
LEARNING TO TRANSFER: UNSUPERVISED META DOMAIN TRANSLATION

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ABSTRACT

Unsupervised domain translation has recently achieved impressive performance with rapidly developed generative adversarial network (GAN) and availability of sufficient training data. However, existing domain translation frameworks form in a disposable way where the learning experiences are ignored. In this work, we take this research direction toward unsupervised meta domain translation problem. We propose a meta translation model called MT-GAN to find parameter initialization of a conditional GAN, which can quickly adapt for a new domain translation task with limited training samples. In the meta-training procedure, MT-GAN is explicitly fine-tuned with a primary translation task and a synthesized dual translation task. Then we design a meta-optimization objective to require the fine-tuned MT-GAN to produce good generalization performance. We demonstrate effectiveness of our model on ten diverse two-domain translation tasks and multiple face identity translation tasks. We show that our proposed approach significantly outperforms the existing domain translation methods when using no more than 10 training samples in each image domain. Our code is publicly available at <https://github.com/linjx-ustc1106/MT-GAN-PyTorch>.

1 Introduction

Unsupervised domain translation tasks [1, 2], which aim at learning a mapping that can transfer images from a source domain to a target domain using unpaired training data only, have been widely investigated in recent years. However, recent literature focuses on learning a model for a specific translation task, which lacks the ability to generalize to other tasks. In comparison, human intelligence has the ability to quickly learn new concepts with prior learning experiences. Taking painting as an example, after being able to paint a natural scene in Monet’s style, people have learned the basic skills of painting with usage of painting brush, palette, etc. When learning to paint Van Gogh’s style, we do not need to learn how to draw from the beginning. Instead, we can quickly adapt to this new task by viewing a few Van Gogh’s paintings, since we have remembered the basic patterns of painting from the prior learning experiences. To this end, we would like to require the domain translation agents to effectively utilize prior experiences and knowledge from other translation tasks when learning a new translation task.

In this paper, we take a step toward unsupervised meta domain translation (UMDT) problem which aims to effectively leverage learning experiences from domain translation tasks. Specifically, we propose a meta translation model called MT-GAN to develop strategies that are robust to different task contexts. In other words, we want to find the initialization of a conditional GAN’s parameters that could be quickly adapted to a new domain translation task with a limited amount of training samples. Our model contains two meta-learners, i.e., a meta-generator G which keeps the memory of prior translation experiences and a meta-discriminator D which teaches G how to quickly generalize to a new task. Our approach combines model-agnostic meta-learning algorithm (MAML) [3] and GAN learning [4] to iteratively update G and D . Within a meta-training minibatch, for a specific translation task, we synthesize its dual translation task with current states of MT-GAN and train these two tasks in a dual learning form [1, 5]. Then we design a meta-optimization objective to evaluate the performance of fine-tuned MT-GAN, and minimize the expected losses on the meta-testing samples with respect to parameters of MT-GAN, which ensures that the direction taken to fine-tuning leads to a good generalization performance.

We extensively evaluate the effectiveness and generalizing ability of the proposed MT-GAN algorithm on two kinds of translation task distributions. The first one contains 10 diverse two-domain translation tasks covering a wide range of scenarios, including labels \leftrightarrow photos, horses \leftrightarrow zebras, summer \leftrightarrow winter, etc. The second one is established by repeatedly sampling two arbitrary identities, which forms a two-domain translation task, from a multiple identity dataset [6]. For each translation task, we take the other 9 tasks as the training dataset and test the meta-learned parameter initialization on the task. Our experiments only use 10 samples at most in an image domain of a translation task and show that the proposed meta-learning approach outperforms ordinary domain translation models, such as CycleGAN [1] and StarGAN [2].

We summarize our contributions as follow: 1) We present a novel domain translation problem in this work, i.e., UMDT. 2) We propose a MT-GAN that jointly trains two meta-learners in an adversarial and dual form, which has not been explored by existing meta-learning approaches. 3) We extensively verify the effectiveness of our meta-learning based approach on a wide range of translation tasks.

2 Related works

Generative Adversarial Network In recent years, generative adversarial network (GAN) [4] has gained a wide range of interests in generative modeling. In a GAN, a generator is trained to produce fake but plausible images, while a discriminator is trained to distinguish difference between real and fake images. Conditional generative adversarial network (CGAN) [7] is the conditional version of GAN in which the generator is feeded with noise vector together with additional data (e.g., class labels) that conditions on both the generator and discriminator. Deep convolutional generative adversarial network (DCGAN) [8] is an extensive exploration of convolution neural network architectures in GAN and contributes to improve the quality of image synthesis. GANs have been successfully leveraged to many image generation applications [9, 10, 11, 12]. Our method adopts the adversarial loss to render images from the generators to be real in the target domain and make meta-training performance improve meta-learners' generalization.

Unsupervised Domain Translation Domain translation works has also achieved impressive performance thanks to recent development of GAN and availability of sufficient training data. Isola et al. [13] proposed a general conditional GAN (Pix2Pix) framework for a wide range of supervised domain translation tasks. Since obtaining an amount of paired training data can be difficult and impractical for many domain translation tasks, DualGAN [14], DiscoGAN [15] and CycleGAN [1] were proposed to learn two cross-domain translation models that obey the cycle consistent rule from unpaired data. Choi et al. [2] further proposed a unified unpaired domain translation model (StarGAN) to perform domain translation for multiple domains. Liu et al. [16] also proposed a UFDN to learn domain-invariant representation for multiple domain translation and can perform diverse domain translation and manipulation. A related work similar to our work may be Benaim et al. [17], in which they proposed a one-shot cross domain translation which transfers one and only one image in a source domain to a target domain with sufficient data in the target domain. However, all these existing unsupervised domain translation models mainly rely on training data of current translation task, and omit to utilize the meta-knowledge from prior learning experiences like humans. In this work, we focus on meta image translation that incorporates the prior learning experiences from other translation tasks for new translation tasks' learning.

Meta-Learning Meta-learning, which aims to learn a particular process to adjust meta-learners that perform well on a new task, can be traced back to early works [18, 19, 20]. Some recent meta-learning studies have focused on learning a shared metric by comparing similarity among data samples. Specifically, Vinyals et al. [21] proposed a Matching Networks that learns an embedding function and measures similarity using the cosine distance in an attention kernel. Snell et al. [22] also proposed to compare new examples in a learned metric space but used the Euclidean distance with a linear classifier. Another popular approach to meta-learning is to learn a shared initialization of network parameters. For example, Finn et al. [3] presented a model-agnostic meta-learning (MAML) to optimize the parameters of a meta-learner with the objective of maximizing its performance on a new task after a small number of gradient steps. Several other methods [23, 24] utilized an additional memory based network (e.g., LSTM) as the meta-learner. Observing that meta-learning methods usually require labeled datasets, recent works [25, 26] also proposed to tackle the unsupervised meta-learning. In this paper, we extend the concept of meta-learning to meta image translation. Specifically, we jointly train two meta-learners in a adversarial and dual form, which have not been explored before.

3 Meta Translation

3.1 Problem Formulation

The goal of unsupervised meta domain translation (UMDT) is to first leverage unpaired data for efficient training, and then the obtained model can be applied on a wide range of new domain translation tasks. We formally define the UMDT

problem as follows. Assuming that there are a series of tasks following distribution $P(\mathcal{T})$. Each task \mathcal{T} is associated with an underlying distribution $P_{X \times Y}^{\mathcal{T}}(x, y)$ of two domains X and Y . More specifically, the objective of task \mathcal{T} is to learn a function that can map samples from domain X to domain Y . Concretely, we assume that we have a set of training sample tasks $\{\mathcal{T}_i\}_{i=1}^N$, where N is the number of training tasks. Each training task \mathcal{T} is a tuple $\mathcal{T} = (S_{\mathcal{T}}, Q_{\mathcal{T}})$, where $S_{\mathcal{T}}$ denotes the support set, and $Q_{\mathcal{T}}$ denotes the query set. The support set $S_{\mathcal{T}} = \{\{x_i\}_{i=1}^K \in X_{\mathcal{T}}^s, \{y_i\}_{i=1}^K \in Y_{\mathcal{T}}^s\}$ contains $2K$ unpaired samples from two different domains. $Q_{\mathcal{T}} = \{\{x_i\}_{i=1}^L \in X_{\mathcal{T}}^q, \{y_i\}_{i=1}^L \in Y_{\mathcal{T}}^q\}$ is the query set that contains $2L$ unpaired samples from the same two domains. A UMDT algorithm takes $\{\mathcal{T}_i\}_{i=1}^N$ as inputs and produces a learning strategy to two meta-learners, i.e., a meta-generator G and a meta-discriminator D . When a new translation task $\mathcal{T}_{N+1} = \{\{x\}_{i=1}^K \in X_{\mathcal{T}_{N+1}}, \{y\}_{i=1}^K \in Y_{\mathcal{T}_{N+1}}\}$ comes at the test time, the learning strategy should learn a fine-tuned G and a fine-tuned D that accomplish \mathcal{T}_{N+1} . We denote the above process as K -shot domain translation. In general, the meta-learners iteratively adjust the meta-parameters on data from support set and assess their generalization performance by calculating meta-objective with data from query set.

3.2 Our Approach

We introduce the formulation of MT-GAN as following: For a K -shot domain translation problem $P(\mathcal{T})$ and dataset $\{\mathcal{T}_i\}_{i=1}^N$, our goal is to find a meta-generator G that transfers samples from a source domain to a target domain, and a meta-discriminator D that discriminates whether a sample is from real image domain or generator. Formally the generator G and discriminator D are parameterized by θ_g and θ_d respectively. For a specific translation task $\mathcal{T} \sim P(\mathcal{T})$, there have two image domains X and Y . Our primary target is to learn a mapping function $F: X \rightarrow Y$ that is derived from G . Since there has no paired data for training and observing that there naturally exists a dual task which learns another mapping direction $H: Y \rightarrow X$, we utilize these two translation tasks as a two-agent game for fine-tuning in the meta-training period. Specifically, two discriminators D_Y and D_X are used to render images from the generators to be real in the target domain. In the first iteration, we update the parameters of discriminators and generators as:

$$\theta'_{d_Y,0} = \theta_d + \alpha \nabla_{\theta_d} \mathcal{L}_{\mathcal{T},0}; \quad \theta'_{d_X,0} = \theta_{d,wc} + \alpha \nabla_{\theta_{d,wc}} \mathcal{L}_{\mathcal{T},0}, \quad (1)$$

$$\theta'_{f,0} = \theta_g - \alpha \nabla_{\theta_g} \mathcal{L}_{\mathcal{T},0}; \quad \theta'_{h,0} = \theta_{g,wc} - \alpha \nabla_{\theta_{g,wc}} \mathcal{L}_{\mathcal{T},0}, \quad (2)$$

where α is the learning rate during the meta-training period. $\theta'_{d_Y,0}$, $\theta'_{f,0}$, $\theta'_{d_X,0}$ and $\theta'_{h,0}$ are the parameters of D_Y , F , D_X and H respectively at the first meta-training iteration $t = 0$. $\theta_{d,wc}$ and $\theta_{g,wc}$ are the parameters of $wc(D)$ and $wc(G)$, where wc is the network weights copy operation that detaches back-propagation gradient from meta-optimization objectives. G and D can be parameter initialization for any translation task in practice. However, in a specific \mathcal{T} , using G for fine-tuning of both F and H is ambiguous since the meta-optimization objective will become to require G and D to be well adapted for both $X \rightarrow Y$ and $Y \rightarrow X$ at the same time. Therefore, we update G and D only for $X \rightarrow Y$ translation with wc operation. The overall objective $\mathcal{L}_{\mathcal{T},0}$ for training the discriminators and generators at iteration $t = 0$ is given as:

$$\begin{aligned} \mathcal{L}_{\mathcal{T},0}(G, D, X_{\mathcal{T}}^s, Y_{\mathcal{T}}^s) = & \mathcal{L}_{\text{adv}}(G, D, X_{\mathcal{T}}^s, Y_{\mathcal{T}}^s) + \mathcal{L}_{\text{adv}}(wc(G), wc(D), Y_{\mathcal{T}}^s, X_{\mathcal{T}}^s) \\ & + \lambda_{\text{cyc}} \mathcal{L}_{\text{cyc}}(G, wc(G), X_{\mathcal{T}}^s, Y_{\mathcal{T}}^s) + \lambda_{\text{idt}} \mathcal{L}_{\text{idt}}(G, wc(G), X_{\mathcal{T}}^s, Y_{\mathcal{T}}^s), \end{aligned} \quad (3)$$

$$\mathcal{L}_{\text{adv}}(G, D, X_{\mathcal{T}}^s, Y_{\mathcal{T}}^s) = \mathbb{E}_{y \sim Y_{\mathcal{T}}^s} [\log D(y)] + \mathbb{E}_{x \sim X_{\mathcal{T}}^s} [\log(1 - D(G(x)))], \quad (4)$$

$$\mathcal{L}_{\text{cyc}}(G_1, G_2, X_{\mathcal{T}}^s, Y_{\mathcal{T}}^s) = \mathbb{E}_{x \sim X_{\mathcal{T}}^s} [\|G_2(G_1(x)) - x\|_1] + \mathbb{E}_{y \sim Y_{\mathcal{T}}^s} [\|G_1(G_2(y)) - y\|_1], \quad (5)$$

$$\mathcal{L}_{\text{idt}}(G_1, G_2, X_{\mathcal{T}}^s, Y_{\mathcal{T}}^s) = \mathbb{E}_{x \sim X_{\mathcal{T}}^s} [\|G_2(x) - x\|_1] + \mathbb{E}_{y \sim Y_{\mathcal{T}}^s} [\|G_1(y) - y\|_1], \quad (6)$$

where \mathcal{L}_{adv} , \mathcal{L}_{cyc} and \mathcal{L}_{idt} are adversarial loss, cycle-consistency loss and identity loss respectively. λ_{cyc} and λ_{idt} are the weights to balance different loss terms. At iteration $t \neq 0$, we follow the popular unsupervised domain translation model, e.g., CycleGAN, to fine-tune the initialized d_X , d_Y , F and H to quickly adapt to the \mathcal{T} task. Formally we update the parameters as follow:

$$\theta'_{d_Y,t+1} = \theta'_{d_Y,t} + \alpha \nabla_{\theta'_{d_Y,t}} \mathcal{L}_{\mathcal{T},t+1}; \quad \theta'_{d_X,t+1} = \theta'_{d_X,t} + \alpha \nabla_{\theta'_{d_X,t}} \mathcal{L}_{\mathcal{T},t+1}, \quad (7)$$

$$\theta'_{f,t+1} = \theta'_{f,t} - \alpha \nabla_{\theta'_{f,t}} \mathcal{L}_{\mathcal{T},t+1}; \quad \theta'_{h,t+1} = \theta'_{h,t} - \alpha \nabla_{\theta'_{h,t}} \mathcal{L}_{\mathcal{T},t+1}, \quad (8)$$

$$\begin{aligned} \mathcal{L}_{\mathcal{T},t+1}(F_t, H_t, D_{X,t}, D_{Y,t}, X_{\mathcal{T}}^s, Y_{\mathcal{T}}^s) = & \mathcal{L}_{\text{adv}}(F_t, D_{Y,t}, X_{\mathcal{T}}^s, Y_{\mathcal{T}}^s) + \mathcal{L}_{\text{adv}}(H_t, D_{X,t}, Y_{\mathcal{T}}^s, X_{\mathcal{T}}^s) \\ & + \lambda_{\text{cyc}} \mathcal{L}_{\text{cyc}}(F_t, H_t, X_{\mathcal{T}}^s, Y_{\mathcal{T}}^s) + \lambda_{\text{idt}} \mathcal{L}_{\text{idt}}(F_t, H_t, X_{\mathcal{T}}^s, Y_{\mathcal{T}}^s), \end{aligned} \quad (9)$$

where $D_{Y,t}$, F_t , $D_{X,t}$ and H_t are the state of the D_Y , F , D_X and H at meta-training iteration t . For meta-optimization, we minimize the expected loss on query set $Q_{\mathcal{T}}$ with updated discriminators and generators across the task \mathcal{T} to train the initial parameters of D and G . Our MT-GAN model can be trained as follows:

$$\theta_d = \theta_d + \beta \nabla_{\theta_d} \mathcal{L}_{\mathcal{T}, T+1}^q, \quad (10)$$

$$\theta_g = \theta_g - \beta \nabla_{\theta_g} \mathcal{L}_{\mathcal{T}, T+1}^q, \quad (11)$$

$$\begin{aligned} \mathcal{L}_{\mathcal{T}, T+1}^q(F_T, H_T, D_{X,T}, D_{Y,T}, X_{\mathcal{T}}^q, Y_{\mathcal{T}}^q) = & \mathcal{L}_{\text{adv}}(F_T, D_{Y,T}, X_{\mathcal{T}}^q, Y_{\mathcal{T}}^q) + \mathcal{L}_{\text{adv}}(H_T, D_{X,T}, Y_{\mathcal{T}}^q, X_{\mathcal{T}}^q) \\ & + \lambda_{\text{cyc}} \mathcal{L}_{\text{cyc}}(F_T, H_T, X_{\mathcal{T}}^q, Y_{\mathcal{T}}^q) + \lambda_{\text{idt}} \mathcal{L}_{\text{idt}}(F_T, H_T, X_{\mathcal{T}}^q, Y_{\mathcal{T}}^q) \end{aligned} \quad (12)$$

where β is the learning rate for the meta-optimization, and T is the overall iteration number of meta-training. The full algorithm of MT-GAN is outlined in Algorithm 1 in a general case.

Algorithm 1 MT-GAN training process

Require: : Distribution over domain translation tasks $P(\mathcal{T})$

Require: : Hyperparameters $\alpha, \beta, \lambda_{\text{cyc}}, \lambda_{\text{idt}}, K$

- 1: Randomly initialize parameters θ_g of G and θ_d of D
 - 2: **while** not converged **do**
 - 3: Sample batch of tasks $\mathcal{T}_i \sim P(\mathcal{T})$
 - 4: Split support set and query set: $S_{\mathcal{T}_i}$ and $Q_{\mathcal{T}_i} \leftarrow \mathcal{T}_i$
 - 5: **for all** $S_{\mathcal{T}_i}$ **do**
 - 6: **Meta-training:**
 - 7: Compute fine-tuned parameters $\theta'_{d_X,0}, \theta'_{d_Y,0}, \theta'_{F,0}, \theta'_{H,0}$ with
 - 8: gradient descent by Eqn.(1) and Eqn.(2)
 - 9: **for** t **in** iterations T **do**
 - 10: Compute fine-tuned parameters $\theta'_{d_X,t+1}, \theta'_{d_Y,t+1}, \theta'_{F,t+1}, \theta'_{H,t+1}$ with
 - 11: gradient descent by Eqn.(7) and Eqn.(8)
 - 12: **end for**
 - 13: **Meta-testing:**
 - 14: Compute meta-objective $\mathcal{L}_{\mathcal{T}_i, T+1}^q$ on $Q_{\mathcal{T}_i}$ according to Eqn.(12)
 - 15: **end for**
 - 16: **Meta-Optimization:**
 - 17: Update $\theta_d = \theta_d + \beta \nabla_{\theta_d} \sum_{\mathcal{T}_i \sim P(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i, T+1}^q$
 - 18: Update $\theta_g = \theta_g - \beta \nabla_{\theta_g} \sum_{\mathcal{T}_i \sim P(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i, T+1}^q$
 - 19: **end while**
-

At inference time, for an unseen translation task $\mathcal{T}_{N+1} = \{\{x_i\}_{i=1}^K \in X_{\mathcal{T}_{N+1}}, \{y_i\}_{i=1}^K \in Y_{\mathcal{T}_{N+1}}\}$, we iteratively fine-tune the obtained G and D with meta-training steps from Eqn.(1) to Eqn.(9) to obtain an F that transfers $\{x_i\}_{i=1}^K$ to Y domain and an H that transfers $\{y_i\}_{i=1}^K$ to X domain.

4 Experiments

4.1 Experimental Setup

We extensively evaluate the effectiveness and generalizing ability of the proposed MT-GAN algorithm for UMDT problem on two kinds of translation task distributions. The first one (denoted as $P_1(\mathcal{T})$) contains 10 diverse translation tasks collected by [1]: labels \leftrightarrow photos, horses \leftrightarrow zebras, summer \leftrightarrow winter, apple \leftrightarrow orange, monet \leftrightarrow photo, cezanne \leftrightarrow photo, ukiyoe \leftrightarrow photo, vangogh \leftrightarrow photo, photos \leftrightarrow maps and labels \leftrightarrow facades. In addition, the Facescrub dataset [6], which comprises 531 different celebrities, is utilized as another collection of domain translation tasks (denoted as $P_2(\mathcal{T})$) that are less diverse, in which different identities are viewed as different domains. Then we can sample arbitrary two identities to form a two-domain translation task that aims to transfer the identity of face images while preserving original face orientation and expression.

In our experiments, for both $P_1(\mathcal{T})$ and $P_2(\mathcal{T})$, we simulate the meta domain translation scenarios by randomly select $N = 9$ tasks as a training dataset and select the other 1 task as the testing dataset/task. We establish 10 training datasets and 10 corresponding testing datasets for both $P_1(\mathcal{T})$ and $P_2(\mathcal{T})$. For each training dataset, we randomly select overall 2000 meta batches from the 9 tasks for model training. We set the meta batch-size to 2 to fit the memory limit of the GPU. Following the common settings of few-shot learning, we mainly focus on 5-shot domain translation and 10-shot

domain translation in all experiments. Moreover, we set the query set’s size L to 10. For the testing task, we randomly select 5 meta batches from the 1 task for model testing.

For each meta-training period, we use stochastic gradient descent (SGD) with learning rate $\alpha = 0.0001$ to fine-tune the generators and discriminators. At meta-optimization time, we use the Adam optimizer [27] with learning rate $\beta = 0.0002$ to update both meta-generator and meta-discriminator. For model fine-tuning on the testing tasks, we also use the Adam optimizer with learning rate $\beta = 0.0002$ to fine-tune both meta-generator and meta-discriminator. The overall iteration number of meta-training T is set to 100. We set the loss function balance parameters λ_{cyc} and λ_{idt} to be 10 and 5.

For each K -shot domain translation task, we fine-tune the trained MT-GAN on each meta batch of the testing dataset, and report the average score and its standard deviation. The Frechet Inception Distance (FID) [28] that measures similarity between generated image dataset and real image dataset is used to evaluate translation results’ quality. The lower the FID is, the better the translation results are. In addition, we perform face classification experiments on face identity translation tasks. We re-trained VGG-16 network [29] on Facescrub, and compute the top-1 and top-5 classification accuracy rates of the translation results.

4.2 Model configuration

We follow [1] to configure the models. The meta-generator G network consists of two convolution layers with stride 2 and kernel size 3×3 , six residual blocks [30] with kernel size 3×3 and two transposed convolution layers with stride 0.5 and kernel size 3×3 . For meta-discriminator D , we use PatchGANs [13] that consists of five convolution layers with stride 2 and kernel size 4×4 . For both G and D , we use batch normalization [31] among network layers.

4.3 Results

Qualitative and Quantitative Evaluation We compare our method with two baseline domain translation models, i.e., CycleGAN [1] and StarGAN [2]. We retrain both CycleGAN and StarGAN on each meta batch in testing dataset of a given K -shot domain translation task, and report their average performance with the retrained models. We show qualitative comparison results of the testing tasks in Figure 1. We observe that StarGAN typically produces quite blurry and noisy outputs, and obviously suffers from the limited training samples. CycleGAN maintains the main structure of the source inputs in most cases and transfers some domain-specific features of the target domains in the translation results. However, CycleGAN still fails to locate the accurate regions that domain-specific features should be transferred in, and produces unnatural images. For example, the translated apple by CycleGAN in 10-shot orange→apple is surrounded by inaccurate apple features, and the translated map by CycleGAN in 10-shot photos→maps mistakenly transfers the land and houses to water label. On the contrary, most of our results well preserve the domain-invariant features [32, 33] and accurately transfer the domain-specific features [32, 33] in the translation results. It should be noticed that, even with limited unpaired training samples, our model is still able to detect semantic regions of source inputs. For instance, our model successfully detect the water area and land in 10-shot domain translation of the Figure 1 (f) and (g).

For the quantitative evaluation, we present the FID score results of various testing tasks in Table 1. For face identity translation, we report the top-1 and top-5 face recognition accuracy of generated images from CycleGAN, StarGAN and our model in Table 2. We can observe that the quantitative results are quite related to the qualitative results in Figure 1, in which our model consistently outperforms CycleGAN and StarGAN. We also find that improvement brought by our model on some natural image generation tasks, such as four painting↔photo tasks, is less significant than other tasks, such as photos↔maps and labels↔photos. Such result is not surprising because only limited samples are hard to include all patterns for natural image generation, while the patterns of photos↔maps or labels↔photos are more simple and regularized.

Comparing the performance of MT-GAN on 5-shot and 10-shot domain translation tasks, we can see that the proposed meta-learning approach is quite robust to the drop in the amount of training samples. With only 5 training samples, MT-GAN still successfully transfers source inputs to target domains in most cases. With the increase of training samples, MT-GAN steadily improves performance on 10-shot domain translation tasks.

Convergence Rate The meta-learning based approach has demonstrated that, with several domain translation tasks, it can incorporate the prior learning experiences on these tasks and generalize to a new task with better performance than ordinary translation models in the above experiments. We show that meta-learning brings another benefit, i.e., faster convergence rate in a training process. We show the training curves of cycle-consistency loss with respect to training steps on the different testing tasks in Figure 2. We choose cycle-consistency loss to reflect the convergence rate because a smaller cycle-consistency loss indicates that the two translation models well relate two domains. Comparing training

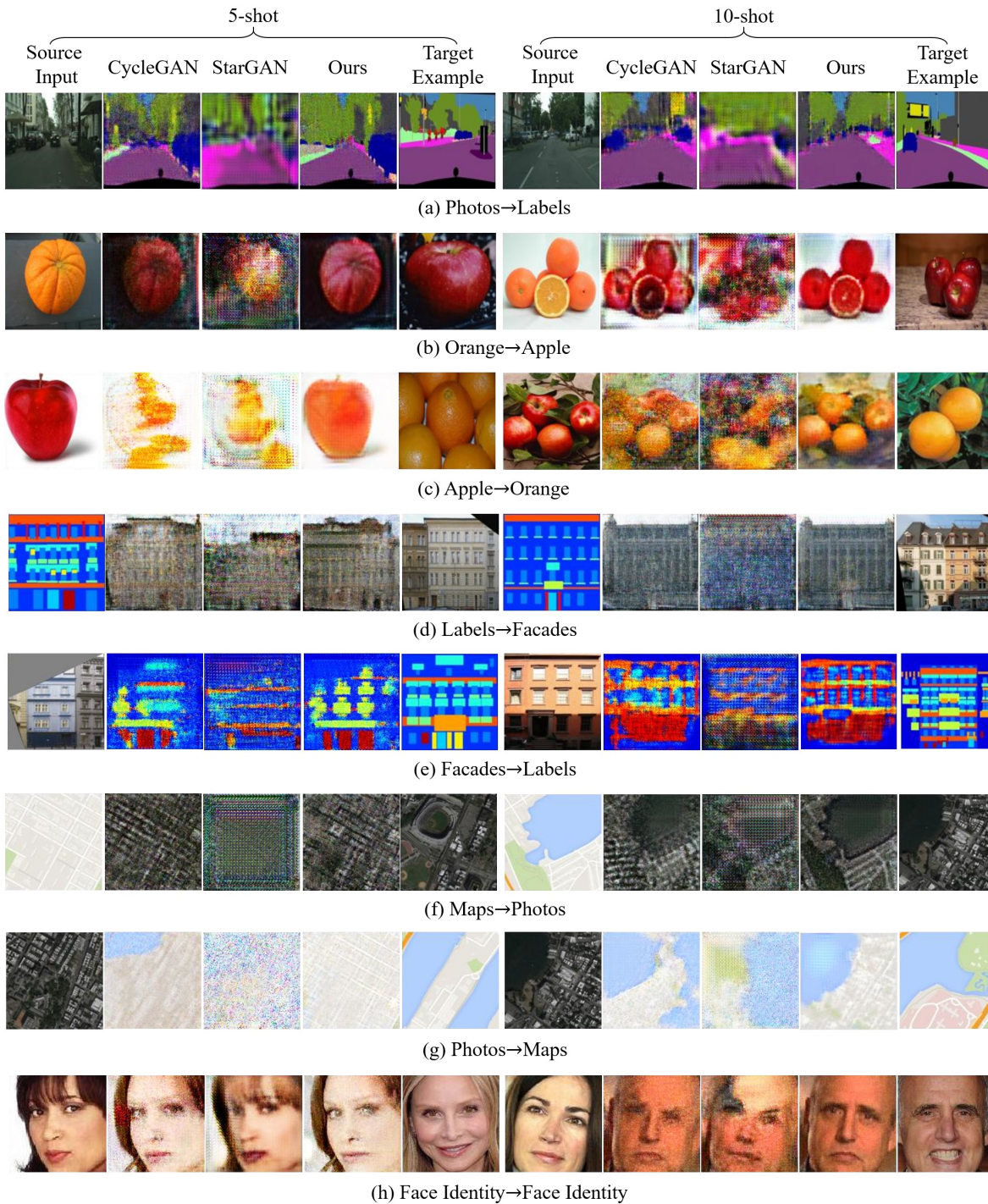


Figure 1: Translation results of various testing tasks using CycleGAN, StarGAN and our MT-GAN. Left part: 5-shot domain translation. Right part: 10-shot domain translation. From left to right, the columns represent inputs from the source domain, CycleGAN’s results, StarGAN’s results, our results and examples in the target domain respectively.

curves of CycleGAN and our model, we observe that our model rapidly minimizes the cycle-consistency loss in the first

	CycleGAN [1]		StarGAN [2]		Ours	
	←	→	←	→	←	→
labels↔photos	15.10 ± 1.72	28.69 ± 1.54	22.56 ± 1.55	39.27 ± 1.48	12.16 ± 1.19	26.08 ± 1.25
horses↔zebras	31.96 ± 1.63	31.45 ± 2.29	34.94 ± 1.72	35.83 ± 1.81	31.80 ± 1.28	30.68 ± 2.09
summer↔winter	23.43 ± 2.12	19.24 ± 2.02	32.18 ± 1.98	34.95 ± 1.89	21.50 ± 1.71	17.95 ± 1.93
apple↔orange	33.16 ± 1.83	34.30 ± 1.51	38.93 ± 1.69	43.58 ± 1.87	31.34 ± 1.57	31.93 ± 1.92
monet↔photo	18.97 ± 1.75	19.93 ± 2.21	33.38 ± 2.27	35.95 ± 2.18	18.42 ± 2.11	19.73 ± 2.08
cezanne↔photo	22.85 ± 1.71	23.24 ± 1.89	29.23 ± 1.85	31.37 ± 1.97	22.00 ± 1.66	22.57 ± 1.78
ukiyo↔photo	22.90 ± 2.05	21.16 ± 2.14	24.87 ± 2.25	28.99 ± 2.23	21.88 ± 2.18	20.86 ± 1.96
vangogh↔photo	22.65 ± 2.29	19.26 ± 2.18	34.91 ± 2.26	36.68 ± 2.32	21.57 ± 2.14	18.42 ± 2.05
photos↔maps	25.57 ± 1.96	27.17 ± 1.72	35.61 ± 1.88	31.36 ± 1.95	19.64 ± 1.64	23.44 ± 1.72
labels↔facades	23.06 ± 1.86	26.35 ± 1.73	26.55 ± 2.03	32.80 ± 2.11	21.72 ± 2.09	25.34 ± 1.96

Table 1: Average FID scores ($\times 10$) of various 10-shot testing tasks. \leftarrow represents the reverse translation direction, such as labels \leftarrow photos, and \rightarrow represents the forward translation direction, such as labels \rightarrow photos. For each translation direction, the best FID scores are in bold.

		CycleGAN [1]	StarGAN [2]	Ours
		5-shot	Top-1	11.21 ± 0.91%
	Top-5	37.12 ± 1.63%	15.35 ± 1.11%	40.02 ± 1.22%
10-shot	Top-1	19.04 ± 1.21%	10.38 ± 0.78%	21.12 ± 1.03%
	Top-5	45.56 ± 1.56%	37.34 ± 1.43%	48.27 ± 1.54%

Table 2: Average classification accuracy of 5-shot and 10-shot face identity translation tasks. The best top-1 and top-5 classification accuracy are in bold.

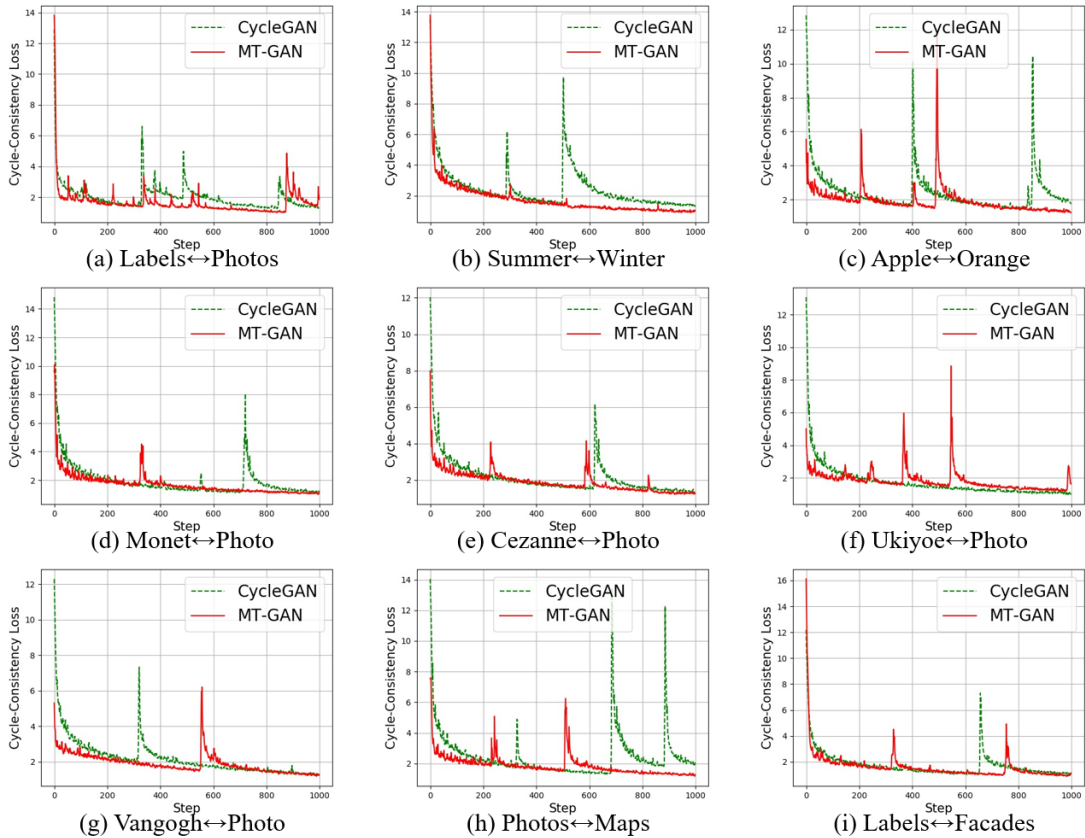


Figure 2: The training curves of cycle-consistency loss with respect to training step on the different testing tasks.

several steps. In addition, our model achieves lower cycle-consistency loss than CycleGAN after numerous iteration steps in most cases. When training abnormality of GAN occurs, we can see that our model can recover to original training

states more quickly than CycleGAN. These results demonstrate that our model indeed learns adaptation strategies from previous translation tasks, and helps to converge more quickly in current tasks.

5 Conclusions

In this work, we devise the unsupervised meta domain translation (UMDT) problem which aims to effectively incorporate prior domain translation experiences. Accordingly, we propose a model called MT-GAN to find the initialization of a meta-generator and a meta-discriminator that can be used for initialization of any translation task. We jointly train two meta-learners in an adversarial and dual form. We demonstrate our model on ten diverse domain translation tasks and face identity translation tasks. Both qualitative and quantitative results show that the meta-learning based approach significantly outperforms ordinary translation models. In addition, we show that our model can achieve a faster convergence rate than CycleGAN, which further demonstrates MT-GAN indeed learns adaptation strategies from previous learning experiences.

For future works, it will be interesting to extend the training paradigm of MT-GAN to other image generation or domain transfer learning tasks. In addition, how to learn the adaptation strategies from many-shot domain translation tasks will be worthy to explore.

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