In-Domain GAN Inversion for Real Image Editing

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Abstract. Recent work has shown that a variety of controllable semantics emerges in the latent space of the Generative Adversarial Networks (GANs) when being trained to synthesize images. However, it is difficult to use these learned semantics for real image editing. A common practice of feeding a real image to a trained GAN generator is to invert it back to a latent code. However, we find that existing inversion methods typically focus on reconstructing the target image by pixel values yet fail to land the inverted code in the semantic domain of the original latent space. As a result, the reconstructed image cannot well support semantic editing through varying the latent code. To solve this problem, we propose an in-domain GAN inversion approach, which not only faithfully reconstructs the input image but also ensures the inverted code to be semantically meaningful for editing. We first learn a novel domain-guided encoder to project any given image to the native latent space of GANs. We then propose a domain-regularized optimization by involving the encoder as a regularizer to fine-tune the code produced by the encoder, which better recovers the target image. Extensive experiments suggest that our inversion method achieves satisfying real image reconstruction and more importantly facilitates various image editing tasks, such as image interpolation and semantic manipulation, significantly outperforming start-of-the-arts.¹

Keywords: GAN inversion, image editing

1 Introduction

Generative Adversarial Networks (GANs) [11] are formulated as a two-player game, where a discriminator aims at differentiating synthesized data from real data while a generator takes a randomly sampled latent code as the input to produce a realistic image to fool the discriminator. After the training converges, the generator has learned to map a random vector sampled from the latent distribution to a realistic image as the output. Recent work [10,14,25] has shown

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¹ Code and models are available at this link.
that GANs spontaneously learn to encode rich semantics inside the latent space and varying the latent code leads to the manipulation of the corresponding attributes occurred in the output image. However, it remains difficult to apply such manipulation capability to real images since GANs lack the ability of taking a particular image as the input to infer its latent code.

Many attempts have been made to reverse the generation process by mapping the image space back to the latent space, which is known as GAN inversion. They either learn an extra encoder beyond the GAN [20,31,3] or directly optimize the latent code for an individual image [19,21,7,12]. However the existing methods mainly focus on reconstructing the pixel values of the input image, leaving some important open questions about the property of the inverted code. For example, does the inverted code lie in the original latent space of GANs? Can the inverted code semantically represent the corresponding image? Does the inverted code support image editing, *e.g.*, image interpolation and semantic manipulation, by reusing the knowledge learned by GANs? Can we use a well-trained GAN to invert any image? Answering these questions not only deepens our understanding of the internal mechanism in GANs, but is also able to unleash the pre-trained GANs for the versatile image editing capability.

In this work, we show that a good GAN inversion method should not only reconstruct the target image at pixel level, but also align the inverted code with the *semantic* knowledge encoded in the latent space. We call the codes...
that are semantically meaningful as *in-domain* codes, since they underlie the semantic domain learned by GANs. We also find that the in-domain codes can better support image editing from the latent space by reusing the rich knowledge emerging in the GAN models. To this end, we propose an *in-domain* GAN inversion approach to recover the input image at both the pixel level and the semantic level. Specifically, we first train a novel *domain-guided* encoder to map the image space to the latent space such that all codes produced by the encoder are in-domain. We then perform instance-level *domain-regularized* optimization by involving the encoder as a regularizer to better reconstruct the pixel values without affecting the semantic property of the resulting inverted code. We summarize our contributions as follows:

- We analyze an important issue in GAN inversion task that the inverted code should go beyond merely recovering the per-pixel values of the input image by considering the semantic information.
- We propose an *in-domain* GAN inversion approach by first learning a *domain-guided* encoder and further use this encoder as a regularizer for *domain-regularized* optimization.
- We evaluate our method on the reconstruction and manipulation of human faces and scenes. Qualitative and Quantitative results suggest that the proposed in-domain inversion can faithfully recover the target image from both the low-level pixels and the high-level semantics, facilitating real image editing as shown in Fig.1.

1.1 Related Work

**Generative Adversarial Networks (GANs).** By learning the distribution of real images via adversarial training, GANs [11] have advanced image synthesis in recent years. Many variants of GANs are proposed to improve the synthesis quality [22,29], training stability [1,13,5], as well as image resolution [16,6,17]. Instead of memorizing the training dataset, GANs are capable of producing unseen data with randomly sampled latent codes [11,1,17]. Recently, GANs are shown to spontaneously learn semantics inside the latent space, which can be further used to control the generation process. Goetschalckx et al. [10] explored how to make the synthesis from GANs more memorable, Jahanian et al. [14] achieved camera movements and color changes by shifting the latent distribution, Shen et al. [25] interpreted the latent space of GANs for semantic face editing, and Yang et al. [27] observed that hierarchical semantics emerge from the layer-wise latent codes of GANs for scene synthesis. However, due to the lack of inference capability in GANs, it remains difficult to apply the rich semantics encoded in the latent space to editing real images.

**GAN Inversion.** To better apply well-trained GANs to real-world applications, GAN inversion enables real image editing from the latent space [31,23,2]. Given a fixed GAN model, GAN inversion aims at finding the most accurate latent code to recover the input image. Existing inversion approaches typically fall into two types. One is learning-based, which first synthesizes a collection of images
with randomly sampled latent codes and then uses the images and codes as inputs and supervisions respectively to train a deterministic model [23,31]. The other is optimization-based, which deals with a single instance at one time by directly optimizing the latent code to minimize the pixel-wise reconstruction loss [19,7,21,24]. Some work combines these two ideas by using the encoder to generate an initialization for optimization [4,3]. There are also some models that take invertibility into account at the training stage by designing new architectures [9,8,30,18], but the synthesis quality is far behind that of uninvertible GANs [6,17].

One important issue omitted by the previous inversion methods is that they merely focus on reconstructing the target image at the pixel level without considering the alignment of semantic information in the inverted code. If the code cannot align with the semantic domain of the latent space, even being able to recover the per-pixel values of the input image, it would still fail to reuse the knowledge learned by GANs for semantic editing. Therefore, we argue that only using the pixel-wise reconstruction loss as the metric to evaluate a GAN inversion approach is not proper enough. Instead, we deeply study the property of the inverted code from the semantic level and propose the in-domain GAN inversion that well supports real image editing.

2 In-Domain GAN Inversion

As discussed above, when inverting a GAN model, besides recovering the input image by pixel values, we also care about whether the inverted code is semantically meaningful. Here, the semantics corresponds to the emergent knowledge that the generator of GAN has learned from the observed data [10,14,25,27]. For this purpose, we propose to first train a domain-guided encoder and then use this encoder as a regularizer for a further domain-regularized optimization, as shown in Fig.2.

Problem Statement Before going into details, we briefly introduce the problem setting with some basic notations. A GAN model typically consists of two components, i.e., a generator $G(\cdot) : \mathcal{Z} \rightarrow \mathcal{X}$ to synthesize high-quality images, and a discriminator $D(\cdot)$ to distinguish real from synthesized data. GAN inversion studies the reverse mapping compared to $G(\cdot)$, which is to find the best latent code $z^{\text{inv}}$ to recover a given real image $x^{\text{real}}$. As pointed out by prior work [10,14,25], GANs spontaneously learn to encode rich semantics, denoted as $S$, inside the latent space. We would like $z^{\text{inv}}$ to also align with the prior knowledge $S$ in the pre-trained GAN model.

2.1 Domain-Guided Encoder

Training an encoder is commonly used for GAN inversion problem [23,31,4,3] considering its fast inference speed. However, existing methods simply learn a deterministic model with no regard to whether the code produced by the encoder is consistent with the semantic knowledge learned by $G(\cdot)$. As shown on the top
In-Domain GAN Inversion for Real Image Editing

![Diagram of GAN inversion](image)

Fig. 2. (a) The comparison between the training of conventional encoder and domain-guided encoder for GAN inversion. Model blocks in blue are trainable and red dashed arrows indicate the supervisions. Instead of being trained with synthesized data to recover the latent code, our domain-guided encoder is trained with the objective to recover the real images. The fixed generator is involved to make sure the codes produced by the encoder lie in the native latent space of the generator and stay semantically meaningful. (b) The comparison between the conventional optimization and our domain-regularized optimization. The well-trained domain-guided encoder is included as a regularizer to land the latent code in the semantic domain during the optimization process.

of Fig.2 (a), a collection of latent codes $z^{sam}$ are randomly sampled from $Z$ and fed into $G(\cdot)$ to get the corresponding synthesis $x^{syn}$. Then, the encoder $E(\cdot)$ takes $x^{syn}$ and $z^{sam}$ as inputs and supervisions respectively and is trained to reconstruct the latent codes with

$$\min_{\Theta_E} \mathcal{L}_E = ||z^{sam} - E(G(z^{sam}))||_2,$$  

(1)

where $|| \cdot ||_2$ denotes the $l_2$ distance and $\Theta_E$ represents the parameters of the encoder $E(\cdot)$. We argue that the supervision by only reconstructing $z^{sam}$ is not powerful enough to train an accurate encoder. Also, the generator is actually omitted and cannot provide its domain knowledge to guide the training of encoder, since the gradients from $G(\cdot)$ are not taken into account at all.

To solve these problems, we propose to train a domain-guided encoder, which is illustrated in the bottom row of Fig.2 (a). There are three main differences compared to the conventional encoder: (i) The output of the encoder is fed into the generator to reconstruct the input image such that the objective function comes from the image space instead of latent space. This involves semantic knowledge from the generator in training and provides more informative and accurate supervision. The output code is therefore guaranteed to align with the semantic domain of the generator. (ii) Instead of being trained with synthesized images, the domain-guided encoder is trained with real images. This makes our encoder more applicable to real image applications. (iii) To make sure the reconstructed image is realistic enough, we employ the discriminator to compete with the encoder. In this way, we can acquire as much information as possible from the GAN model (i.e., both two components of GAN are used), and use the adversarial training manner to further ensure that the output code can
semantically fit the generator as much as possible. We also introduce perceptual loss [15] by using the feature extracted by VGG [26]. Hence, the training process can be formulated as

\[
\min_{\Theta} L_E = ||x_{real} - G(E(x_{real}))||_2 + \lambda_1 ||F(x_{real}) - F(G(E(x_{real})))||_2 - \lambda_2 \mathbb{E}_{x_{real} \sim P_{data}}[D(G(E(x_{real})))],
\]

(2)

\[
\min_{\Theta} L_D = \mathbb{E}_{x_{real} \sim P_{data}}[D(G(E(x_{real})))] - \mathbb{E}_{x_{real} \sim P_{data}}[D(x_{real})] + \frac{\gamma}{2} \mathbb{E}_{x_{real} \sim P_{data}}[||\nabla_x D(x_{real})||_2^2],
\]

(3)

where \(P_{data}\) denotes the probability distribution of the real data and \(\gamma\) is the hyper-parameter for the gradient regularization. \(\lambda_1\) and \(\lambda_2\) are loss weights to balance different energy functions. \(F(\cdot)\) denotes the VGG feature extraction model.

### 2.2 Domain-Regularized Optimization

Unlike the generation process of GANs which learns a mapping at the distribution level, i.e., from latent distribution to real image distribution, GAN inversion is more like an instance-level task which is to best reconstruct a given individual image. From this point of view, it is hard to learn a perfect reverse mapping with an encoder alone due to its limited representation capability. Therefore, even though the inverted code from the proposed domain-guided encoder can well reconstruct the input image based on the pre-trained generator and ensure the code itself to be semantically meaningful, we still need to refine the code to make it better fit the target individual image at the pixel values.

Previous methods [7,21,24] propose to gradient descent algorithm to optimize the code. The top row of Fig.2 (b) illustrates the optimization process where the latent code is optimized “freely” based on the generator only. It may very likely produce an out-of-domain inversion since there are no constraints on the latent code at all. Relying on our domain-guided encoder, we design a domain-regularized optimization with two improvements, as shown at the bottom of Fig.2 (b): (i) We use the output of the domain-guided encoder as an ideal starting point which avoids the code from getting stuck at a local minimum and also significantly shortens the optimization process. (ii) We include the domain-guided encoder as a regularizer to preserve the latent code within the semantic domain of the generator. To summarize, the objective function for optimization is

\[
z^{inv} = \arg \min_z ||x - G(z)||_2 + \lambda_3 ||F(x) - F(G(z))||_2 + \lambda_4 ||z - E(G(z))||_2,
\]

(4)

where \(x\) is the target image to invert. \(\lambda_3\) and \(\lambda_4\) are loss weights to balance different terms.
3 Experiments

In this section, we experimentally show the superiority of the proposed in-domain GAN inversion over existing methods in terms of preserving semantic information, inversion quality, inference speed, as well as real image editing.

3.1 Experimental Settings

We conduct experiments on FFHQ dataset [17], which contains 70,000 high-quality face images, and LSUN dataset [28], which consists of images from 10 different scene categories. Only results on the tower category are shown in the main paper. More results on other datasets and the continuous change can be found in the Appendix. The GANs to invert are pre-trained following StyleGAN [17] by optimizing the minimax objective between the generator and the discriminator

\[ \min_{G} \max_{D} \mathbb{E}_{x \sim P_{data}(x)} \log D(x) + \mathbb{E}_{z \sim P_{noise}(z)} \log (1 - D(G(z))) \]

During the encoder’s training process, the generator is fixed and we only update the encoder and discriminator according to Eq. (2) and Eq. (3), respectively. As for the perceptual loss in Eq. (2), we take conv4_3 as the VGG [26] output. Loss weights are set as \( \lambda_1 = 5e^{-5}, \lambda_2 = 0.1, \) and \( \gamma = 10. \) As for the domain-regularized optimization, we set \( \lambda_3 = 5e^{-5} \) and \( \lambda_4 = 2. \)

3.2 Semantic Analysis of the Inverted Codes

A good GAN inversion should not only reconstruct the target image from per-pixel values but also align the inverted code with the semantic knowledge GANs have encoded in the latent space. As pointed out by prior work [17,25], the latent space of GANs is linearly separable in terms of semantics. In particular, for a binary attribute (e.g., gender which consists of male and female), it is possible to find a boundary in the latent space such that all points from the same side correspond to the synthesis with the same attribute. We use this property to evaluate the alignment between the inverted codes and the latent semantics.

We collect 7,000 real face images, and use off-the-shelf attribute classifiers to predict age (young v.s. old), gender (female v.s. male), eyeglasses (absence v.s. presence).
Fig. 4. Qualitative comparison on image reconstruction with different GAN inversion methods. (a) Input image. (b) Conventional encoder [31]. (c) Image2StyleGAN [24]. (d) Our proposed domain-guided encoder. (e) Our proposed in-domain inversion.

presence), and pose (left v.s. right). These predictions are considered as ground-truth. Then, we use the state-of-the-art GAN inversion method, Image2StyleGAN [24], and our proposed in-domain GAN inversion to invert these images back to the latent space of a fixed StyleGAN model trained on FFHQ dataset [17]. InterFaceGAN [25] is used to search the semantic boundaries for the aforementioned attributes in the latent space. Then, we use these boundaries to evaluate the attribute classification performance using the inverted codes from Image2StyleGAN and our approach. Fig.3 shows the precision-recall curves on various semantics. We can easily tell that the codes inverted by our method are more semantically meaningful, significantly outperforming Image2StyleGAN. This quantitatively demonstrates the effectiveness of our proposed in-domain inversion for preserving the semantics property of the inverted code.

3.3 Inversion Quality and Speed

As discussed above, our method can produce in-domain codes for GAN inversion task. In this part, we would like to verify that the improvement of our approach
Table 1. Quantitative comparison on image reconstruction with different inversion methods. For each model, face and tower, we invert 500 images for evaluation. ↓ means lower number is better.

| Method                     | Speed | FID ↓ | SWD ↓ | MSE ↓ | FID ↓ | SWD ↓ | MSE ↓ |
|----------------------------|-------|-------|-------|-------|-------|-------|-------|
| Traditional Encoder [31]   | 0.008s| 88.48 | 100.5 | 0.507 | 73.02 | 69.19 | 0.455 |
| MSE-based Optimization [24]| 290s  | 58.04 | 29.19 | 0.026 | 69.16 | 55.35 | 0.068 |
| Domain-guided Encoder (Ours)| 0.017s| 52.85 | 13.02 | 0.062 | 46.81 | 27.13 | 0.071 |
| In-domain Inversion (Ours) | 142s  | 42.64 | 13.44 | 0.030 | 44.77 | 26.44 | 0.052 |

from the semantic aspect does not affect its performance on the traditional evaluation metric, i.e., image reconstruction quality. Fig.4 shows the qualitative comparison between different inversion methods including training traditional encoder [31], MSE-based optimization [24], as well as our proposed domain-guided encoder and the in-domain inversion. Comparison between Fig.4(b) and Fig.4(d) shows the superiority of our domain-guided encoder in learning a better mapping from the image space to the latent space. Also, our full algorithm (Fig.4(e)) shows the best reconstruction quality. Tab.1 gives the quantitative comparison results, where in-domain inversion surpasses other competitors from all metrics. The inference speed is also shown in Tab.1. The domain-guided encoder can produce much better reconstruction results compared to the traditional encoder with comparable inference time. It also provides a better initialization for further domain-regularized optimization, leading to a significantly faster speed than the state-of-the-art optimization-based method [24].

3.4 Real Image Editing

In this section, we evaluate our in-domain GAN inversion approach on real image editing tasks, including image interpolation and semantic image manipulation.

**Interpolation.** Image interpolation aims at semantically interpolating two images, which is suitable for investigating the semantics contained in the inverted codes. In other words, for a good inversion, the semantic should vary continuously when interpolating two inverted codes. We would expect the images generated from those interpolated codes are still meaningful.

Fig.5 shows the comparison results on the image interpolation task between Image2StyleGAN [24] and our proposed in-domain inversion approach. We do experiments on both face and tower datasets to more comprehensively analyze the semantic property. For the face dataset, our method achieves much smoother interpolated faces than Image2StyleGAN. For example, in the first two rows of Fig.5, eyeglasses are distorted during the interpolation process with Image2StyleGAN and the change from female to male is unnatural. By contrast, our inverted codes lead to a more smooth interpolation. As for the second example in Fig.5, our method better interpolates the hair and the mouth, outperforming Image2StyleGAN. For tower images, which are much more diverse than faces, the interpolation results from Image2StyleGAN exhibit artifacts and blurriness in the interpolated images. However, our in-domain inversion shows satisfying results. One noticeable thing is that during interpolating between two towers
with different types (e.g., one with one spire and the other with multiple spires), the interpolated images using our approach still make sense to the tower category (i.e., all interpolations are still high-quality towers). This demonstrates the in-domain property of our GAN inversion algorithm. This can also be concluded by the quantitative evaluation shown in Tab.2.

**Manipulation.** Image manipulation is another way to examine whether the embedded latent codes align with the semantic knowledge learned by GANs. As pointed out by prior work [25,27], GANs can learn rich semantics in the latent space, enabling image manipulation by linearly transforming the latent
Table 2. Quantitative comparison on image interpolation and manipulation between Image2StyleGAN [24] and our in-domain inversion. ↓ means lower number is better.

| Method                        | Face FID | Face SWD | Tower FID | Tower SWD |
|-------------------------------|----------|----------|-----------|-----------|
| MSE-based Optimization [24]   | 112.09   | 38.20    | 121.38    | 67.75     |
| In-domain Inversion (Ours)    | 91.18    | 33.91    | 57.22     | 28.24     |

representation. This can be formulated as

\[ x^{\text{edit}} = G(z^{\text{inv}} + \alpha n), \]  

where \( n \) is the normal direction corresponding to a particular semantic in the latent space, and \( \alpha \) is the step for manipulation. In other words, if a latent code is moved towards this direction, the semantics contained in the output image should vary accordingly. We follow [25] to search the semantic direction \( n \).

Fig.6 and Fig.7 show the comparison results of manipulating faces and towers using Images2StyleGAN [24] and our in-domain GAN inversion. We can see that our method shows more satisfying manipulation results than Image2StyleGAN. Taking face manipulation as an example, in the first sample (first row) of Fig.6, the hair of the actor is affected when adding eyeglasses using the inverted code from Image2StyleGAN. On the contrary, our in-domain inversion can preserve most other details when editing a particular facial attribute. In the second sample of Fig.6, the neck of the actress becomes blurred after manipulation with Image2StyleGAN. That is because it only focuses on the reconstruction of the per-pixel values yet omits the semantic information contained in the inverted codes. Instead, our in-domain inversion achieves more photo-realistic manipulation.

For tower manipulation, we observe from Fig.7 that our in-domain approach surpasses MSE-based optimization by both decreasing and increasing the semantic level. For example, when removing or adding clouds in the sky, Image2StyleGAN will blur the tower together with the sky, since it only recovers the image at pixel level regardless of the semantic meaning of the recovered objects. By contrast, our algorithm barely affects the tower itself when editing clouds, suggesting that our in-domain inversion can produce semantically meaningful latent codes for image reconstruction. Another interesting thing is that in the second sample (last row) of Fig.7, the red bus is ignored by our approach. That is because the bus object is out of the semantic domain of the tower synthesis model. Forcibly over-fitting the bus may influence the semantic property of the inverted code. We also include the quantitative evaluation on the manipulation task in Tab.2. We can tell that our in-domain inversion outperforms Image2StyleGAN from all evaluation metrics.

### 3.5 Ablation Study

In this part, we conduct an ablation study to analyze the proposed in-domain inversion. After the initial training of the encoder, we perform the domain-regularized optimization on each image to further improve the reconstruction...
Fig. 6. Comparison of two methods on semantic manipulation task with face synthesis model. Odd rows are the results obtained by Image2StyleGAN [24], while even rows show the results obtained using our in-domain inversion. For each instance, the first two columns represent the input and the reconstruction results after inversion, respectively. Last three columns show the results by editing various attributes.

quality. Different from the previous MSE-based optimization, we involve the learned domain-guided encoder as a regularizer to land the inverted code inside the semantic domain, as described in Eq. (4). Here, we study the role of the encoder in the optimization process by varying the weight $\lambda_4$ in Eq. (4). Fig. 8 shows the comparison between $\lambda_4 = 0, 2, 40$. We observe the trade-off between the image reconstruction quality and the manipulation quality. Larger $\lambda_4$ will bias the optimization towards the domain constraint such that the inverted codes are more semantically meaningful. Instead, the cost is that the target image cannot be ideally recovered for per-pixel values. In practice, we set $\lambda_4 = 2$.

4 Discussion and Conclusion

In this work, we explore the semantic property of the inverted codes in the GAN inversion task and propose a novel in-domain inversion method. To the best of our knowledge, this is the first attempt to invert a pre-trained GAN model explicitly considering the semantic knowledge encoded in the latent space. We show that
Fig. 7. Comparison of two methods on semantic manipulation task with the tower synthesis model. The odd rows are the results obtained by Image2StyleGAN [24], while the even rows show the results obtained using our in-domain inversion. For each instance, the first two columns represent the input and reconstruction results after inversion, respectively. The last four columns show the manipulation of two attributes, by either decreasing or increasing the semantic degree.

the code that simply recovers the pixel value of the target image is not sufficient to represent the image at the semantic level. For example, in Fig.9, we invert different types of image instances (i.e., face, cat face, and bedroom) with the face synthesis model. The last column shows the results from Image2StyleGAN [24] which recovers a cat or a bedroom with the domain knowledge learned to synthesis human faces. By contrast, the face outline can still be observed in the reconstructions using our in-domain inversion (third column). This demonstrates, from a different angle, the superiority of our approach in producing semantically meaningful codes. Taking inverting bedroom (third row) as an example, the bedroom image is outside the domain of the training data and the GAN model should not be able to learn the bedroom-related semantics. Accordingly, reusing the face knowledge to represent a bedroom is ill-defined. Even though we can always use more parameters to over-fit the pixel values of the bedroom, such over-fitting would fail to support semantic image manipulation. From this viewpoint, our in-domain inversion lands the inverted code inside the original domain to make it semantically meaningful. In other words, we aim at finding the most adequate code to recover the target image from both the pixel level and the semantic level. Such in-domain inversion significantly facilitates real image editing.
Fig. 8. Ablation study on the loss weight for the domain-regularized optimization. From top to bottom: original images, reconstructed images, and manipulation results (wearing eyeglasses). For each group of images, the weight $\lambda_4$ is set to be 0, 2, 40 for the domain-regularized optimization. When $\lambda_4$ equals to 0, it produces the best reconstructed results but relatively poor manipulation results. When $\lambda_4$ equals to 40, we get worse reconstruction but more satisfying manipulation.

Fig. 9. Results on inverting face, cat face, and bedroom using the same face synthesis model. From left to right: target images, reconstruction results with the outputs from the domain-guided encoder, reconstruction results with the proposed in-domain inversion, reconstruction results by directly optimizing the latent code w/o considering domain alignment [24].
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Appendix

A Overview

The appendix is organized as follows: In Sec.B, we show image reconstruction results using the model trained on LSUN bedroom dataset [28] and make a comparison with existing GAN inversion methods. In Sec.C and Sec.D, we show more results of image interpolation and image manipulation respectively to demonstrate that in-domain GAN inversion can not only well recover the pixel values of the input image, but also align the image with the rich semantics encoded in GAN’s latent space. Please also find the demo video for the continuous change. In Sec.E, we show style mixing results.

B Reconstruction

Image reconstruction is one of the most important metrics to evaluate a GAN inversion method. Besides the results on human faces and towers (outdoor scene) shown in the main submission, we also do experiments on bedrooms (indoor scene) and show comparison results between different methods in Fig.10. The GAN model is pre-trained on LSUN bedroom dataset [28] with StyleGAN structure [17]. We can tell that our proposed domain-guided encoder produces much better reconstructions than the conventional encoder [31]. The further domain-regularized optimization also surpasses the start-of-the-art optimization-based inversion method, Image2StyleGAN [24], with higher reconstruction quality.

C Interpolation

Although focused on by most previous work, image reconstruction at pixel level is not the only crux for GAN inversion. We argue that GAN inversion should not only find a proper latent code to recover the per-pixel values of the input image, but also align the inverted code with the semantic knowledge learn by GAN models, i.e., in-domain.

In this section, we use image interpolation to evaluate whether the inverted codes are semantically meaningful. Fig.11, Fig.12, and Fig.13 show the comparison results between Image2StyleGAN [24] and our in-domain inversion on faces, towers (outdoor scene), and bedrooms (indoor scene) respectively. We observe that the interpolations from Image2StyleGAN show unsatisfying artifacts and blurs, especially when the source and target images are with large discrepancy (e.g., the first and last sample in Fig.11). Meanwhile, some interpolations made by Image2StyleGAN are not semantically meaningful (e.g., interpolated images are no longer a tower any more in the last sample in Fig.12). That is because merely recovering the pixel values is not enough to reuse the knowledge learned by GANs for image interpolation from semantic level. On the contrary, our method makes sure that all interpolated samples are still with high quality and explanatory
Fig. 10. Qualitative comparison on image reconstruction with different GAN inversion methods. (a) Input image. (b) Conventional encoder [31]. (c) Image2StyleGAN [24]. (d) Our proposed domain-guided encoder. (e) Our proposed in-domain inversion.

semantics. We show more interpolation results in Fig.14 (face), Fig.15 (tower), and Fig.16 (bedroom). In Fig.14, we manage to interpolate male and female, wearing-eyeglasses person and no-eyeglasses person, or even painting and real person. In Fig.15, we interpolate one type of tower to various other types in a large diversity. Each individual interpolation is realistic enough for a “new type” of tower. In Fig.16, we can interpolate between bedrooms from different viewpoints. It is also noteworthy that windows and paintings on the wall can also be adequately interpolated using our method.

D Manipulation

Prior work has shown that a well-trained GAN model is able to encode interpretable semantics inside the latent space [25,14,27]. These learned semantics can be further used for real image manipulation together with GAN inversion. In this section, we compare our in-domain inversion with Image2StyleGAN [24] on the
semantic manipulation task. Results are shown in Fig.17 (face), Fig.18 (tower), and Fig.19 (bedroom). It turns out that we can achieve impressive semantic editing with respect to various attributes, significantly surpassing Image2StyleGAN which usually produces results with artifacts. That is because the code inverted by Image2StyleGAN is not aligned with the rich semantics encoded in the latent space. On the contrary, our proposed in-domain inversion is able to better reuse the semantic knowledge learned by GANs.

E Style Mixing

We also evaluate our approach on style mixing task, which aims at transferring the style of a style image to a content image. For this purpose, we invert both the style image and the content image to layer-wise latent codes. Then, we replace the codes at the last four layers of the content image with those from the style image. Fig.20 shows mixing results. We can tell that each mixture successfully inherits painting style from artistic face (first column) yet maintains most details from the content image (first row). This suggests that our in-domain inversion manages to convert input images to semantically meaningful latent codes.
Fig. 11. Qualitative comparison on face interpolation between Image2StyleGAN [24] (odd rows) and our in-domain inversion (even rows). Zoom in for details.
Fig. 12. Qualitative comparison on tower interpolation between Image2StyleGAN [24] (odd rows) and our *in-domain* inversion (even rows). Zoom in for details.
Fig. 13. Qualitative comparison on bedroom interpolation between Image2StyleGAN [24] (odd rows) and our in-domain inversion (even rows). Zoom in for details.
Fig. 14. Face interpolation results using our in-domain GAN inversion method. Zoom in for details.
Fig. 15. Tower interpolation results using our *in-domain* GAN inversion method. Zoom in for details.
Fig. 16. Bedroom interpolation results using our in-domain GAN inversion method. Zoom in for details.
Fig. 17. Comparison results on manipulating face images between Image2StyleGAN [24] and our in-domain GAN inversion.
Fig. 18. Comparison results on manipulating tower images between Image2StyleGAN [24] and our in-domain GAN inversion.
Fig. 19. Comparison results on manipulating bedroom images between Image2StyleGAN [24] and our *in-domain* GAN inversion.
Fig. 20. Style mixing results using our in-domain GAN inversion method. First column indicates style images and first row shows content images.