Multimodal Image-to-Image Translation via Mutual Information Estimation and Maximization

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Abstract

Multimodal image-to-image translation (I2IT) aims to learn a conditional distribution that explores multiple possible images in the target domain given an input image in the source domain. Conditional generative adversarial networks (cGANs) are often adopted for modeling such a conditional distribution. However, cGANs are prone to ignore the latent code and learn a unimodal distribution in conditional image synthesis, which is also known as the mode collapse issue of GANs. To solve the problem, we propose a simple yet effective method that explicitly estimates and maximizes the mutual information between the latent code and the output image in cGANs by using a deep mutual information neural estimator in this paper. Maximizing the mutual information strengthens the statistical dependency between the latent code and the output image, which prevents the generator from ignoring the latent code and encourages cGANs to fully utilize the latent code for synthesizing diverse results. Our method not only provides a new perspective from information theory to improve diversity for I2IT but also achieves disentanglement between the source domain content and the target domain style for free. Extensive experiments under both paired and unpaired I2IT settings demonstrate the effectiveness of our method to achieve diverse results without loss of quality. Our code will be made publicly available soon.

1. Introduction

In recent years, Generative Adversarial Networks (GANs) [20] have emerged as a promising generative model that can capture complex and high-dimensional image data distributions. Extended on GANs, conditional GANs (cGANs) [41] which take extra contextual information as input are widely applied in conditional image synthesis tasks and achieve great success, such as image to image translation [25], super resolution [32], image inpainting [47], and text-to-image synthesis [60].

Domain mapping or image-to-image translation (I2IT) aims to learn the mapping from the source image domain \(\mathcal{A}\) to the target image domain \(\mathcal{B}\). Many conditional image synthesis tasks can be seen as special cases of I2IT, e.g., super resolution [32], colorization [31], image inpainting [47], and style transfer [18]. However, many previous works [25, 54, 37, 64] on I2IT only learn a deterministic mapping function. I2IT should be capable of producing multiple possible outputs even for a single input image, e.g., a Yosemite winter photo may correspond to multiple summer photos that vary in light, the amount of clouds, or the luxuriance of vegetation. A straightforward way to produce diverse results for cGANs is to distill such variations in latent noise \(Z\) that can be sampled from a simple distribution, such as an isotropic Gaussian. However, this problem is inherently ill-posed as there are usually only one or even no corresponding images available in the target domain for an input image in the source domain during training. And the signal from high-dimensional and structured input image is usually stronger than that of the low-dimensional latent noise in cGANs. It has been reported in the literature of conditional image synthesis [25, 38, 40, 65] that cGANs are prone to overlook the latent noise, which is also known as the mode collapse issue [19, 20, 50] of GANs.

To encourage diversity for I2IT, many existing works [1, 24, 33, 63, 65] propose to learn a one-to-one mapping between the latent space and the generated image space by using informative encoders to recover the latent code from the generated image, which we refer to as the latent code reconstruction loss in this paper. From a perspective of information theory, we show that this loss is highly related to the variational mutual information maximization [3, 9] between the latent code \(Z\) and the output image \(\hat{B}\) as follows (refer to supplementary materials for detailed derivation):

\[
\mathcal{I}(Z; \hat{B}) = H(Z) - H(Z|\hat{B}) \geq H(Z) - \mathcal{L}_R \tag{1}
\]

where \(\mathcal{I}(\cdot; \cdot)\), \(H(\cdot)\), and \(\mathcal{L}_R\) are the mutual information, the
Shannon entropy and the latent code reconstruction loss, respectively. As the entropy \( H(Z) \) is a constant (the prior distribution \( p_z \) is often predefined), minimizing the latent code reconstruction loss \( L_R \) amounts to maximizing a variational lower bound on the mutual information between \( Z \) and \( \hat{B} \). Maximizing the mutual information improves diversity for cGANs as it enhances the statistical dependency between \( Z \) and \( \hat{B} \) and prevents the generator from ignoring \( Z \). However, the latent code reconstruction loss is limited by the design of the specific task \([24, 63, 65]\) and the capacity of the encoders to learn useful information \([25, 30]\). To bypass such restrictions and fully encourage the statistical dependency between the latent code \( Z \) and the output image \( \hat{B} \), in this paper, we propose an alternative and straightforward way - discarding the encoders and directly maximizing the mutual information between them. This is achieved by the deep mutual information neural estimator \([4]\). Specifically, our method introduces a statistics network \( T \) to estimate and maximize the mutual information between the latent code \( Z \) and the output image \( \hat{B} = G(\cdot, Z) \) by discriminating the corresponding positive samples \((z_1, G(\cdot, z_1))\) from the non-corresponding negative samples \((z_1, G(\cdot, z_2))\), as shown in Figure 1. Intuitively, this implies the statistics network tries to discover the unique link between the latent code and the images generated by it, which also indirectly decouples the target domain style from the source domain content.

We augment existing paired or unpaired I2IT methods with our proposed additional loss term that maximizes the mutual information between the latent code and the generated image to encourage diversity for them, e.g., pix2pix \([25]\) and GeGAN \([17]\). A simple architectural enhancement is shown to suffice for the utilization of our proposed loss, which results in an elegant new model we name as Statistics Enhanced GAN (SEGAN) in this paper (see Figure 2). Both qualitative and quantitative evaluations under paired and unpaired I2IT settings verify the effectiveness of our method for improving diversity without loss of image quality.

Our contributions in this paper are summarized below:

- We propose a novel method from information theory that explicitly estimates and maximizes the mutual information between the latent code and the output image to palliate mode collapse in cGANs.
- Our method also achieves disentanglement between the source domain content and the target domain style for free.
- The proposed method can facilitate many existing I2IT methods to improve diversity with a simple network extension.
- Extensive experiments show the effectiveness of our method to improve diversity without sacrificing image quality of generated samples.

2. Related Works

2.1. Generative adversarial networks

Generative Adversarial Networks (GANs) \([20]\) compose of two modules: a discriminator that tries to distinguish real data samples from generated samples, and a generator that tries to generate samples to fool the discriminator. Many important works are proposed to improve the original GAN for more stabilized training and producing high-quality samples, such as by proposing better loss functions or regularizations \([2, 21, 7, 39, 42, 62]\), changing network structures \([13, 26, 27, 48, 59]\), or combining inference networks or autoencoders \([8, 14, 16, 30, 51, 53]\). In this work, we rely on GANs to synthesize realistic and diverse images for multimodal image-to-image translation.

2.2. Multimodal image-to-image translation

We classify the current multimodal image-to-image translation (I2IT) methods into three categories according to the techniques encouraging diversity for them: (1) latent code reconstruction loss, including AugCycleGAN \([1]\), BicycleGAN \([65]\), MUNIT \([24]\), DRIT \([33]\), SDIT \([55]\), and DMIT \([58]\), (2) simply maximizing the pixel difference between the generated images, including MS-GAN \([38]\) and DSGAN \([56]\), and (3) the combination of both the above two techniques, including StarGANv2 \([10]\) and DRIT++ \([34]\). Specifically, SDIT \([55]\), DMIT \([58]\), DRIT++ \([34]\), and StarGANv2 \([10]\) combine the multimodal and the multidomain I2IT in a unified model by uti-
lizing a domain label. However, these methods still rely on the techniques mentioned above to encourage diverse results. In later experiments, we will compare our method with BicycleGAN [65] and MSGAN [38] under a paired setting, and MUNIT [24], DRIT [33], and DRIT++ [34] under an unpaired setting, to demonstrate the effectiveness and superiority of our proposed method.

2.3. Mutual information

Mutual Information (MI) is a fundamental quantity for measuring the relationship between random variables. In contrast to correlation, mutual information can capture nonlinear statistical dependencies between variables, and thus can act as a measure of true dependence [29]. Methods based on Mutual Information (MI) can date back to the inomax principle [5, 36], which advocates maximizing MI between the input and the output of the neural networks. Notably, InfoGAN [9] proposed to maximize the MI between a small part of the latent code and the generated outputs in GANs for discovering disentangled latent representations. Our method, though shares a similar idea with InfoGAN about maximizing the MI, yet differs from InfoGAN in two main aspects. First, in methodology, InfoGAN minimizes a variational lower bound on the conditional entropy and ignores the sample entropy of the MI (refer to supplementary materials), while our method explicitly estimates and maximizes the whole MI term. Second, in target, InfoGAN aims to disentangle latent factors in GANs, while our method mainly attacks the mode collapse issue in cGANs. On the other hand, in BicycleGAN [65], the authors attempted to use cLRGAN which is a conditional version of InfoGAN to encourage diversity for paired I2IT, but it resulted in less variation in the output and sometimes failed in severe mode collapse, probably because the simple latent code reconstruction loss does not fulfill the maximization of the MI in conditional image synthesis. In contrast, we show that our proposed method can successfully maximize the MI and therefore improves diversity for I2IT.

Some neural estimators of MI have been proposed in recent years, such as MINE [4] and InfoNCE [45]. Intuitively, these methods estimate MI between random variables \( X \) and \( Y \) by training a classifier to distinguish between the corresponding samples drawn from the joint distribution \( p(x,y) \) and the non-corresponding samples drawn from the product of marginals \( p(x)p(y) \). ALICE [35] revealed that cycle consistency [28, 64, 57] is actually maximizing a lower bound on the MI between the input and the output of the generator. Based on that, CUT [46] adopts the InfoNCE loss to maximize the MI between the corresponding patches of the input and the output to preserve content information for unpaired I2IT recently. However, our target and methodology are totally different from CUT: (1) The target of CUT is to better preserve the content for unpaired I2IT, which can only produce unimodal results. Our method aims to yield diverse results for I2IT and theoretically can be combined with CUT to encourage diversity for it. (2) The methodology is also different. CUT uses NCE loss to maximize MI between the corresponding patches of the input and the output images, which cannot be used in our case. We formulate a JSD MI estimator to estimate and
maximize the MI between the latent code and the output image. The mathematical form of our loss is a binary cross-entropy, which does not require a large negative sample size per positive sample as in NCE loss; thus, it is more stable and easier to implement.

3. Statistics Enhanced GAN

3.1. Preliminaries

Suppose we have a source image domain $A \subset \mathbb{R}^{H \times W \times 3}$ and a target image domain $B \subset \mathbb{R}^{H \times W \times 3}$, multimodal image-to-image translation (I2IT) refers to learning a generator’s function $G(a,z)$ such that $a \in A$, $\hat{b} = G(a,z) \in B$ and $\hat{b}$ preserves some underlying spatial information of $a$\(^1\). We refer to such underlying spatial information and the semantic difference of the target image domain as “content” and “style” respectively. An adversarial loss shown below is used to ensure $G(a,z)$ to look like real samples from the target image domain. And the latent code $Z$ is responsible for the style variations of the output image $\hat{b}$.

\[
\max_{D_b} \min_{G, \gamma} \mathbb{E}_{b \sim \rho(b)}[\log D_b(b)] + \\
\mathbb{E}_{a \sim \rho(a), z \sim \rho(z)}[\log(1 - D_b(G_\gamma(a,z)))]
\]  

(2)

where $D$, $D(\cdot)$, $\theta$, $G$, $G(\cdot, \cdot)$, and $\gamma$ are the discriminator, the discriminator’s critic function, the parameters of the discriminator, the generator, the generator’s function, and the parameters of the generator, respectively.

For simplicity, $Z$ often follows a standard Gaussian such that $z \sim \mathcal{N}(0, I)$. After training, we expect that varying the latent noise conditioned on an input image can produce different images varying in style while preserving the content. However, several previous works [25, 38, 40, 65] have reported that naively adding the noise can hardly produce diverse results, probably because of the mode collapse issue of GANs.

3.2. Probabilistic analysis

To encourage diversity for image-to-image translation (I2IT), we propose to enhance the connection between the latent noise $Z$ and the output image $\hat{B}$ in a statistical manner by maximizing the mutual information between them, therefore we call our proposed model Statistics Enhanced GAN (SEGAN).

Why maximizing the MI between $Z$ and $\hat{B}$ helps to reduce mode collapse in cGANs? Suppose the latent noise $Z$ is ignored by the generator which is often encountered in conditional image synthesis tasks [25, 38, 40, 65], the generator’s function $G(a,z)$ and the conditional distribution $p(\hat{b}|a,z)$ modeled by cGANs would degenerate to $G(a)$ and $p(\hat{b}|a)$ respectively, which means $Z$ is independent of $\hat{B}$ and the translation becomes deterministic. In information theory, such dependency is measured by the Mutual Information (MI). The MI between the latent code $Z$ and the output image $\hat{B}$

\[
\mathcal{I}(\hat{B}; Z) = H(\hat{B}) - H(\hat{B}|Z) = H(Z) - H(Z|\hat{B})
\]

(3)

quantifies the “amount of information” of $\hat{B}$ through observing $Z$. When the generator overlooks $Z$ (which means $Z$ is independent of $\hat{B}$), the MI attains its minimal value 0, because knowing $Z$ reveals nothing about $\hat{B}$ under such circumstances. In contrast, if $Z$ and $\hat{B}$ are closely related by an invertible function, e.g., $Z$ is utilized by the generator to represent different styles of the target image domain, then the MI attains its maximum. From another perspective, the direct way to encourage diversity of a random variable is to maximize its entropy. As the generated sample’s entropy $H(\hat{B})$ is intractable, we use the MI between $\hat{B}$ and $Z$ as a proxy. As shown in Equation 3, the MI can be seen as a lower bound on $H(\hat{B})$.

3.3. Architecture and disentanglement

SEGAN is simple and neat in its architecture: it is merely an extension upon cGANs with a statistics network $T$ as shown in Figure 2. The statistics network is used to estimate and maximize the Mutual Information (MI) between the latent noise $Z$ and the output image $\hat{B}$.

In our method, the statistics network $T$ estimates and maximizes the MI by performing a binary classification between the “positive samples” $(z, G(\cdot, z))$ (the latent code and the images generated by it) and the “negative samples” $(z', G(\cdot, z))$ (the latent code and the images not generated by it). This indicates the statistics network has to find out the universal influence that the latent code $z$ puts on the output image $G(a,z)$ regardless of the input image $a$ (because a fixed $z$ can be combined with many different source domain images $a$). As such, the method forces the latent code to represent the style of the target image domain instead of the noises or the structures of the content. Once successfully trained, our method therefore achieves disentanglement between the source domain content and the target domain style for free.

3.4. Loss functions

**Mutual information loss.** Formally, the Mutual Information (MI) between random variables $X$ and $Y$ is defined as the Kullback-Leibler (KL) divergence between the joint distribution $p(x,y)$ and the product of the marginals $p(x)p(y)$:

\[
\mathcal{I}(X;Y) = D_{KL}[p(x,y)||p(x)p(y)]
\]

\[
= \mathbb{E}_{p(x,y)} \left[ \log \frac{p(x,y)}{p(x)p(y)} \right]
\]

(4)
Belghazi et al. [4] propose several neural estimators of MI based on the dual formulations of the KL-divergence, that are trainable through back-propagation and highly consistent, such as the Donsker-Varadhan (DV) representation [15] and the f-divergence representation [43, 44]. However, these estimators have some defeats making them difficult to be applied for practical use, such as biased estimate of the batch gradient and unbounded value [4]. For a more stabilized training, we adopt a neural estimator that lower bounds the Jensen-Shannon Divergence (JSD) between the joint and the product of the marginals following the formulation of f-GAN [44]. This JSD MI estimator is more stable and positively correlated with MI (refer to supplementary materials for the proof):

$$\text{JSD} \left[p(z, \hat{b})\| p(z)p(\hat{b}) \right] \geq \nonumber \hat{J}_{\omega}^{\text{JSD}}(Z; G_\gamma(\cdot, Z)) = \mathbb{E}_{p_z} \left[\log (\sigma (T_\omega(z, G_\gamma(\cdot, z))))\right] + \mathbb{E}_{p_z \times p_{\hat{z}}} \left[\log (1 - \sigma (T_\omega(z', G_\gamma(\cdot, z'))))\right]$$

(5)

where \(\hat{b} = G_\gamma(\cdot, z), T_\omega(\cdot, \cdot)\) is the statistics network’s function with parameters \(\omega\) that outputs a scalar, \(p_z = \hat{p}_z = \mathcal{N}(0, I)\), \(z\) and \(z'\) are different samples from \(\mathcal{N}(0, I)\), and \(\sigma(\cdot)\) is the sigmoid function. The mathematical form of the JSD MI estimator amounts to the familiar binary cross-entropy. The MI is estimated by maximizing \(\hat{J}_{\omega}^{\text{JSD}}\) in Equation 5 w.r.t. the statistics network’s parameters \(\omega\). As maximizing MI follows the same direction of estimating MI, we jointly optimize the generator and the statistics network by the mutual information loss below:

$$\mathcal{L}_{\text{MI}} = \max_{T_\omega, G_\gamma} \hat{J}_{\omega}^{\text{JSD}}(Z; G_\gamma(\cdot, Z))$$

(6)

**Total loss.** Our method can be combined with any existing I2IT methods to improve diversity for them as long as they are built on cGANs. Thus, the final loss function for training can be formulated by adding our proposed mutual information loss to the original losses of the existing method:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{ori}} + \lambda_{\text{MI}} \mathcal{L}_{\text{MI}}$$

(7)

where \(\mathcal{L}_{\text{ori}}\) is the original losses and \(\lambda_{\text{MI}}\) is the weight that controls the importance of our mutual information loss.

4. Experiments

4.1. Baselines and compared methods

We evaluate our method by building it on pix2pix [25] and GcGAN [17] under paired and unpaired settings respectively. Therefore, the baselines are naively adding noise to pix2pix and GcGAN and we call them as SEGAN w/o MI. Under a paired setting, we also compare our method (SEGAN) with two of the state-of-the-art methods: BicycleGAN [65] and MSGAN [38]. Under an unpaired setting, we compare ours with some state-of-the-art multimodal unsupervised I2IT methods, e.g., MUNIT [24], DRIT [33], and DRIT++ [34].

4.2. Datasets

Under a paired setting, we evaluate on Google maps→satellite (Maps) [25] and labels→images (Facades) [11]. Under an unpaired setting, we perform experiments on a shape-invariant dataset: Yosemite winter→summer [64] and a shape-variant dataset: cat→dog [33].

4.3. Metrics

For quantitative evaluation, we mainly use four metrics: FID [22], NDB [49], JSD [49], and LPIPS [61].

**FID.** FID measures the quality of generated images by calculating the distance between the model distribution and the real one through deep features extracted by Inception network [32]. Lower FID values indicate higher quality.

**NDB and JSD.** NDB and JSD [49] are two bin-based metrics. The training data is first clustered by K-means into different bins which can be viewed as modes of the real data.
distribution. Then each generated sample is assigned to the bin of its nearest neighbor. Two-sample test is performed on each bin and then the number of statistically-different bins (NDB) is reported. The Jensen-Shannon Divergence (JSD) between the training data’s bins distribution and the generated data’s bins distribution is also reported. For both two metrics, lower values indicate higher diversity.

**LPIPS.** LPIPS [61] measures the averaged feature distances between generated samples conditioned on the same input image. Higher LPIPS score indicates better diversity among the generated images.

### 4.4. Implementation details

We adopt the original non-saturation GAN loss [20] for training. As our proposed neural estimator needs a relatively large batch size to stabilize the training and reduce variance in estimation, we use a batch size of 32 in our experiments. After a hyperparameter search on $\lambda_{\text{MI}}$ in preliminary experiments, we find setting it as 3 is the best and consistently set $\lambda_{\text{MI}} = 3$ in all our experiments. The statistics network is a Convolutional Neural Network (CNN) followed by a few fully-connected layers. The choice of sampling strategy is important to make our algorithm work. As suggested in [23], we exclude the positive samples from the product of marginals. For more details, please refer to the supplementary materials.

### 4.5. Mutual information maximization

Figure 5 shows the change of the estimate of MI by our JSD MI estimator during training on the Facades dataset. In the beginning, as $Z$ does not play a role in producing diverse results, the statistics network can not tell the positive samples apart from the negative samples, and thus it makes a random guess on them, resulting in a quantity of $\log 0.5 + \log 0.5 \approx -1.386$ (see Equation 5). And as the training proceeds, the estimate of the MI is maximized to 0, which means the statistics network can faithfully discriminate the positive samples from negative samples.

### 4.6. Paired image-to-image translation

We build our method on pix2pix [25] under a paired I2I setting. For a fair comparison, all methods use the same network architecture as in BicycleGAN [65]. We set the weight of L1 loss as 3 in our method. SEGAN consistently improves on all metrics over the baseline method as shown in Table 1. Note that SEGAN w/o MI has better FIDs than BicycleGAN and MSGAN [38], probably due to the relatively large batch size we used. We also tried using the same batch size for training BicycleGAN and MSGAN but obtained no performance gains. Compared with the state-of-the-art methods, our method’s diversity outper-
forms BicycleGAN and is comparable to MSGAN (as measured by NDB, JSD, and LPIPS) while with a higher quality (as measured by FID). We can also observe that MSGAN sometimes produces images with artifacts and distortions as shown in Figure 3, which may be caused by the objective function of MSGAN that simply maximizes the pixel difference between output images. More qualitative results can be found in supplementary materials.

4.7. Unpaired image-to-image translation

Under an unpaired setting, we choose a one-sided unpaired I2IT method GeGAN [17] as the baseline (theoretically our method can also be combined with DistanceGAN [6] or CUT [46]), resulting in a much simpler and fast-training framework compared with methods like MUNIT [24], DRIT [33], and DRIT++ [34] (see Figure 2). For simplicity, we use a U-net generator and a multi-scale discriminator as in BicycleGAN [65]. The U-net generator can also help preserve the content as its skip-connections propagate the shape information directly from input to output. We set the weight of geometry-consistency (GC) loss as 20. We find that GC loss is useful for shape-invariant datasets like Yosemite winter→summer, but may degrade the quality for shape-variant datasets like cat→dog. So we omit it when trained on cat→dog and find that the U-net generator architecture is sufficient for preserving the input image’s pose.

Figure 4 and Table 2 show different methods’ qualitative and quantitative results on Yosemite winter→summer and cat→dog datasets. Our method surpasses the baseline method on diversity without loss of quality. While with a much simpler network architecture and a smaller training budget than the state-of-the-art methods, e.g., MUNIT and DRIT++, our method also beat them with a noticeable margin, verifying the robustness of our method to improve diversity without loss of quality for I2IT.

Our method can also achieve disentanglement between the source domain content and the target domain style for free. We produce synchronized results using the same code for each style on the Yosemite winter→summer dataset. In Figure 6, it can be seen that each latent code represents a

Table 1. Quantitative results of different methods on the Facades and the Maps datasets under a paired setting.

| Dataset   | Facades          | Maps           |
|-----------|------------------|----------------|
|           | SEGAN w/o MI     | SEGAN          | BicycleGAN [65] | MSGAN [38] |
| FID ↓     | 89.14 ± 0.99     | **78.43 ± 1.15** | 98.85 ± 1.21 | 92.84 ± 1.00 |
| NDB ↓     | 14.40 ± 0.65     | **11.60 ± 0.80** | 13.80 ± 0.45 | 12.40 ± 0.55 |
| JSD ↓     | 0.068 ± 0.003    | **0.036 ± 0.005** | 0.058 ± 0.004 | 0.038 ± 0.0011 |
| LPIPS ↑   | 0.1038 ± 0.0015  | **0.1897 ± 0.0015** | 0.1413 ± 0.0005 | 0.1894 ± 0.0011 |

Table 2. Quantitative results of the Yosemite winter→summer and the cat→dog datasets under an unpaired setting.

| Dataset       | Winter → Summer | Cat → Dog |
|---------------|-----------------|-----------|
|               | SEGAN w/o MI | SEGAN | MUNIT [24] | DRIT [33] | DRIT++ [34] | SEGAN w/o MI | SEGAN | MUNIT [24] | DRIT [33] | DRIT++ [34] |
| FID ↓         | 50.05 ± 0.64   | **40.72 ± 0.82** | 57.09 ± 0.37 | 41.34 ± 0.20 | 41.02 ± 0.24 |
| NDB ↓         | 10.33 ± 0.85   | **9.15 ± 0.67** | 9.53 ± 0.64 | 9.38 ± 0.74 | 9.22 ± 0.97 |
| JSD ↓         | 0.302 ± 0.052  | **0.210 ± 0.070** | 0.293 ± 0.062 | 0.304 ± 0.075 | 0.222 ± 0.070 |
| LPIPS ↑       | 0.1032 ± 0.0007 | **0.1381 ± 0.0004** | 0.1136 ± 0.0008 | 0.0965 ± 0.0004 | 0.1183 ± 0.0007 |

| Dataset       | Winter → Summer | Cat → Dog |
|---------------|-----------------|-----------|
|               | SEGAN w/o MI | SEGAN | MUNIT [24] | DRIT [33] | DRIT++ [34] | SEGAN w/o MI | SEGAN | MUNIT [24] | DRIT [33] | DRIT++ [34] |
| FID ↓         | 28.86 ± 0.35   | **17.20 ± 0.22** | 22.13 ± 0.71 | 24.31 ± 0.33 | 17.25 ± 0.65 |
| NDB ↓         | 9.70 ± 0.51    | **7.52 ± 1.35** | 8.21 ± 1.17 | 8.16 ± 1.60 | 7.57 ± 1.25 |
| JSD ↓         | 0.144 ± 0.030  | **0.037 ± 0.023** | 0.132 ± 0.066 | 0.075 ± 0.046 | 0.041 ± 0.014 |
| LPIPS ↑       | 0.231 ± 0.002  | **0.282 ± 0.002** | 0.244 ± 0.002 | 0.245 ± 0.002 | 0.280 ± 0.002 |
uniform style regardless of the input image. In addition, we perform linear interpolation between two given latent codes to show the generalization of our method to capture the conditional distribution. In Figure 7, the interpolation reflects smooth changes in semantic level, e.g., the daylight and the tongue pattern changes gradually with the variations of the latent codes. More qualitative results can be found in supplementary materials.

5. Conclusions and discussions

We have presented a novel method to encourage diversity for image-to-image translation by adopting a deep neural estimator to estimate and maximize the mutual information between the latent code and the generated image in cGANs. A simple network enhancement to cGANs is proved to be sufficient for using our proposed loss. Our method can also disentangle target domain style from the source domain content for free. Extensive qualitative and quantitative evaluations demonstrate the effectiveness of our method to improve diversity without loss of quality.

Furthermore, we would like to discuss the wide application domains that may benefit from our method, e.g., other conditional image synthesis tasks that desire diversity (like image inpainting, text-to-image synthesis, and style transfer), disentangling latent factors in a conditional generative model setting, and encouraging diversity in conditional image generation (like on ImageNet [12]).
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A. On the Latent Code Reconstruction Loss and the Variational Mutual Information Maximization

We show that the latent code reconstruction loss is closely related to the variational mutual information maximization [3, 9]. The latent code reconstruction loss is defined as follows:

\[
\mathcal{L}_R = \mathbb{E}_z \left[ \| E(G(\cdot, z)) - z \|_1 \right]
\]  

where \( z \) is the latent code, \( \hat{b} = G(\cdot, z) \) is the generated image, and \( G(\cdot, z) \) and \( E(\cdot) \) are the generator’s and the encoder’s function respectively.

From [9], the variational lower bound on the mutual information between the latent code \( Z \) and the output image \( \hat{B} \) can be derived below:

\[
\mathcal{I}(Z; \hat{B}) = H(Z) - H(Z|\hat{B})
\]

\[
= \mathbb{E}_{b \sim G(\cdot, z)} [\mathbb{E}_{z \sim p(z|b)} [\log p(z|\hat{b})]] + H(Z)
\]

\[
\geq \mathbb{E}_{b \sim G(\cdot, z), z \sim p(z)} [\log q(z|\hat{b})] + H(Z)
\]

\[
\geq \mathbb{E}_{b \sim G(\cdot, z), z \sim p(z)} [\log q(z|\hat{b})] + H(Z)
\]

\[
(9)
\]

where \( p(z|\hat{b}) \) and \( q(z|\hat{b}) \) are the true posterior distribution and the variational posterior distribution respectively. If we choose the variational distribution \( q(z|\hat{b}) \) as a Laplace parameterized by the encoder, then we have the latent code reconstruction loss as shown in Equation 8.

B. On the Jensen-Shannon Divergence and Mutual Information

Although it has been pointed in [23], for self-containment of the paper, we also show the relation between the Jensen-Shannon Divergence (JSD) between the joint and the product of marginals and the Mutual Information (MI). They are related by Pointwise Mutual Information (PMI)

\[
\text{PMI}(x; y) \equiv \log \frac{p(x, y)}{p(x)p(y)} = \log \frac{p(y|x)}{p(y)}
\]  

\[
\text{MI} \equiv \mathcal{I}(X; Y) = D_{\text{KL}}[p(x, y)||p(x)p(y)]
\]

\[
= \mathbb{E}_{p(x, y)} \left[ \log \frac{p(x, y)}{p(x)p(y)} \right]
\]  

\[
= \mathbb{E}_{p(x, y)} \left[ \text{PMI}(x; y) \right]
\]  

\[
(10)
\]

\[
(11)
\]

\[
(12)
\]

Derivation from [23], we have

\[
\text{JSD} [p(x, y) || p(x)p(y)] \propto \mathbb{E}_{p(x, y)} \left[ \log \frac{p(y|x)}{p(y)} \right]
\]

\[
(12)
\]

The quantity inside the expectation of Equation 12 is a concave, monotonically increasing function of the ratio \( \frac{p(y|x)}{p(y)} \), which is \( e^{\text{PMI}(x,y)} \). Therefore, positive correlation exists between the MI and the JSD between the joint and the product of marginals.

C. Network Architecture of the Statistics Network

In this section, we show the network architecture of the statistics network. The latent code is replicated to form a feature map with \(|z|\) channels and the proper spatial size to concatenate with every convolutional layer’s input. The latent code is also concatenated with the last convolution layer’s output to feed into the first fully-connected layer. The network architecture is shown in Table 3.

D. Sampling Strategies

We tried different sampling strategies for obtaining negative samples. A batchwise sampling strategy which takes all the non-corresponding pairs within the batch as the negative samples would easily run out of GPU memory. While the sampling strategy which obtains non-corresponding samples by resampling from one of the marginal distributions performs badly in our experiments. Instead, following [23], we exclude the positive samples from the negative samples and resample negative samples with the same size as the positive samples by generating another batch of images and sample non-corresponding latent codes for them. We find such a sampling strategy is stable and memory-efficient in our experiments.

E. Evaluation Details

For the FID, similar to [38], we randomly generate 50 images per input image in the test set. We randomly choose 100 input images and their corresponding generated images to form 5,000 generated samples. We use the 5,000 generated samples and all samples in training set to compute FID.

For the LPIPS distance, we follow the settings from [65]. We use 100 input images from the test set and sample 19 pairs of translated images for each input image. Then we average over them.

For NDB and JSD, we follow the suggestion of [49] and make sure there are at least 10 training samples for each.
cluster. And similar to [38], we employ all the training samples for clustering and choose $K = 20$ bins for the Facades dataset, and $K = 50$ for other datasets.

**F. More Qualitative Results under a Paired Setting**

Here we display more qualitative results of our method on the Facades and the Maps datasets under a paired image-to-image translation setting in Figure 8 and Figure 9 respectively. All the translated samples are produced by synchronized latent codes on different input images.

**G. More Qualitative Results under an Unpaired Setting**

More qualitative results of our method on the Yosemite winter $\rightarrow$ summer and the cat $\rightarrow$ dog datasets under an unpaired setting are shown in Figure 10 and Figure 11 respectively. All the translated samples are produced by synchronized latent codes on different input images.
| Statistics network | 
|------------------|
| **Input image** $a \in \mathbb{R}^{256 \times 256 \times 3}$ & **Latent code** $z \in \mathbb{R}^8$ |
| layer | input size | output size | non-linearity |
| 4×4 conv. stride 2. | 3+8. | 32. | ELU. |
| 4×4 conv. stride 2. | 32+8. | 64. | ELU. |
| 4×4 conv. stride 2. | 64+8. | 128. | ELU. |
| 4×4 conv. stride 2. | 128+8. | 256. | ELU. |
| 4×4 conv. stride 2. | 256+8. | 512. | ELU. |
| 4×4 conv. stride 2. | 512+8. | 512. | ELU. |
| FC. | $4 \times 4 \times 512 + 8.$ | 512. | ELU. |
| FC. | 512. | 1. | none. |

Table 3. The statistics network’s architecture.

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**Figure 8.** More qualitative results of our method on the Facades dataset under a paired setting.
Figure 9. More qualitative results of our method on the Maps dataset under a paired setting.

Figure 10. More qualitative results of our method on the Yosemite winter→summer dataset under an unpaired setting.
Translated samples (synchronized latent codes)

Figure 11. More qualitative results of our method on the cat–dog dataset under an unpaired setting.