# ZstGAN: An Adversarial Approach for Unsupervised Zero-Shot Image-to-Image Translation

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# **Abstract**

Image-to-image translation models have shown remarkable ability on transferring images among different domains. Most of existing work follows the setting that the source domain and target domain keep the same at training and inference phases, which cannot be generalized to the scenarios for translating an image from an unseen domain to an another unseen domain. In this work, we propose the Unsupervised Zero-Shot Image-to-image Translation (UZSIT) problem, which aims to learn a model that can transfer translation knowledge from seen domains to unseen domains. Accordingly, we propose a framework called ZstGAN: By introducing an adversarial training scheme, ZstGAN learns to model each domain with domain-specific feature distribution that is semantically consistent on vision and attribute modalities. Then the domain-invariant features are disentangled with an shared encoder for image generation. We carry out extensive experiments on CUB and FLO datasets, and the results demonstrate the effectiveness of proposed method on UZSIT task. Moreover, Zst-GAN shows significant accuracy improvements over stateof-the-art zero-shot learning methods on CUB and FLO. Our code is publicly available at https://github. com/linjx-ustc1106/ZstGAN-PyTorch.

# 1. Introduction

Image-to-image translation tasks [14, 36], which aim at learning mappings that can convert an image among different domains while preserving the main representations of the input images, have been widely investigated in recent years. Existing image-to-image translation usually works on the following setting: Given M domains of interests, denoted as  $\mathcal{X}_1, \mathcal{X}_2, \cdots \mathcal{X}_M$  where  $M \geq 2$ , the objective is to learn mappings  $f_{ij}: \mathcal{X}_i \mapsto \mathcal{X}_j$ , where  $i \neq j$ . After obtaining these  $f_{ij}$ 's, we can achieve the translations among these M domains. Specially, many models have been pro-

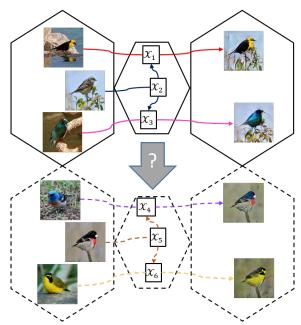


Figure 1. Suppose that  $\mathcal{X}_1$ ,  $\mathcal{X}_2$  and  $\mathcal{X}_3$  are seen domains for image translator training, and  $\mathcal{X}_4$ ,  $\mathcal{X}_5$  and  $\mathcal{X}_6$  are unseen domains at inference phase. The aim of unsupervised zero-shot image-to-image translation is to translate images on unseen domains using translator trained on seen domains.

posed for the setting M=2 like CycleGAN [36], Disco-GAN [15], etc and for the setting M>2 like StarGAN [7].

One limitation of existing models is, the  $f_{ij}$ 's can only achieve mappings among these given domains, without the generalization abilities to other unseen domains. That is, existing image-to-image translation models cannot translate an image from an unseen domain or to another unseen domain. Take the bird translation shown in Figure 1 as an example. Assume a model f is trained on domain  $\mathcal{X}_1$ ,  $\mathcal{X}_2$  and  $\mathcal{X}_3$ . Therefore, it is natural that f can achieve translation among these three domains (see the upper half part of Figure 1), but f cannot be applied to unseen domains  $\mathcal{X}_4$ ,  $\mathcal{X}_5$  and  $\mathcal{X}_6$ . In practice, new image domains always come and it

is impractical to train new translation models from scratch covering the new domains. Therefore we aim to generalize f to unseen domains as shown in the bottom half part of Figure 1.

Zero-Shot Learning (ZSL) [18, 26, 22] aims to recognize objects whose instances might not have been seen during training. In order to generalize to unseen classes, a common assumption in zero-shot learning assuming is that some side-information about the classes is available, such as class attributes or textual descriptions, which provides semantic information about the classes.

As far as we can survey, there is no literature works on zero-shot learning for unsupervised image translation. To fulfill such a blank in image-to-image translation, we propose a new problem, unsupervised zero-shot image-toimage translation (briefly, UZSIT). Compared to the standard ZSL, UZSIT is more challenging: (1) The target of image translation is more complex than classification, which not only requires us to generate representative features across seen and unseen domains but also generate reasonable translation images. (2) Unlike ZSL methods trained in a supervised way on seen domains, we do not have any paired data between any two domains. This requires us to learn the mappings in a fully unsupervised manner for both seen domains and unseen domains. Therefore, we devise a framework, called ZstGAN, for UZSIT problem. There are two key steps in ZstGAN.

- (1) We model each seen/unseen domain using a domain-specific feature distribution constrained by semantic consistency. Specifically, a visual-to-semantic encoder and an attribute-to-semantic encoder are introduced. They are jointly trained to extract domain-specific features from images and attributes respectively while preserving the same semantic information between these two modalities. The adversarial and classification losses are introduced to the two encoders to regularize training.
- (2) We disentangle domain-invariant features from the domain-specific features and combine them to generate translation results, which is achieved by one adversarial learning loss and two reconstruction losses.

We work on two datasets commonly used in ZSL, Caltech-UCSD-Birds 200-2011 (CUB) [31] and Oxford Flowers (FLO) [25], to verify the effectiveness of our method on UZSIT task. We also generalize our model to traditional ZSL tasks, and find that our model can achieve significant improvement over state-of-the-art ZSL methods on CUB and FLO datasets.

The remaining part is organized as follows: We present a brief over review of related works in Section 2. We detail the problem formulation of UZSIT and a description of our approach in Section 3. The datasets and experimental results are reported in Section 4. Finally, we summarize our work and present several future directions in the Section 5.

# 2. Related Works

Generative Adversarial Networks Image generation has been widely investigated in recent years. Most of works focus on modeling the natural image distribution. Generative Adversarial Network (GAN) [9] was firstly proposed to generate images from random variables by a two-player minimax game: a generator G tries to create fake but plausible images, while a discriminator D is trained to distinguish difference between real and fake images. To address the stability issues in GAN, Wasserstein-GAN (WGAN) [2] was proposed to optimize an approximation of the Wasserstein distance. To further improve the vanishing and exploding gradient problems of WGAN, Gulrajani et al. [10] proposed a WGAN-GP that uses gradient penalty instead of the weight clipping to enforce the Lipschitz constrain in WGAN. Mao et al. [24] also proposed a LSGAN and found that optimizing the least square cost function is the same as optimizing a Pearson  $\chi^2$  divergence. In this paper, we combine with WGAN-GP [10] to generate domain-specific features and translation images.

**Image-to-Image Translation** Recently, Isola et al. [14] proposed a general conditional GAN (Pix2Pix) for a wide range of supervised image-to-image translation tasks, including label-to-street scene, aerial-to-map, day-to-night and so on. Discovering that image translation between two domains should obey the cycle consistent rule, Dual-GAN [35], DiscoGAN [15] and CycleGAN [36] were proposed to tackle the unpaired image translation problem by training two cross-domain translation models at the same time. However, CycleGANs lack the ability to control the translated results in the target domain and their results usually lack of diversity. In order to control the translated results in the target domain and obtain more diverse outputs with a fixed input, works [21, 13, 19] divided the latent space whin translation into domain-invariant and domainspecific portions. The different domains share the same domain-invariant latent space while each domain has different domain-specific latent spaces. Choi et al. [7] further proposed to perform image-to-image translations for multiple domains. For the low-resource unpaired image-toimage translation, Benaim et al. [3] first proposed a oneshot cross-domain translation which transfers one and only one image in a source domain to a target domain. Lin et al. [20] also proposed a DosGAN that is able to translate images from unseen face identities without any fine-tuning once the model is trained on seen face identities, which is most related to our work. In this work, we focus on a different setting from these two works as zero-shot image translation which learns to transfer images from unseen domains to other unseen domains with the availability of both visual and semantic modalities.

**Zero-Shot Learning** Zero-Shot Learning (ZSL) was first introduced by [18], where train and test classes are dis-

joint for object recognition. Traditional methods for ZSL are based on learning an embedding from the visual space to the semantic space. In the test period, the semantic vector of an unseen sample is extracted and the most likely class is predicted by nearest neighbor method [32, 26, 29]. Recent works on ZSL have widely explored the idea of generative models. Wang et al. [33] presented a deep generative model for ZSL based on VAE [17]. Due to the rapidly developed GANs, other approaches used GANs to synthesize visual representations for the seen and unseen classes [22, 4]. However, the generate images usually lack sufficient quality to train a classifier for both the seen and unseen classes. Hence authors [34, 8] used GANs to synthesizes CNN features rather than image pixels conditioned on class-level semantic information. On the other hand, considering that ZSL is a domain shift problem, [30, 5] presented the Generalized ZSL (GZSL) that leverages both seen and unseen classes at test time.

# 3. Framework

#### 3.1. Problem Formulation

We provide a mathematical formulation of UZSIT in this subsection.

Let  $\mathcal{X}$  be the collection of images. Let  $\mathcal{L}^s$  and  $\mathcal{L}^u$  be two disjoint image categories, where  $\mathcal{L}^s = \{l_1^s, l_2^s, \cdots, l_M^s\}$  and  $\mathcal{L}^u = \{l_1^u, l_2^u, \cdots, l_N^u\}, \ M \geq 2, \ N \geq 1 \ \text{and} \ \mathcal{L}^s \cap \mathcal{L}^u = \emptyset.$  For ease of reference, define  $\mathcal{L} = \mathcal{L}^s \cup \mathcal{L}^u$ . Let  $\mathcal{A}$  denote the set of attributes or textual descriptions of images. Each sample can be represented by a  $(x, l, a) \in \mathcal{X} \times \mathcal{L} \times \mathcal{A}$  where x is a picture, l is the corresponding label (e.g. a bird or a cat, etc) and a is the attribute (e.g., the color, position, etc). We have two different sets, a training set  $\mathcal{S} = \{(x, l, a) | x \in \mathcal{X}, l \in \mathcal{L}^s, a \in \mathcal{A}\}$  and a test set  $\mathcal{U} = \{(x, l, a) | x \in \mathcal{X}, l \in \mathcal{L}^u, a \in \mathcal{A}\}$ .

The objective of UZSIT is to train an image-to-image translation model f on  $\mathcal S$  without touching  $\mathcal U$ . Then evaluating the obtained model f on  $\mathcal U$  without any further tuning. An assumption that  $\mathcal S$  and  $\mathcal U$  shares a common semantic space is required. Specifically, while  $\mathcal S$  and  $\mathcal U$  have different category sets ( $\mathcal L^s$  and  $\mathcal L^u$ ), they are required to share the same image and attribute spaces ( $\mathcal X$  and  $\mathcal A$ ) where semantic information is extracted from.

An implicit assumption in image-to-image translation is that an image contains two kinds of features [21, 13, 19]: domain-invariant features  $x^i \in \mathbb{R}^d$  and domains-specific features  $x^s \in \mathbb{R}^d$  for any  $x \in \mathcal{X}, d \in \mathbb{N}$ . With an oracle image merge operator  $\oplus$ ,  $x = x^i \oplus x^s$ .

In existing image-to-image translation models, the domains-specific features of different domains are usually extracted without depicting them in a common semantic space. So implicit relationship among different domains is omitted by this kind of features. In this paper, we argue that

domains-specific features should be not only discriminative for different domains, but also representative to align different domains in a common semantic space. We will discuss how to learn the domains-specific features in the following subsection.

Depending on where the domains-specific features are extracted from, we devise two kinds of image translation problems at zero-shot testing phase.

- (1) Vision-driven image translation:  $f_v : \mathcal{X} \times \mathcal{X} \mapsto \mathcal{X}$ ;
- (2) Attribute-driven image translation:  $f_a: \mathcal{X} \times \mathcal{A} \mapsto \mathcal{X}$ .

In  $f_v$  and  $f_a$ , the first input is used to provide domain-invariant features and the second input is used to specify domain-specific features: one uses an image and the other use attribute.

#### 3.2. Architecture

The architecture of our proposed ZstGAN is shown in Figure 2. We use  $\mathcal{N}(0,I)$  to denote a Gaussian distribution. There are three encoders in out framework,  $E_i:\mathcal{X}\mapsto\mathbb{R}^d$ ,  $E_v:\mathcal{X}\mapsto\mathbb{R}^d$  and  $E_a:\mathcal{A}\times\mathcal{N}(0,I)\to\mathbb{R}^d$ , which work on extracting domain-invariant features, vision-based domain-specific features and attribute-based domain-specific features respectively. A decoder  $G(\cdot,\cdot)$  is also needed to convert the hidden representations into natural images, where the first input is domain-invariant features and the second input is domain-specific features. That is, to generate an image,  $f_v$  and  $f_a$  works as follows:

$$f_v(x_1, x_2) = G(E_i(x_1), E_v(x_2))$$
  

$$f_a(x_1, a_2) = G(E_i(x_1), E_a(a_2, z)).$$
(1)

where  $x_1, x_2 \in \mathcal{X}$  and  $a_2 \in \mathcal{A}$ . We denote these two mappings with V-ZstGAN and A-ZstGAN respectively. In our configuration, we do not explicitly train  $f_a$  in the training stage and it is naturally obtained by training  $f_v$  with the following constraints.

The objective function is designed according to the following criteria:

(1) Domain-specific features with semantic consistency

Given a tuple  $(x_2, l_2, a_2) \in \mathcal{S}$ , the image  $x_2$  and the attribute  $a_2$  should share the same semantic representation. For such purpose, we utilize an adversarial training scheme which requires outputs of  $E_v$  and  $E_a$  to follow the same distribution conditioned on domain attributes. We need a domain-specific features discriminator  $D_s$  which is used to distinguish outputs of  $E_v$  and  $E_a$ . In detail, the adversarial training objective for  $E_v$  and  $E_a$  is:

$$\ell_{\text{GAN s}} = D_s(E_v(x_2), a_2) - D_s(E_a(a_2, z), a_2), \tag{2}$$

where z is a noise vector sampled from  $\mathcal{N}(0, I)$ .

Using adversarial training can only ensure the distributions of the vision based domain-specific features and the attribute based domain-specific features to fit with each other.

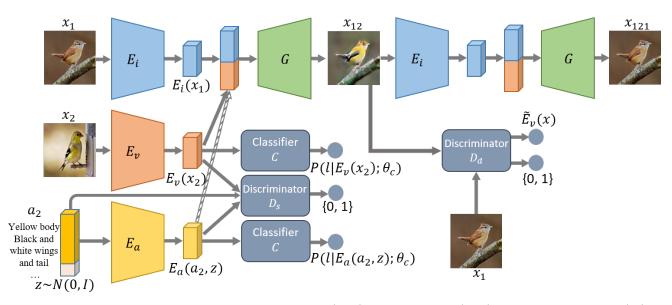


Figure 2. The proposed ZstGAN framework. The dash line of  $E_a(a_2,z)$  represents that  $E_a(a_2,z)$  can be combined with  $E_i(x_1)$  to generate translation result at inference phase.  $\tilde{E}_v(x)$  represents domain-specific feature prediction of input to  $D_d$ .

However, such features lack the ability to identify which domain the input images/attributes come from, causing meaninglessness of term "domain-specific". Thus, we require the  $E_v(x_2)$  and  $E_a(a_2,z)$  to be correctly classified by a classifier C. The classification loss is given as:

$$\ell_{\text{CLS,v}} = -P(l = l_2 | E_v(x_2); \theta_c), \ell_{\text{CLS,a}} = -P(l = l_2 | E_a(a_2, z); \theta_c),$$
(3)

where  $\theta_c$  is parameters of the classifier C.

#### (2) Domain-invariant features disentanglement

Given a domain-invariant encoder  $E_i$  and a generator G illustrated in Figure 2 and another tuple  $(x_1,l_1,a_1)\in\mathcal{S}$ , we have domain-invariant features  $E_i(x_1)$ , domain-specific features  $E_v(x_1)$ . To translate image  $x_1$  from domain  $\mathcal{X}_1$  to domain  $\mathcal{X}_2$ , we can combine  $E_i(x_1)$  and  $E_v(x_2)$  to obtain  $x_{12}=G(E_i(x_1),E_v(x_2))$ . To ensure the translated result  $x_{12}$  lie in the target domain  $\mathcal{X}_2$  and in the real image domain, we introduce a domain discriminator  $D_d$ .  $D_d^{\mathrm{m}}$  of  $D_d$  takes a real or fake image as input, and maximizes the mutual information between the target domain-specific features and the input as InfoGAN [6]. Also,  $D_d^{\mathrm{g}}$  of  $D_d$  outputs a probability of the input belonging to the real image domain. We illustrate the objective functions as below:

$$\ell_{\text{MUT,r}} = \|D_d^{\text{m}}(x_1) - E_v(x_1)\|_1,$$
  

$$\ell_{\text{MUT,f}} = \|D_d^{\text{m}}(x_{12}) - E_v(x_2)\|_1,$$
(4)

$$\ell_{\text{GAN,d}} = D_d^{g}(x_1) - D_d^{g}(x_{12}).$$
 (5)

To ensure the disentanglement of domain-invariant features with domain-specific features, we introduce a self-reconstruction loss  $\ell_{REC,s}$  and a cross-reconstruction loss

 $\ell_{\rm REC,c}$ . We can obtain the self-reconstructed image  $x_{11} = G(E_i(x_1), E_v(x_1))$  and the cross-reconstructed image  $x_{121} = G(E_i(x_{12}), E_v(x_1))$ . The  $\ell_{\rm REC,s}$  is to minimize the L1 norm between  $x_1$  and  $x_{11}$ :

$$\ell_{\text{REC.s}} = \|x_1 - x_{11}\|_1. \tag{6}$$

The  $\ell_{\rm REC,c}$  is to minimize the L1 norm between  $x_1$  and  $x_{121}$ :

$$\ell_{\text{REC},c} = \|x_1 - x_{121}\|_1. \tag{7}$$

If  $x_{11}$  optimally minimized  $\ell_{\text{REC},s}$  and  $x_{12}$  optimally minimized  $\ell_{\text{MUT,f}}$ , we can find that the difference between  $x_{11}$  and  $x_{12}$ , which are from two domains, only lies in the difference between  $E_v(x_1)$  and  $E_v(x_2)$ . Thus it implies that  $E_v(x_1)$  and  $E_v(x_2)$  are domain-specific features that determine which domain image belongs to. On the other hand, if  $x_{11}$  optimally minimized  $\ell_{\text{REC,s}}$  and  $x_{121}$  optimally minimized  $\ell_{\text{REC,c}}$ , we can find that the difference between  $x_{11}$  and  $x_{121}$ , which are both the reconstruction images of the same  $x_1$ , only lies in the difference between  $E_i(x_1)$  and  $E_i(x_{12})$ . Thus it further implies that  $E_i(x_1)$  and  $E_i(x_{12})$  are domain-invariant features that maintain across different domains.

#### (3) The overall training objective

The overall objective for above mentioned encoders, discriminators, classifier and generator  $E_v$ ,  $E_a$ , C,  $D_s$ ,  $E_i$ , G and  $D_d$  is given by:

$$\begin{split} \ell_{E_{v}}^{\text{all}} &= \ell_{\text{GAN,s}} + \lambda_{c} \ell_{\text{CLS,v}}, \ell_{E_{a}}^{\text{all}} = \ell_{\text{GAN,s}} + \lambda_{c} \ell_{\text{CLS,a}}, \\ \ell_{C}^{\text{all}} &= \ell_{\text{CLS,v}}, \ell_{D_{s}}^{\text{all}} = -\ell_{\text{GAN,s}}, \\ \ell_{E_{i}}^{\text{all}} &= \lambda_{r} \ell_{\text{REC,s}} + \lambda_{r} \ell_{\text{REC,c}} + \lambda_{m} \ell_{\text{MUT,f}} + \ell_{\text{GAN,d}}, \\ \ell_{G}^{\text{all}} &= \lambda_{r} \ell_{\text{REC,s}} + \lambda_{r} \ell_{\text{REC,c}} + \lambda_{m} \ell_{\text{MUT,f}} + \ell_{\text{GAN,d}}, \\ \ell_{D_{d}}^{\text{all}} &= \lambda_{m} \ell_{\text{MUT,r}} - \ell_{\text{GAN,d}}, \end{split} \tag{8}$$

where  $\lambda_c$ ,  $\lambda_r$  and  $\lambda_m$  are weights to achieve balance among different loss terms. Note that, unlike [34] that utilizes a pre-trained CNN feature extractor as a fixed visual-to-semantic encoder, our  $E_v$  is updated with the adversarial and classification losses. The pre-trained CNN feature extractor restrict itself to adapt with specific domains and attributes, while our approach enables the  $E_v$  to extract domain-specific features that are both discriminative for different domains and representative to align the visual images with attributes in a common semantic space. Experiment in the Section 4.2 also demonstrates that our approach significantly improves performance of [34].

# 3.3. Implementation details

For  $E_v$ , we use the 50-layer ResNet [11] to encode image to domain attribute-specific features of 2048 dimensions. One fully-connected layer (C) is connected to  $E_v$  for classification output. For  $E_a$ , it consists of two fully-connected layers and takes both attributes and noise as inputs. For discriminator  $D_s$ , it consists of two fully-connected layers as [34]. For domain discriminator  $D_d$ , we use PatchGANs [14] that consists of six  $4 \times 4$  stride 2 convolution layers, and two separated convolution layers for discrimination output and domain-specific feature prediction. For  $E_i$ , it has one  $7 \times 7$  stride 1 convolution layer, two stride  $4 \times 4$  2 convolution layers and 16 residual blocks [11]. For generator G, it first adds domain attribute-specific features to domaininvariant features from encoder  $E_i$  with Adaptive Instance Normalization (AdaIN) [13]. Then the combined feature is input to 16 residual blocks, two  $5 \times 5$  stride 2 deconvolution layers and one  $7 \times 7$  stride 1 convolution layer.

For all experiments, we resize the images to  $128 \times 128$  resolution as inputs. The dimension of domain-specific features is set to 2048. The dimension of z is set to 312. We set the weight parameters  $\lambda_c=1, \lambda_r=1$  and  $\lambda_m=50$  for CUB experiments and  $\lambda_m=200$  for FLO experiments. We train our networks using Adam [16] with learning rate of 0.0001. For all experiments, we train models with a learning rate of 0.0001 in the first 100000 iterations and linearly decay the learning every 1000 iteration.

# 4. Experiments

**Datasets** We conduct extensive quantitative and qualitative evaluations on Caltech-UCSD-Birds 200-2011 (CUB) [31] and Oxford Flowers (FLO) [25] which are commonly used in ZSL tasks. CUB contains 200 bird species with 11,788 images. We crop all images in CUB with bounding boxes given in [31]. FLO contains 8,189 images of flowers from 102 different categories. For every image in CUB and FLO datasets, we extract 1024-dim character-based CNN-RNN [27] (10 captions are provided for each image) as the attribute set  $\mathcal{A}$ . We split each dataset into domain-disjoint train and test sets. CUB is split to 150 train domains and 50 unseen domains. Within 50 unseen domains, 25% data is used as test data; FLO is split to 82 train domains and 20 unseen domains. Within 20 unseen domains, 25% data is used as test data.

# 4.1. Zero-Shot Image Translation Comparison

Since there is no previous work on UZSIT problem, we compare with our model with StarGAN [7] that can be viewed as an unsupervised many-shot image-to-image translation model which is trained with data of unseen domains. We train StarGAN with data of total 200 domains on CUB dataset, and with data of total 102 domains on FLO dataset.

The translation results of StarGAN and our model on CUB and FLO are shown in Figure 3 and Figure 4. We can find that although our ZstGAN is trained without data of unseen domains and StarGAN is trained with data of unseen domains, our ZstGAN shows even better translation quality with StarGAN in both CUB and FLO. For example, in the forth column of Figure 3(b), our V-ZstGAN and A-ZstGAN accurately transfers the attributes of gray wings, black rectrices and bright yellow beak to the translation results, while StarGAN only shows little yellow and gray color without accurate position in the translation result. In the third column of Figure 4(a), both A-ZstGAN and V-ZstGAN successfully transfer the "long and very thin bright yellow petals" description to the translation results, while StarGAN fails to change the shape of the original flower. Such results are mainly due to the design of StarGAN that simply uses domain codes as domain-specific features, which make it difficult to align different domains with a common semantic space. We can also see that translation results of A-ZstGAN highly correlate with V-ZstGAN's, which verifies the effectiveness of adversarial learning for vision based and attribute based domain-specific features alignment.

For quantitative evaluation, we translate source images from a random unseen domain to a random unseen domain in each test minibatch, and report the top-1 and top-5 classification accuracy of translated images of StarGAN and our model in Table 1, and Frchet Inception Distance (FID) [12] scores in Table 2. We can observe that the quantitative re-

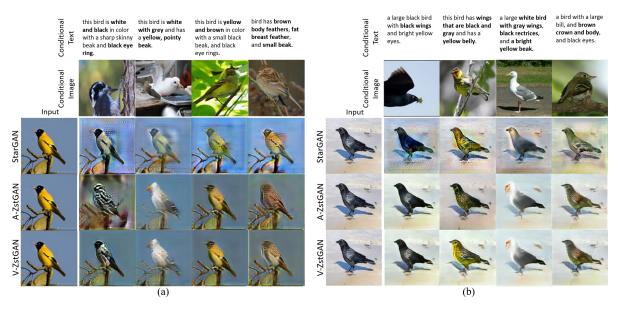


Figure 3. Image translation results of StarGAN and our ZstGAN on unseen domains of CUB dataset. The first column is inputs  $x_1$ . The first row is  $a_2$  for A-ZstGAN, and the second row is  $x_2$  for V-ZstGAN and examples of target domain for StarGAN. Other images are the translation results. Note that StarGAN is trained on unseen domains of CUB. Key attributes contained in our translation results are in bold.

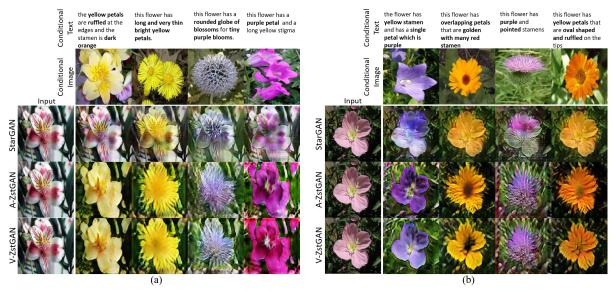


Figure 4. Image translation results of StarGAN and our ZstGAN on unseen domains of FLO dataset. Note that StarGAN is trained on unseen domains of FLO. Key attributes contained in our translation results are in bold.

sults are consistent with results in Figure 3 and Figure 4, where our ZstGAN achieves better classification accuracy and FID scores than StarGAN.

# 4.2. Generalizing to ZSL and GZSL

The domain-specific features outputted from visual-to-semantic encoder  $E_v$  and attribute-to-semantic encoder  $E_a$  in our ZstGAN can also be used for ZSL and Generalized ZSL (GZSL) problems [30, 5], where in GZSL set-

ting the seen domains can also be leveraged for testing. Specifically, we train two additional softmax classifiers that use generated domain-specific features from  $E_a$  and corresponding labels as [34] for ZSL and GZSL testing respectively. In ZSL setting, only average per-class top-1 accuracy on unseen domains is computed. In GZSL setting, we compute average per-class top-1 accuracy on unseen domains (denoted as  $\bf U$ ), average per-class top-1 accuracy on seen domains (denoted as  $\bf S$ ) and their harmonic mean, i.e.,

Table 1. Top-1 and top-5 classification accuracy (%) for translation results of StarGAN and our ZstGAN on unseen domains of CUB and FLO datasets.

Dataset	StarGAN	A-ZstGAN	V-ZstGAN
CUB(Top-1)	15.24	19.63	24.04
CUB(Top-5)	43.32	51.87	58.27
FLO(Top-1)	27.29	28.94	34.06
FLO(Top-5)	67.91	70.86	75.12

Table 2. FID scores for translation results of StarGAN and our ZstGAN on unseen domains of CUB and FLO datasets.

Dataset	StarGAN	A-ZstGAN	V-ZstGAN
CUB	99.95	81.98	82.35
FLO	110.2	96.46	94.87

$$\mathbf{H} = 2 \times (\mathbf{U} \times \mathbf{S}) / (\mathbf{U} + \mathbf{S}).$$

We compare our ZstGAN with three state-of-the-art ZSL and GZSL methods, e.g., SJE [1], ESZSL [28] and f-CLSWGAN [34]. The ZSL results on CUB and FLO are shown in Table 3. The GZSL results on CUB and FLO are shown in Table 4. The experiments clearly demonstrate the advantage of our ZstGAN for GZSL and ZSL since it achieves the best top-1 accuracy results in all the results, with improvements from 5.2% to more than 44.7%. While our modification on f-CLSWGAN is not difficult to implement, our intuition is sound from the aspect of image-toimage translation and the improvement is rather significant. We also find that the classification accuracy of our model for ZSL is higher than the results for UZSIT in Table 1, this is because UZSIT is more challenging than ZSL since UZSIT needs to generate images that should properly fuse the domain-specific features with domain-invariant features to look like real target images.

We also show the t-SNE [23] visualization of domain-specific features extracted by  $E_v$  and  $E_a$  on unseen domains of FLO in Figure 5. We can observe that: (1) Both Figure 5(a) and Figure 5(b) show clear clusters for different domains, which indicates that the  $E_v$  and  $E_a$  indeed learn to generalize to unseen domains; (2) Patterns of domain-specific features extracted by  $E_v$  and  $E_a$  are highly consistent to each other. For example, the samples of the 5th domain (green color) in Figure 5(a) are mixed in some samples of the 17th domains, and the same phenomenon is observed in Figure 5(b). Such result indicates that  $E_v$  and  $E_a$  indeed learn to mapping the visual images and attributes to the same semantic space.

Table 3. Top-1 accuracy results (%) of ZSL on the unseen domains of CUB and FLO datasets.

Dataset	SJE	ESZSL	f-CLSWGAN	Ours
CUB	53.9	53.9	57.3	66.3
FLO	53.4	51.0	67.2	70.7

Table 4. Top-1 accuracy results (%) of GZSL on the unseen domains (**U**), the seen domains (**S**) and the harmonic mean (**H**).

Dataset		SJE	ESZSL	f-CLSWGAN	Ours
CUB	U	23.5	12.6	43.7	61.5
	$\mathbf{S}$	59.2	63.8	57.7	83.5
	H	33.6	21.0	49.7	70.8
FLO	U	13.9	11.4	59.0	67.0
	$\mathbf{S}$	47.6	56.8	73.8	92.1
	H	21.5	19.0	65.6	77.6

# 4.3. Analyzing Different Influence Factors of Zst-GAN

#### 4.3.1 Influence of domain-specific features losses

The main difference between existing image translation models and our ZstGAN is that we can extract domain-specific features that can be transferred from seen domains to unseen domains. And this advantage is mainly built on the introducing of adversarial and classification losses for jointly optimization. So we first investigate the influence of following two aspects on ZstGAN.

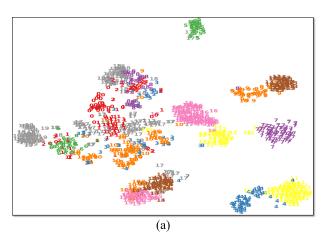
**ZstGAN-CLS**. To verify the effectiveness of classification losses for domain-specific features, we remove the  $\ell_{\text{CLS,v}}$  loss for  $E_v$  optimization and  $\ell_{\text{CLS,a}}$  loss for  $E_a$  optimization.

**ZstGAN-GAN.** To verify the effectiveness of adversarial leaning for domain-specific features, we remove the  $\ell_{\text{GAN,s}}$  loss for  $E_v$  and  $E_a$  optimization.

The classification accuracy on FLO is also reported in Figure 6. We can observe that there is a big accuracy drop for both ZstGAN-CLS and ZstGAN-GAN. Specially, we find that A-ZstGAN-GAN's classification accuracy is much lower than V-ZstGAN-GAN's, which is because domain-specific features from the images and attributes are not aligned any more without adversarial learning.

#### **4.3.2** Influence of M Seen Domains

To investigate how the number of seen domains influences the performance of zero-shot image translation on unseen domains. We train ZstGAN with different M seen domains on FLO and show the classification accuracy results on unseen domains in Table 5. As we can see, with the decrease of M, the classification accuracy of translation results also



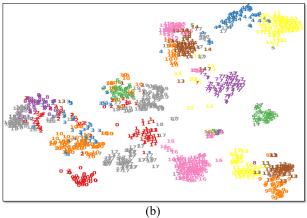


Figure 5. t-SNE visualization of domain-specific features on FLO's unseen domains. (a) Domain-specific features extracted by  $E_v$ . (b) Domain-specific features extracted by  $E_a$ . The different colors and corresponding numbers indicate data of different unseen domains.

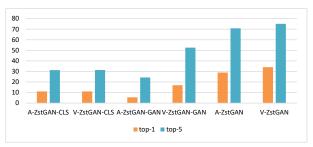


Figure 6. Top-1 and top-5 classification accuracy (%) for translation results of ZstGAN-CLS, ZstGAN-GAN and ZstGAN on unseen domains of FLO dataset.

Table 5. Top-1 classification accuracy (%) for translation results of our ZstGAN trained on different M seen domain of FLO dataset.

	M=20	M=40	M=60	M=82
A-ZstGAN	17.07	17.13	18.39	28.94
V-ZstGAN	17.13	20.01	23.31	34.06

decreases. Such results are not surprising since the image translation on unseen domains is based on the semantic representation of seen domains. If semantic representation learned from seen domains is not adequate to represent semantic information of unseen domains, translation model may fail to translate image to the target domain.

# 4.4. Interpolation

To verify that the generality of our model is not only limited on the unseen domains given by specific datasets, we interpolate domain-specific features generated by images or texts from unseen domains for image translation. Specifically, given two conditional images, we linearly interpolate between their domain-specific features and combine them with domain-invariant features of input. Similar

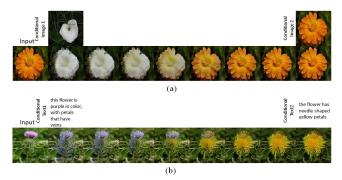


Figure 7. Domain-specific features interpolations results on unseen domains. The translation results are generated by combining input's domain-invariant features with domain-specific features interpolated linearly from left conditional input's to right conditional input's. (a) The interpolated domain-specific features are from conditional images. (b) The interpolated domain-specific features are from conditional texts.

operation is used for conditional texts interpolation. The results of domain-specific features interpolations are shown in Figure 7. We observe that our model can produce continuous translations through variation of domain-specific features from both images and texts. This indicates that (1) our model indeed learn to generalize to unseen domains which are not only discrete ones given by specific datasets but also can be a continuous space covering the whole semantic representations; (2) our model learns to disentangle the domain-specific features and domain-invariant features since the domain-invariant features, such as leaves in the background, almost keep unchanged for different domain-specific features.

# 5. Conclusions

In this paper, we propose an Unsupervised Zero-Shot Image-to-image Translation (UZSIT) problem, which aims to generalize image translation models from seen domains to unseen domains. Accordingly, we proposed a ZstGAN to this end. The ZstGAN models each seen/unseen domain using a domain-specific feature distribution conditioned on domain attributes, disentangles domain-invariant features from domain-specific features and combines them for image generation. Experiments show that our ZstGAN can effectively tackle zero-shot image translation on CUB and FLO datasets. In addition, we show that ZstGAN can achieve much better performance than state-of-the-art ZSL and GZSL methods on CUB and FLO datasets.

For future work, there are many interesting directions. First, it is interesting to design better models with better understanding of UZSIT. Second, achieving zero-shot translation without attributes is also valuable. Third, we may generalize the UZSIT to other relevant fields, such as domain adaptation and neural machine translation.

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