Cycle Encoding of a StyleGAN Encoder for Improved Reconstruction and Editability

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Figure 1: Image editing via our StyleGAN Inversion method. Our method enables high-quality reconstruction and editing for out-of-domain cartoon images.

ABSTRACT
GAN inversion aims to invert an input image into the latent space of a pre-trained GAN. Despite the recent advances in GAN inversion, there remain challenges to mitigate the tradeoff between distortion and editability, i.e. reconstructing the input image accurately and editing the inverted image with a small visual quality drop. The recently proposed pivotal tuning model makes significant progress towards reconstruction and editability, by using a two-step approach that first inverts the input image into a latent code, called pivot code, and then alters the generator so that the input image can be accurately mapped into the pivot code. Here, we show that both reconstruction and editability can be improved by a proper design of the pivot code. We present a simple yet effective method, named cycle encoding, for a high-quality pivot code.

The key idea of our method is to progressively train an encoder in varying spaces according to a cycle scheme: $W \rightarrow W_+ \rightarrow W$. This training methodology preserves the properties of both $W$ and $W_+$ spaces, i.e. high editability of $W$ and low distortion of $W_+$. To further decrease the distortion, we also propose to refine the pivot code with an optimization-based method, where a regularization term is introduced to reduce the degradation in editability. Qualitative and quantitative comparisons to several state-of-the-art methods demonstrate the superiority of our approach.

CCS CONCEPTS
• Computing methodologies → Reconstruction; Image manipulation.

KEYWORDS
GAN, GAN Inversion, Image Manipulation, Cycle Encoding

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In recent years, Generative Adversarial Networks (GANs) [18] have revolutionized unconditional image synthesis. State-of-the-art models, especially StyleGAN [25–27], can now generate realistic and visually appealing images in various domains. Furthermore, the intermediate latent space of StyleGAN, which is obtained from the input latent space through a mapping network, has been demonstrated as holding the disentanglement property. Based on this property, there emerges numerous models [1, 4, 12, 27, 36, 41–45, 49, 53, 58] for StyleGAN inversion and real image manipulation.

The target of StyleGAN inversion is to invert an input image into StyleGAN’s latent space. Typically, there are two types of latent spaces for StyleGAN inversion. One is StyleGAN’s native latent space $\mathcal{W}$ [3, 20, 23, 43, 47], where the style code is a 512-dimensional vector, and the other is an extended latent space $\mathcal{W}^+$ [1, 2, 41, 49, 62], where the style code consists of 18 different 512-dimensional vectors. It has been shown [6, 42, 49, 64] that the original space $\mathcal{W}$ is more editable while the extended space $\mathcal{W}^+$ is more expressive.

Recently, Roich et al. [42] propose Pivotal Tuning Inversion (PTI), a two-step approach that achieves significant progress towards reconstruction and editability in StyleGAN inversion. PTI first inverts the input image into a latent code, called pivot code, using an existing per-image optimization inversion method [27], and then slightly alters the generator so that the input image can be accurately mapped to the pivot code. It is revealed [42] that the quality of the pivot code is of crucial importance to the final inversion. To decrease the distortion of the pivot code, one simple method is to apply more training steps during the first step. However, we observe that the per-image optimization method can easily cause overfitting and thereby lead to poor editability.

Instead of using the per-image optimization method, we propose an encoder-based method, named cycle encoding, for a high-quality pivot code. The idea is to preserve the properties of both $\mathcal{W}$ and $\mathcal{W}^+$ spaces, by progressively training an encoder according to a cycle scheme: $\mathcal{W} \rightarrow \mathcal{W}^+ \rightarrow \mathcal{W}$. Specifically, the encoder starts the training in the $\mathcal{W}$ space, then gradually shifts the space from $\mathcal{W}$ to $\mathcal{W}^+$, and finally shifts it back from $\mathcal{W}^+$ to $\mathcal{W}$. We demonstrate that our method yields lower distortion, higher editability, and less inference time compared to PTI.

Recent evidence [19, 62] reveals that the hybrid method exploits the advantages of both encoder-based and optimization-based methods. Inspired by this, we also propose to refine the pivot code obtained in cycle encoding by applying an optimization-based method. Different from existing per-image optimization methods [1, 27] which optimize the latent code directly, our method refines the reconstruction by updating the encoder towards the input image so that an additional regularization term can be used to prevent overfitting. This refinement mechanism decreases the distortion at the cost of a subtle degradation in editability. Figure 2 shows the framework of our approach.

We compare our method with several state-of-the-art StyleGAN inversion methods through qualitative and quantitative evaluation, and demonstrate that our method outperforms these methods in both reconstruction and editability. In Figure 1, we show that our method enables high-quality reconstruction and editing even for out-of-domain cartoon images. Our code is available at https://github.com/xudongmao/CycleEncoding.

2 RELATED WORK

2.1 Latent Space Embedding

The high visual quality of GAN synthesis [9, 24, 26, 27] has prompted the researchers to study the latent space of GAN. One fundamental task is GAN inversion [33, 63], where a given image is inverted into the latent space of GAN. In general, GAN inversion methods can typically be divided into three categories [59]: (1) optimization-based methods [1, 2, 13, 14, 16, 22, 27, 30, 32, 40, 48] which directly optimize over the latent code, (2) encoder-based methods [5, 7, 10, 19, 28, 31, 34, 37, 38, 41, 49, 55, 56] which learn an encoder to map the input image into the latent space, and (3) hybrid methods [8, 35, 60, 62, 63] which combine the above two methods. Typically, optimization-based methods achieve lower distortion but take a substantially longer time for computation compared to encoder-based methods. Specifically, Abdal et al. [1] optimize the latent code in...
the extended \(W^+\) space and show that even out-of-domain images can be reconstructed. Karras et al. [27] perform the optimization over not only the latent code in the original \(W\) space but also the stochastic noise inputs of the StyleGAN generator. Richardson et al. [41] introduce a feature pyramid network architecture for the encoder which encodes the input image into the \(W^+\) space. Roich et al. [42] propose to first invert the input image into a latent code using the optimization-based method and then slightly alter the generator such that the input image can be accurately mapped to the latent code.

2.2 Latent Space Manipulation

To edit a real image, one may first invert the image into the latent space, and then perform the latent space manipulation techniques. Numerous methods have been proposed to find semantically meaningful directions in the latent space of GANs, where semantic directions can be determined through fully-supervised approaches [3, 17, 43, 50, 57, 65], self-supervised approaches [23, 39, 46, 47], or unsupervised approaches [11, 20, 29, 44, 51, 52, 54]. Specifically, Jahanian et al. [23] find semantic directions for camera motion and color transformation in a self-supervised manner. Shen et al. [43] use binary facial attribute labels to determine semantic directions. Härkönen et al. [20] show that using principal component analysis can identify meaningful semantic directions in an unsupervised manner.

2.3 Distortion-editability Tradeoff

The \(W^+\) space is superior in achieving low distortion because it is an enlarged space and thus more expressive. However, recent works [42, 49, 64] show that the \(W\) space obtains better editability than the \(W^+\) space, since StyleGAN is originally trained on this space. Tov et al. [49] analyze the distortion-editability tradeoff and present an encoder-based method to balance the tradeoff. Zhu et al. [64] introduce a new normalized space and a regularization term to address the distortion-editability tradeoff. Roich et al. [42] mitigate the distortion-editability tradeoff by combining the editability of the \(W\) space with an accurate reconstruction technique which slightly alters the generator.

3 ANALYSIS OF PIVOTAL TUNING INVERSION

3.1 Pivotal Tuning Inversion

PTI [42] is a two-step method for StyleGAN inversion. Different from previous methods that find the latent code within the StyleGAN’s latent space, PTI augments the latent space by slightly altering the generator. Specifically, in the first step, PTI inverts the input image \(x\) into a latent code \(w_p \in W\), called pivot code, using an existing optimization-based method [27] which optimizes the following objective:

\[
\begin{align}
    w_p &= \arg \min_{w,n} L_{\text{LPIPS}}(x, G(w, n)) + \lambda_n L_n(n),
\end{align}
\]

where \(G(w, n)\) is the generated image by the generator \(G\). \(L_{\text{LPIPS}}\) is the LPIPS perceptual loss [61], \(n\) is a noise vector. \(L_n\) is a noise regularization term, and \(\lambda_n\) controls the weight of \(L_n\). In the second step, the generator \(G\) is tuned so that the input image \(x\) can be accurately mapped to the pivot code \(w_p\) by optimizing:

\[
\begin{align}
    L_{\text{PTI}}(x) &= L_{\text{LPIPS}}(x, G(w_p)) + \lambda_{L2} L_{L2}(x, G(w_p)),
\end{align}
\]

where \(L_{L2}\) is the pixel-wise L2 loss and \(\lambda_{L2}\) controls the loss weight.

3.2 Distortion-Editability Tradeoff

Although the distortion can be diminished significantly during the second step of PTI, the distortion in the first step is of crucial importance to the final inversion. Figure 3 shows an example, and one can see that lower distortion in the first step (Column 2) leads to lower distortion of the final inversion (Column 3). One simple method to decrease the distortion is to apply more training steps in the first step (Eq. 1). However, we observe that applying more training steps will decrease the editability of the final inversion, as shown in Figure 3. The reason may be that the per-image optimization method suffers from overfitting when training too many steps on a single image. Therefore, the per-image optimization method for the pivot code can hardly balance the distortion-editability tradeoff. We instead train an encoder using a novel training methodology for the pivot code, resulting in a more accurate, more editable, and faster inversion.

4 METHOD

Our target is to improve the quality of the pivot code in PTI. We adopt the encoder-based method to infer the pivot code, because the per-image optimization method can hardly balance the distortion-editability tradeoff as discussed in Section 3. Recent studies [6, 49, 64] reveal that the extended space \(W^+\) is more expressive while the original space \(W\) is more editable. The key idea of our method is to exploit the advantages of both \(W^+\) and \(W\) spaces by training an encoder in both spaces. We propose a novel training methodology that gradually changes the output space of the encoder according to a cycle scheme: \(W^+ \rightarrow W \rightarrow W\). To further decrease the distortion, we then follow the hybrid method [19, 62] to refine the pivot code obtained from the encoder, by iteratively updating the encoder towards the input image where a regularization term is introduced to alleviate the overfitting problem. Finally, using the latent code obtained from cycle encoding or from the refinement as the pivot code, the generator is slightly tuned so that the input image can be accurately mapped to the pivot code. Figure 2 shows the framework of our method.
4.1 Cycle Encoding

In cycle encoding, we seek to achieve optimal editability for the pivot code. To this end, we select the $W$ space as the final state for cycle encoding, as the $W$ space provides better editability than the $W+$ space [49]. Nevertheless, the $W+$ space is more expressive and induces less distortion. To exploit both advantages of the $W$ and $W+$ spaces, we propose to train an encoder in varying spaces according to a cycle scheme: $W\rightarrow W^+\rightarrow W$. Starting and ending with the $W$ space provide high editability for the pivot code, and shifting to the $W+$ space provides high expressiveness for the pivot code. For $W\rightarrow W^+$, we follow [49] to sequentially allow the latent vectors to be different to the first latent vector. For $W^+\rightarrow W$, it is more crucial to the final inversion, as it determines the final state of the pivot code. We propose a new progressive training methodology for $W^+\rightarrow W$, which changes the space more smoothly. In the following, we detail the training mechanism that consists of two steps:

4.1.1 $W\rightarrow W^+$

We follow the e4e model [49] to control the output space of the encoder by using the delta regularization loss which measures the difference between each latent vector. Formally, let $E(x) = (w_0, w_1, ..., w_{N-1}) = (w_0, w_0 + \Delta_1, ..., w_0 + \Delta_{N-1})$ denote the output of the encoder, where $N$ is the number of the latent vectors and $\Delta_i$ is the offset from the first latent vector $w_0$. The delta regularization loss is defined as:

$$L_{\text{delta}}(x) = \sum_{i=1}^{N-1} ||\Delta_i||_2.$$  (3)

The encoder starts the training in the $W$ space by setting $\forall i: \Delta_i = 0$, and then gradually shifts the space from $W$ to $W^+$ by training $\Delta_i$ sequentially every $T_0$ iterations.

4.1.2 $W^+\rightarrow W$

In this step, we also utilize the delta regularization loss to control the shift from $W^+$ to $W$. We empirically find that smoothly changing the output space of the encoder is beneficial to the editability of the pivot code. To this end, we propose a new progressive training methodology that shifts the space from $W^+$ to $W$ more smoothly. Specifically, we first gradually increase the weight of the delta regularization loss by a factor $\beta$ every $T_1$ iterations. A large weight of the delta regularization loss enforces $\Delta_i$ to be very close to 0. After this procedure, the output space of the encoder lies close to the $W$ space with a small variance. Then, we set from $\Delta_{N-1} = 0$ to $\Delta_1 = 0$ sequentially every $T_2$ iterations. Finally, the output space of the encoder ends at the $W$ space with $\forall i: \Delta_i = 0$.

Increasing the weight of the delta regularization loss can be viewed as a “soft” operation, and setting $\Delta_1 = 0$ can be viewed as a “hard” operation. In short, our progressive training methodology first performs the soft operation and then performs the hard operation. Compared with directly performing the hard operation, our method changes the output space of the encoder more smoothly and favors better property preservation of the $W$ and $W^+$ spaces.

The overall objective of cycle encoding is:

$$L(x) = \lambda_{L_2}L_{L_2}(x) + \lambda_{\text{lpips}}L_{\text{lpips}}(x) + \lambda_{\text{id}}L_{\text{id}}(x) + \lambda_{\text{adv}}L_{\text{adv}}(x) + \lambda_{\text{delta}}L_{\text{delta}}(x),$$  (4)

where $L_{\text{id}}$ is the identity loss [15], $L_{\text{adv}}$ [34, 49] is an adversarial loss to encourage $w_i$ to lie close to the true distribution of $W$, and $\lambda$ controls the weight of each loss.

4.2 Decreasing Distortion via Optimization

The hybrid method [19, 62] has proved the effectiveness of utilizing the optimization-based method to refine the output of the encoder. Inspired by this, we also explore applying optimization to the result of cycle encoding to further decrease the distortion. However, as we discussed in Section 3, optimizing over a single image is prone to overfitting, which then decreases the editability. Instead of optimizing the latent code, our method iteratively updates the encoder towards the input image where a regularization term is introduced to alleviate the overfitting problem. At each iteration, we randomly sample $M$ images $x^*$ from the training set and apply the following regularization term:

$$L_{\text{reg}}(x^*) = \frac{1}{M} \sum_{i=0}^{M-1} L_S(x^*_i, G(E(x^*_i))),$$  (5)
we use a StyleGAN2 [27] generator pre-trained on the FFHQ [26] where \( x \) and \( \lambda \) are the input image and \( \lambda_{\text{reg}} \) controls the loss weight. Moreover, we apply this optimization in the \( W^+ \) space, as we empirically find that learning in the \( W^+ \) space in this step is cost-effective in decreasing the distortion with a subtle degradation in editability. The reason may be that slight and local changes to the pivot code can be applied without damaging its editing capability.

Note that this optimization step is optional in practice, and we recommend applying this step for challenging images as skipping this step reduces the inference time. Furthermore, a small number (15 in our experiments) of iterations is sufficient, since the reconstruction quality of cycle encoding is already quite good.

5 EXPERIMENTS

In this section, we evaluate the effectiveness of our inversion method in terms of reconstruction and editing quality. For all experiments, we use a StyleGAN2 [27] generator pre-trained on the FFHQ [26] dataset.

Datasets. We train our model on the FFHQ [26] dataset which contains 70,000 facial images. The CelebA-HQ [24] test set is used for evaluation. Furthermore, we collect 200 challenging facial images from the web for evaluation, including famous character images and cartoon images.

Baselines. We compare our method with four well-known inversion methods: SG2 [27], SG2+W+ [1], e4e [49], and PTI [42]. SG2 and SG2+W+ are optimization-based methods that invert the input images into the \( W \) and \( W^+ \) spaces, respectively. The e4e model is an encoder-based method that extends the psp model [41] by encouraging the latent codes close to \( W \). PTI is a two-step method that first infers the latent code using SG2 and then slightly alters the generator to fit the latent code. The qualitative comparison to SG2+W+ is provided in the Supplementary Materials due to the limited space.

5.1 Implementation Details

In the step of \( W \rightarrow W^+ \), we train the encoder for 500K iterations using the same hyperparameters as described in [49]. In the step of \( W^+ \rightarrow W \), we train the encoder for 250K iterations. Specifically, in the first 150K iterations, we gradually increase \( \lambda_{\text{delta}} \) (Eq. 4) by 20% and decrease \( \lambda_{\text{adv}} \) (Eq. 4) by 50% every 10K iterations. Then, we set from \( \lambda_{\text{delta}} = 0 \) to \( \lambda_{\text{delta}} = 0 \) sequentially every 4K iterations. For the regularized refinement step, we randomly sample 7 images from the FFHQ training set and update the encoder for 15 iterations. For the loss weights in Eq. 5-6, we set \( \lambda_{\text{adv}} = 1, \lambda_{\text{lpips}} = 0.8, \lambda_{\text{id}} = 0.1 \), and \( \lambda_{\text{reg}} = 1 \). For the pivotal tuning step, we use the same hyperparameters as described in [42]. For the quantitative experiments, we follow [42] to evaluate the models on the first 1000 samples.
5.2 Reconstruction Quality

**Qualitative Evaluation.** Figures 4 to 6 present a visually qualitative comparison of the reconstructed images. The results show that our method achieves superior reconstruction for all images from three different data sources. Figures 4 and 5 show that the reconstruction obtained by our method preserves more accurate details, such as cap (row 1, Figure 4), background (row 2, Figure 4), hand (row 1, Figure 5), and makeup (row 3, Figure 5). Figure 6 presents the reconstruction of cartoon images. Inverting cartoon images is more challenging as the cartoon images are completely out-of-domain. In Figure 6, the reconstructed images by PTI tend to be blurry, and some key components (e.g., eye and mouth) are not accurately reconstructed. In contrast, our method successfully reconstructs the cartoon images. Examples of using cycle encoding only (i.e., without applying the optimization step) are provided in Figure 11, and one can see that cycle encoding already outperforms PTI in reconstruction. More visual results are provided in the Supplementary Materials.

**Quantitative Evaluation.** Table 1 presents a quantitative evaluation among different inversion methods. We employ three metrics, including identity similarity score [21], LPIPS [61], and Mean Squared Error (MSE). Following [41], we measure the identity similarity score by using a different face recognition model (Curricularface [21]) to make the similarity score independent from the loss function (ArcFace [15]). The results demonstrate that our method achieves the best reconstruction quality in terms of all three metrics. Our method reduces the inference time of PTI from 102.2 seconds to 80.8 seconds. Without applying the optimization step, the inference time can be further reduced to 67.5 seconds. Moreover, we also evaluate the models on 200 challenging images collected from the web. In Table 2, we see a substantial improvement over PTI from 0.774 to 0.843 in identity similarity. In addition to reconstruction quality, editing quality is another important target for GAN inversion, as the major motivation for GAN inversion is the downstream editing task. Several works [42, 49, 64] employ three methods to evaluate the editing quality: PTI, especially for the challenging cartoon images. The quantitative results in Table 3 also demonstrate that our method outperforms PTI by a substantial margin.

| Rotation Angle | α = 1 | α = 5 | α = 10 |
|---------------|-------|-------|--------|
| SG2 [27]      | 3.83  | 16.70 | 32.68  |
| SG2W+ [1]     | 2.48  | 10.74 | 21.72  |
| e4e [49]      | 3.49  | 14.90 | 29.13  |
| PTI [42]      | 3.44  | 16.64 | 33.09  |
| Ours          | 4.63  | 22.20 | 42.54  |

Table 4: Quantitative editing quality by evaluating the editing magnitude (e.g., rotation angle) when applying the same editing weight α.

| Identity | Angle±5 | Angle±10 | Angle±15 |
|----------|---------|----------|----------|
| SG2 [27] | 0.188   | 0.179    | 0.166    |
| SG2W+ [1]| 0.621   | 0.538    | 0.454    |
| e4e [49] | 0.487   | 0.471    | 0.442    |
| PTI [42] | 0.778   | 0.673    | 0.565    |
| Ours     | 0.812   | 0.728    | 0.638    |

Table 5: Quantitative editing quality by evaluating the identity similarity when applying the same editing magnitude (e.g., rotation angle).
have discussed the editing quality, and they show that the native \( W \) space is superior to the extended \( W^+ \) space in terms of editability. A high editability is expected that given the inverted latent code, one can edit it and obtain the desired editing magnitude with a small reconstruction accuracy drop. In the following experiments, we use the popular editing method, InterfaceGAN [43], for latent-based editing. InterfaceGAN edits the original latent code \( z \) with 
\[
z_{\text{edit}} = z + \alpha n
\]
where \( \alpha \) is the editing weight and \( n \) is a unit normal vector, corresponding to a semantic direction. One can see that the reconstruction quality will decrease as the editing weight \( \alpha \) increases, since \( \alpha n \) will dominate the value of \( z_{\text{edit}} \) when \( \alpha \) is large. Thus we also expect to obtain the desired editing magnitude with a small editing weight \( \alpha \). Based on the above observations, we follow [42] to evaluate the editing quality by using two metrics: editing magnitude when applying the same editing weight, and identity preservation when applying the same editing magnitude.

**Qualitative Evaluation.** In Figures 8 to 10, we provide a qualitative comparison of different methods in editing images. To compare the editing magnitude, in each example, the edited images by different methods are obtained using the same editing weight \( \alpha \). As can be seen in Figures 8 and 10, our method achieves the largest editing magnitude for all the examples, and our method provides the best visually-pleasing editing results and most accurately preserves the identity of the input images. For example, PTI loses the identity and details, such as background (row 1, Figure 8), appearance (row 2, Figure 8), eyes (row 2, Figure 10), and glasses (row 3, Figure 10). SG2 and e4e achieve visually-pleasing editing quality but lose the identity of the input images. We also investigate the performance of our method on more challenging out-of-domain cartoon images in Figure 9. The edited images by PTI tend to be blurry. Our method is the only one that successfully reconstructs and edits the cartoon images. For more editing results, more editing directions, and editing results using StyleClip [36], see the Supplementary Materials.

**Quantitative Evaluation.** Tables 4 and 5 present a quantitative comparison of different methods. As aforementioned, we use editing magnitude and identity preservation to measure the editing quality. We follow [42, 64] to use the pose editing operation for this evaluation, as evaluating the rotation angle is more accurate than the other operations. Microsoft Face API is used to calculate the rotation angle. As shown in Table 4, our method induces the...
largest rotation angle compared to the baselines, especially when the editing weight is large. In Table 5, our method also achieves the best score in terms of identity similarity, which indicates that our method most accurately preserves the identity of the original images when performing the same editing magnitude. For the case of Angle±15, we see a substantial editing quality improvement over PTI from 0.565 to 0.638.

5.4 Ablation Study

Optimization-based Refinement. We first perform an ablation study on the optimization step described in Section 4.2. We compare our model with two variants: skipping the optimization step (denoted as w/o Optim.) and removing the regularization term (w/o Reg.). The quantitative results in Table 6 demonstrate that without the regularization, the model yields inferior editability. The qualitative examples in Figure 11 and 12 show consistent results with the quantitative evaluation. Note that without the optimization step, cycle encoding already outperforms PTI in both reconstruction and editability.

Cycle Encoding. We then perform an ablation study on the cycle encoding step. We compare our model with three variants: training the encoder in \( W \), training the encoder in \( W \rightarrow W^+ \), and training the encoder in \( W^+ \rightarrow W \). The details of the model configurations can be found in the Supplementary Materials, and all the models are trained for the same number of iterations. The quantitative results in Table 7 show that \( W \rightarrow W^+ \) achieves the lowest distortion but poorest editability. Figure 13 also demonstrates that cycle encoding achieves superior editability than \( W \rightarrow W^+ \). For \( W^+ \rightarrow W \), we observe a slight degeneration in both reconstruction and editability compared to cycle encoding from Figure 11 and Table 7. \( W \) behaves poorly in both reconstruction and editability.

6 DISCUSSION AND CONCLUSION

In this work, we propose a StyleGAN inversion method, named cycle encoding, for a high-quality pivot code in PTI. We demonstrate the superior performance of our method in both reconstruction and editability compared to several state-of-the-art methods. Our method even enables high-quality reconstruction and editing for out-of-domain cartoon images. Although our model successfully reconstructs the presented cartoon examples, it can hardly reconstruct more cartoonized images. In the future, we plan to develop a model with stronger generalization ability, so as to invert more challenging images from different domains such as cartoons and sketches.

7 ACKNOWLEDGEMENT

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