger database.
Fig. 7: Qualitative comparison of day $\rightarrow$ night (top) and dog $\rightarrow$ cat (bottom). In each task, first column shows input, and each subsequent column shows 3 random outputs from a method.

**TABLE V:** Quantitative results, where $P$ and $T$ represent parameters of generator (including encoder) and run time when translating input image to 100 images of a target domain, respectively.

| Method              | day $\leftrightarrow$ night | cat $\leftrightarrow$ dog | $\# P$ (M) | $\# T$ (s) |
|---------------------|-----------------------------|---------------------------|------------|------------|
| LPIPS               | Cls_error (%)               | Cls                       | IS         | FID        |
| SoloGAN             | 0.300                       | 0.05                      | 1.031      | 1.090      | 0.226      | 13.99  | 1.053 |
| SoloGAN w/o latent  | 0.217                       | 0.05                      | 1.045      | 1.018      | 0.221      | 13.99  | 1.053 |
| SoloGAN w/o Cls     | 0.253                       | 0.40                      | 1.028      | 1.062      | 0.244      | 13.99  | 1.053 |
| SoloGAN w/o PD      | 0.254                       | 0.50                      | 1.074      | 1.030      | 0.304      | 13.99  | 1.053 |
| MUNIT [1]           | 0.191                       | 5.40                      | 1.075      | 1.185      | 0.490      | 2 x 15.03 | 1.447 |
| DRIT [2]            | 0.280                       | 5.10                      | 1.048      | 1.172      | 0.753      | 2 x 10.65 | 0.976 |
| SingleGAN [27]      | **0.323**                   | 32.15                     | **1.113**  | **1.315**  | **0.732**  | **9.8** | **0.795** |

**Ablation study.** It can be observed from Fig. 7 that the SoloGAN method suffers from a serious mode collapse problem without $L_{\text{latent}}$ (w/o latent, Column 2). To be more specific, the SoloGAN is less effective in generating diverse and realistic images without the classifier (w/o Cls, Column 3) or projection discriminator (w/o PD, Column 4). There are similar phenomena in the quantitative results from Table V. Without $L_{\text{latent}}$ (Line 2), the LPIPS score of the SoloGAN model drops dramatically from 0.300 to 0.217. When using the projection (Line 3) or the classifier (Line 4) only in our discriminator, the SoloGAN method does not perform well in terms of the LPIPS, IS, or FID values. This indicates that the entire proposed projection discriminator is important for image translation among multiple domains. Furthermore, the classification errors achieved by these two variants are approximately 10 times as large as those generated by the proposed whole SoloGAN. These results indicate that each proposed component plays an important role in effectively translating images into target domains.

**Multimodal image translation.** Compared with the proposed SoloGAN (Fig. 7 Column 5), three state-of-the-art multimodal methods have abysmal performance over image translation tasks that involve significant shape changes, e.g. translating a dog to cat images (the rightmost three columns in Fig. 7). Meanwhile, the three compared methods are less effective in image translation on the horse $\leftrightarrow$ zebra dataset (Fig. 8, right-
Fig. 8: Additional qualitative comparison of cat → dog (top), horse → zebra (middle), and zebra → horse (bottom). In each task, first column shows input, and each subsequent column shows 3 random outputs from a method.

most three columns). Although those methods can translate horse into zebra images and vice versa, they cannot effectively retain complex backgrounds, as the color of the grassland is changed for the translation from zebra to horse. This phenomenon occurs because the color of grassland in most training zebra images is not green. Therefore, independent training horse content encoders discard the green color that they believe is not the domain-invariance part, but it truly is. This can also explain why the trees behind the zebra are removed after translation into horses. Generally, these existing methods fail to translate images involving significant shape variations and complex backgrounds, while our SoloGAN can perform well in those challenging tasks.

These visual observations are confirmed when evaluated with the seven objective metrics provided in Table V. The proposed SoloGAN model performs well in generating diverse images on the day↔night dataset and is comparable to the SingleGAN while outperforming the MUNIT and DRIT schemes (Column 2, “LPIPS score”). In terms of the classification error, the SoloGAN model performs favorably against the evaluated schemes, especially the SingleGAN. The error rate of 32.15% means that the SingleGAN is unable to deal with the task of cat↔dog, which involves extreme shape variations. Although the compared methods achieved higher IS scores, they also achieved high Cls_error rates and visual failures. This does not mean that the compared methods can generate more realistic samples than SoloGAN. Instead, those methods have not changed the input images considerably, i.e., the input is almost the same as the output, which we denote as translation failure. In contrast to the IS metric, which does not take any reference during its evaluation, the FID score is designed to compare the statistics of synthetic samples and real-world samples. For instance, it takes real dogs as references when evaluating the generated dogs, and its score is high when the generated samples of expected dogs are cats. This characteristic enables the FID to detect translation failures. Therefore, the FID score can reflect how realistic and diverse the generated samples are and whether the translation fails. The FID value achieved by our model is 0.226, which is much lower than that achieved by any other state-of-the-art method. This indicates the effectiveness of the SoloGAN in handling tasks involving extreme shape variations. We also investigate the efficiency of all the translation methods in terms of parameters of the generator (including encoders) and the latency by using a single Tesla V100. Different from the
MUNIT and DRIT methods, the number of parameters in our model does not increase when the number of domains increases.

Additionally, we conduct an experiment to study the disentangled representation of content and style vectors from SoloGAN and other compared multimodal methods by the task of example-guided translation. When given a content image $x_1$ from domain $y_1$ and a style image $x_2$ from domain $y_2$, the model generates an image $\hat{x}_1$ that recombines the content of $x_1$ and the style of $x_2$ by $G(E^c(x_1), E^s(x_2), y_2)$. Some example-guided translation results are shown in Fig. 9. It can be observed that the styles of outputs from our method are more similar to the given styles than other methods, demonstrating its success in disentangling contents and styles with the same content encoder and style encoder.

![Fig. 10: Human evaluation results collected from 100 reports, where vertical axis indicates percentage of preference. Higher value indicates a majority of users prefer images generated by corresponding method in terms of realistic details and translation success.](image)

Fig. 10 shows the user study results. The images synthesized by the SoloGAN model are considered more realistic than those synthesized by the other schemes. Overall, the SoloGAN model performs efficiently and effectively against the evaluated multimodal methods. This is attributed to the shared content encoder and the projection discriminator with the classifier.

**Multidomain image translation** In addition to comparisons with multimodal methods between two domains, we provide a detailed discussion between our SoloGAN and StarGAN when the number of translation domains is higher than two. In this part, we randomly select one image from the multimodal outputs of our SoloGAN for each domain. Fig. 11 shows the results generated by the SoloGAN and StarGAN models for multidomain translation on the tiger $\rightarrow$ cat, dog and bobcat $\rightarrow$ leopard, lion, tiger datasets, where the corresponding classification errors are given in Table VI. Notably, it is difficult to evaluate the LPIPS, IS, CIS, and FID results, as StarGAN is a unimodal translation method. It can be observed that the StarGAN is ineffective in translating a tiger to cat or dog images (Fig. 11, right column), for which an effective model needs to account for significant shape changes. Nevertheless, the StarGAN has better performance on the bobcat$\rightarrow$leopard, lion, tiger dataset (Fig. 11, bottom) than on the tiger$\rightarrow$cat, dog dataset since this task requires less shape change and more focus on texture (such as strips and dots). The quantitative results are coincident with the qualitative results. SoloGAN achieved much lower classification error rates than StarGAN on both tasks, especially on the cat$\rightarrow$dog$\rightarrow$tiger dataset (0.83% vs. 61%). To summarize, the SoloGAN performs significantly better than the StarGAN model in dealing with multidomain image translations. We argue that our disentangled representation of content and style and the novel discriminator are effective in generating realistic and target domain images.

**Further comparisons.** We provide additional comparisons with some recent works (DRIT++ [41] and StarGANv2 [43]) in Fig. [12] and Fig. [13] We obtain the results of DRIT++ from the official page and retrain StarGANv2 with default settings on our datasets. DRIT++ indeed generates more diverse output than DRIT (Fig. [2]). In addition, the quality of images is improved. However, our SoloGAN, without using any specific mode-seeking as DRIT++, still outperforms the improved DRIT in terms of diversity and quality by a large margin. In addition, StarGANv2 has a similar performance as SoloGAN on the task of cat2dog while failing to generate realistic and background unchanged images on the task of horse2zebra.

**More visual results.** We provide more visual results achieved by our SoloGAN to better understand its mechanism. It is necessary to claim again that there is only one single pair of GANs for each task, no matter how many image domains are involved. Additional translation results on two-domain datasets are presented in Fig. [14] Apart from the results on the horse$\rightarrow$zebra and day$\rightarrow$night datasets, we present the results on the summer$\rightarrow$winter and edges$\rightarrow$bags&shoes datasets. Fig. [15] and Fig. [16] show some synthesized results over two-three domain and two four-domain datasets. It can be observed that all results are partly realistic and have good diversity. The stripes and dots of the translated leopards and tigers are different from each other in the translation task of leopard $\leftrightarrow$ lion $\leftrightarrow$ tiger $\leftrightarrow$ bobcat.

All of the above results indicate that the SoloGAN model is effective in handling unsupervised multimodal I2I translation among multiple domains.

**TABLE VI: Classification errors for multidomain translation generated by SoloGAN and StarGAN.** For fair comparison, we sample one image randomly from multimodal outputs obtained by SoloGAN given an input image.

| Dataset | SoloGAN | StarGAN |
|---------|---------|---------|
| cat $\leftrightarrow$ dog $\leftrightarrow$ tiger | 0.83% | 61.00% |
| leopard $\leftrightarrow$ lion $\leftrightarrow$ tiger $\leftrightarrow$ bobcat | 7.92% | 58.75% |

**G. Limitations.** Although the proposed SoloGAN model performs well in image translation for multiple domains, it is a data-driven approach and is thus limited by the images in the training set (e.g. number of images and pose). For example, as there are no images in the cat dataset with the same head pose as

1http://vllab.ucmerced.edu/hylee/DRIT_pp/
Fig. 11: Qualitative comparison of tiger $\rightarrow$ cat, dog (top) and bobcat $\rightarrow$ leopard, lion, tiger (bottom). In each task, first column shows input, and each subsequent column shows different domain outputs from a method.

For more complex scenarios such as image generation with blended attributes, the current SoloGAN cannot discriminate inputs that belong to multiple domains due to the character of our proposed novel projection with a classification discriminator. Nevertheless, by simply pairing our proposed encoder and with different discriminators for multiple domains such as IntersectGAN [26], the SoloGAN can be extended to deal with blended attribute translation.

V. Conclusion

We have proposed a method for multimodal multidomain image-to-image translation using a single pair of GANs. In the SoloGAN model, the content and style encoder, as well as the generator, are shared among multiple domains, and a projection with a classification discriminator is proposed. Experimental results demonstrated that the SoloGAN model performs favorably in terms of effectiveness and efficiency, especially for translation tasks involving complex image backgrounds or significant shape changes.

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Fig. 14: Translated results achieved by SoloGAN on four two-domain datasets. From top to bottom: multimodal sample outputs for tasks of horse $\leftrightarrow$ zebra, summer $\leftrightarrow$ winter, day $\leftrightarrow$ night, and edges $\leftrightarrow$ bags&shoes.
Fig. 15: Translated results achieved by SoloGAN on two three-domain datasets. From top to bottom: multimodal sample outputs for tasks of cat ↔ dog ↔ tiger and black ↔ blond ↔ brown. Leftmost is input from one domain, and following columns are outputs translated from input into other two domains. Example: in first row, when taking a cat input, from left to right are dogs and tigers, respectively.
Fig. 16: Translated results achieved by SoloGAN on two four-domain datasets. From top to bottom: multimodal sample outputs for tasks of leopard ↔ lion ↔ tiger ↔ bobcat and photo ↔ VanGogh ↔ Monet ↔ Cezanne. Leftmost is input from one domain, while left column lists outputs translated from input into other three domains. For example, taking leopard input as first row, from left to right are generated lions, tigers, and bobcat, respectively.

(a) tiger → cat  (b) horse → zebra

Fig. 17: Typical failure cases of proposed SoloGAN. SoloGAN fails to translate a tiger with unusual face direction and an uncommon white horse in front of a building that has color similar to common horses into a cat and zebra, respectively.

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