

# IMPRINT: Generative Object Compositing by Learning Identity-Preserving Representation

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Figure 1. Top: Comparison with three prior works, *i.e.*, Paint-by-Example [58], ObjectStitch [53], and TF-ICON [35]. Our method **IMPRINT** outperforms others in terms of identity preservation and color/geometry harmonization. Bottom: Given a coarse mask, **IMPRINT** can change the pose of the object to follow the shape of the mask.

## Abstract

Generative object compositing emerges as a promising new avenue for compositional image editing. However, the requirement of object identity preservation poses a signif-

icant challenge, limiting practical usage of most existing methods. In response, this paper introduces **IMPRINT**, a novel diffusion-based generative model trained with a two-stage learning framework that decouples learning of identity preservation from that of compositing. The first stage is

targeted for context-agnostic, identity-preserving pretraining of the object encoder, enabling the encoder to learn an embedding that is both view-invariant and conducive to enhanced detail preservation. The subsequent stage leverages this representation to learn seamless harmonization of the object composited to the background. In addition, IMPRINT incorporates a shape-guidance mechanism offering user-directed control over the compositing process. Extensive experiments demonstrate that IMPRINT significantly outperforms existing methods and various baselines on identity preservation and composition quality. Project page: <https://song630.github.io/IMPRINT-Project-Page/>

## 1. Introduction

Image compositing, the art of merging a reference object with a background to create a cohesive and realistic image, has witnessed transformative advancements with the advent of diffusion models (DM) [17, 40, 43, 46]. These models have catalyzed the emergence of generative object compositing, a novel task that hinges on two critical aspects: identity (ID) preservation and background harmonization. The goal is to ensure that the object in the composite image retains its identity while adapting its color and geometry for seamless integration with the background. Existing methods [35, 53, 58] demonstrate impressive capabilities in generative compositing; however, they often fail in ID-preservation or context consistency.

Recent works [53, 58], typically struggle with balancing ID preservation and background harmony. While these methods have made strides in spatial adjustments, they predominantly capture categorical rather than detailed information. TF-ICON [35] and two concurrent works [6, 60] have advanced subject fidelity but at the expense of limiting pose and view variations for background integration, thus curtailing their applicability in real-world settings.

To address the trade-off between identity preservation with pose adjustment for background alignment, we introduce IMPRINT, a novel two-stage compositing framework that excels in ID preservation. Diverging from previous works, IMPRINT decouples the compositing process into ID preservation and background alignment stages. The first stage involves a novel context-agnostic ID-preserving training, wherein an image encoder is trained to learn view-invariant features, crucial for detail engraving. The second stage focuses on harmonizing the object with the background, utilizing the robust ID-preserving representation from the first stage. This bifurcation allows for unprecedented fidelity in object detail while facilitating adaptable color and geometry harmonization.

Our contributions can be summarized as follows:

- We introduce a novel context-agnostic ID-preserving training, demonstrating superior appearance preservation

through comprehensive experiments.

- Our two-stage framework distinctively separates the tasks of ID preservation and background alignment, enabling realistic compositing effects.
- We incorporate mask control into our model, enhancing shape guidance and generation flexibility.
- We conduct an extensive study on appearance retention, offering insights into various factors influencing identity preservation, *e.g.*, image encoders, multi-view datasets, training strategies, etc.

## 2. Related Work

### 2.1. Image Compositing

Image compositing, a pivotal task in image editing applications, aims to insert a foreground object into a background image seamlessly, striving for realism and high fidelity.

Traditionally, image harmonization [11, 21, 24, 57] and image blending [38, 54, 61, 62] focus on color and lighting consistency between the object and the background. However, these approaches fall short in addressing geometric adjustments. The emergence of GANs [13, 22, 64] has inspired numerous studies [3, 5, 30] that employ GANs to address issues of geometric inconsistency, yet are often domain-specific (*e.g.*, indoor scene) and limited in handling complex transformations (*e.g.*, out-of-plane rotation). Shadow synthesis methods [18, 47–49] mainly focus on realistic lighting effects.

With the advent of diffusion models [1, 2, 12, 17, 41–43, 51, 52], recent research has shifted towards unified frameworks encompassing all aspects of image compositing. Methods like [53, 58] employ CLIP-based adapters for leveraging pretrained models, but they struggle in preserving the object’s identity due to their focus on high-level semantic representations. While TF-ICON [35] improves fidelity by incorporating noise modeling and composite self-attention injection, it faces limitations in object pose adaptability.

Recent research is increasingly centering on appearance preservation in generative object compositing. Two concurrent works, AnyDoor [6] and ControlCom [60], have made strides in this area. AnyDoor combines DINOv2 [37] and high-frequency filter, and ControlCom introduces a local enhancement module. However, these models have limited spatial correction capabilities. In contrast, our model designs a novel approach that substantially enhances visual consistency of the object while maintaining geometry and color harmonization, representing a significant advancement in the field.

### 2.2. Subject-Driven Image Generation

Subject-driven image generation, the task of creating a subject within a novel context, often involves customizing

subject attributes based on text prompts. Based on diffusion models, [9, 23] have led to techniques like using placeholder words for object representation, enabling high-fidelity customizations. Subsequent works [25, 34, 44, 45] extend this by fine-tuning pretrained text-to-image models for new concept learning. These advancements have facilitated diverse applications, such as subject swapping [10], open-world generation [28], instruction-based editing [19] using Large Language Models [31, 32, 63] and non-rigid image editing [4]. However, these methods usually require inference-time fine-tuning or multiple subject images, limiting their practicality. In contrast, our framework offers a fast-forward and background-preserving approach that is versatile for a broad spectrum of real-world data.

### 3. Approach

The proposed object compositing framework, IMPRINT, is summarized in Fig. 2. Formally, given input images of object  $I_{obj} \in \mathbb{R}^{H \times W \times 3}$ , background  $I_{bg} \in \mathbb{R}^{H \times W \times 3}$ , and mask  $M \in \mathbb{R}^{H \times W}$  that indicates the location and scale for object compositing to the background, we aim to learn a compositing model  $\mathcal{C}$  to achieve a composite image  $I_{out} = \mathcal{C}(I_{obj}, I_{bg}, M) \in \mathbb{R}^{H \times W \times 3}$ . The ideal outcome is an  $I_{out}$  that appears visually coherent and natural, *i.e.*,  $\mathcal{C}$  should ensure that the composited object retains the identity of  $I_{obj}$ , aligns to the geometry of  $I_{bg}$ , and blends seamlessly into the background.

In this section, we expand upon our approach. To leverage pretrained text-to-image diffusion models, we design a novel image encoder to replace the text-encoding branch, thus retaining much richer information from the reference object (see Sec. 3.1). Distinct from existing works, our pipeline bifurcates the task into two specialized sub-tasks to concurrently ensure object fidelity and allow for geometric variations. The first stage defines a context-agnostic ID-preserving task, where the image encoder is trained to learn a unified representation of generic objects (Sec. 3.1). The second stage mainly trains the generator for an image compositing task (Sec. 3.2). In addition, we delve into various aspects contributing to the detail retention capability of our framework: Sec. 3.3 discusses the process of paired data collection, and Sec. 3.4 details our training strategy.

#### 3.1. Context-Agnostic ID-preserving Stage

Distinct from prior methods, we introduce a supervised object view reconstruction task as the first stage of the training that help identity preservation. The motivation behind this task is based on the following key observations:

- Existing efforts [6, 35, 60], which successfully improve detail preservation, are limited in geometry harmonization and tend to demonstrate copy-and-paste behavior.
- There is a fundamental trade-off between identity preservation and image compositing: the object is expected to

be altered, in terms of color, lighting, and geometry, to better align with the background, while simultaneously, the object’s original pose, color tone, and illumination effects are memorized by the model and define its appearance.

- Multi-view data plays a significant role in keeping identity, yet acquiring such datasets is costly. Most large-scale multi-view datasets ([7, 59]) lack sufficient contextual information for compositing; they either lack a background entirely or have a background area that is too limited.

Based on the above insights, we give a formal definition of the task (as depicted in Fig. 2a): given an object of two views  $I_{v1}, I_{v2}$  and their associated masks  $M_{v1}, M_{v2}$ , the background is removed and the segmented object pairs are denoted as  $\hat{I}_{v1} = I_{v1} \otimes M_{v1}$ ,  $\hat{I}_{v2} = I_{v2} \otimes M_{v2}$ . We build a view synthesis model  $\mathcal{S} = \{\mathcal{E}_u, \mathcal{G}_\theta\}$  conditioned on  $\hat{I}_{v1}$  to generate the target view  $\hat{I}_{v2}$ , where  $\mathcal{E}_u$  is the image encoder and  $\mathcal{G}_\theta$  is the UNet backbone parameterized by  $\theta$ .

**Image Encoder**  $\mathcal{E}_u$  consists of a pretrained DINOv2 [37] and a content adapter following [53]. DINOv2 is a SOTA ViT model outperforming its predecessors [20, 39, 50] which extracts highly expressive visual features for reference-based generation. The content adapter allows the utilization of pretrained T2I models by bridging the domain gap between image and text embedding spaces.

**Image Decoder**  $\mathcal{G}_\theta$  takes the conditional denoising auto-encoder  $\mathcal{G}_\theta$  from Stable Diffusion [43] and fine-tune its decoder during training. The objective function is defined as (based on [43]):

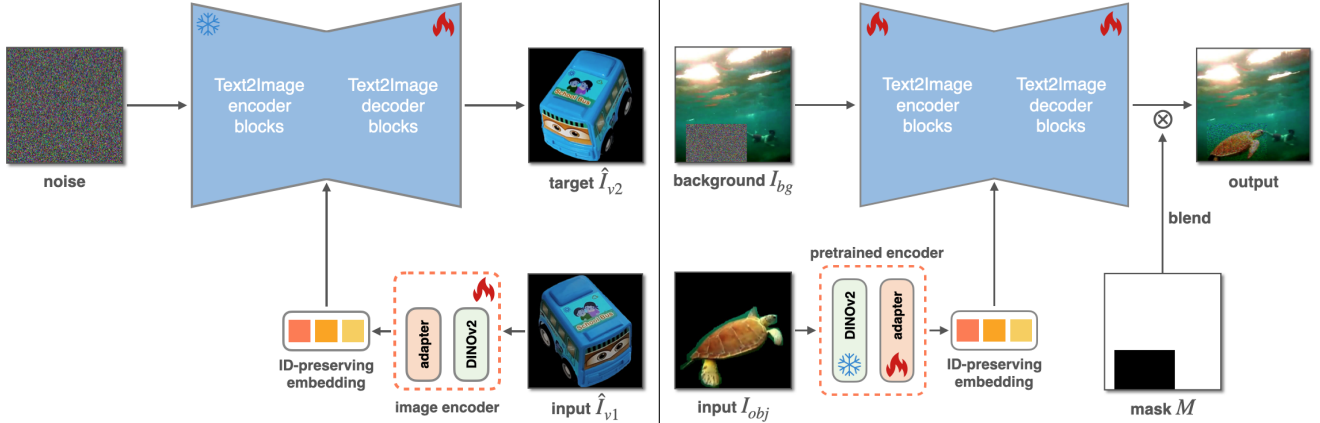
$$\mathcal{L}_{id} = \mathbb{E}_{\hat{I}_{v1}, \hat{I}_{v2}, t, \epsilon} \left[ \left\| \epsilon - \mathcal{G}_\theta \left( \hat{I}_{v2}, t, \mathcal{E}_u \left( \hat{I}_{v1} \right) \right) \right\|_2^2 \right], \quad (1)$$

where  $\mathcal{L}_{id}$  is the ID-preserving loss and  $\epsilon \sim \mathcal{N}(0, 1)$ . The image encoder  $\mathcal{E}_u$  and the decoder blocks of  $\mathcal{G}_\theta$  are optimized in this process. Intuitively, the encoder trained for this task will always extract representations that are view-invariant while keeping identity-related details that are shared across different views. The qualitative results of this stage are shown in Sec. 4.7. Unlike previous view-synthesis works [33], our context-agnostic ID-preserving stage does not require any 3D information (*e.g.*, camera parameters) as conditions, and we mainly focus on ID-preservation instead of geometrical consistency to background (which will be handled in the second stage). Therefore, only the image encoder will be taken to the next stage.

#### 3.2. Compositing Stage

Fig. 2b illustrates the pipeline of the second stage which is trained for the compositing task, comprising the finetuned image encoder  $\mathcal{E}_u$  and a generator  $\mathcal{G}_\phi$  (parameterized by  $\phi$ ) conditioned on the ID-preserving representations.

A simple approach is to ignore the view synthesis stage, training the encoder and generator jointly in a single-stage



(a) Stage of context-agnostic ID-preserving: we design a novel image encoder (with pre-trained DINOv2 as backbone) trained on multi-view object pairs to learn view-invariant ID-preserving representation.

(b) Stage of object compositing: taking the learned image encoder from the first stage and freezing its backbone, the whole model is trained for compositing the object to the masked region (see ?? for the blending process).

Figure 2. The two-stage training pipeline of the proposed IMPRINT.

framework. Unfortunately, we found quality degradation from two aspects in this naive endeavor (see Sec. 4.7):

- When DINOv2 is trained in this stage, the model exhibits more frequent copy-paste-like behavior that composites the object in a very similar view as its original view.
- When object-centric multi-view datasets, *e.g.*, MVIImgNet [59], are enabled in the training set, the model tends to produce more artifacts and exhibit poorer blending results due to the absence of background information in such datasets.

To overcome the issues above, we freeze the backbone of the image encoder (*i.e.*, DINOv2) in the second stage and carefully collect a training set (see Sec. 3.3 for details).

In this stage, we also leverage a pretrained T2I model as the backbone of the generator, which uses the background  $I_{bg}$ , a coarse mask  $M$  as inputs, and is conditioned on a ID-preserving object tokens  $\hat{E}_u = \mathcal{E}_u(I_{obj})$ , where  $I_{obj}$  indicates a masked object image. The generation is guided by injecting object tokens into the cross attention layers of  $\mathcal{G}_\phi$ . The coarse mask also allows the synthesis of shadows, and interactions of the object and the nearby objects.

As  $\hat{E}_u$  already encompasses structured view-invariant details of the object, color and geometric adjustments are no longer limited by identity preservation efforts. This freedom allows for greater variation in compositing.

We define the objective function of this stage as:

$$\mathcal{L}_{comp} = \mathbb{E}_{I_{obj}, I_{bg}^*, M, t, \epsilon} \left[ M \left\| \epsilon - \mathcal{G}_\phi \left( I_{bg}^*, t, \hat{E}_u \right) \right\|_2^2 \right] \quad (2)$$

where  $\mathcal{L}_{comp}$  is the compositing loss,  $I_{bg}^*$  is the target image.  $\mathcal{G}_\phi$  and the adapter are optimized.

**The Background-blending Process** To ensure that the transition area between the object and the background is smooth, we adopt a background-blending strategy. Refer to the Appendix for details.

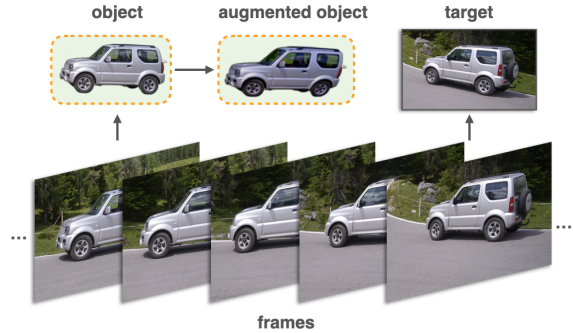


Figure 3. Illustration of the data augmentation pipeline.

**Shape-guided Controllable Compositing** could enable more practical guidance of the pose and view of the generated object by drawing a rough mask. However, most prior works [6, 35, 53] have no such control. In our proposed model, following [55], masks are defined at four levels of precision (see the Appendix), where the most coarse mask is a bounding box. Incorporating multiple levels of masks replicates real-world scenarios, where users often prefer more precise masks. Results are shown in Fig. 1.any

### 3.3. Paired Data Generation

The dataset quality is another key to better identity preservation and pose variation. As proved by [6], multi-view datasets can significantly improve the generation fidelity. In practice, we use a combination of image datasets (Pixabay), panoptic video segmentation datasets (YoutubeVOS [56], VIPSeg [36] and PPR10K [29]) and object-centric datasets (MVIImgNet [59] and Objaverse [7]). They are incorporated in different training stages and associated with various processing procedures in our self-supervised training.

The image datasets we collected have high resolution and rich background information, so they are only utilized in the second stage for better compositing. Inspired by

[53, 58], to simulate the lighting and geometry changes in object compositing, we design an augmentation pipeline  $\hat{I}_{obj} = \mathcal{P}(\mathcal{T}(I_{obj}))$ , where  $\mathcal{T}$  are the affine transformations, and  $\mathcal{P}$  is color and light perturbation, supported by the look-up table in [21]. The perturbed object  $\hat{I}_{obj}$  is used as the input and the natural image  $I_{bg}^*$  containing the original object is used as the target.

Video segmentation datasets usually suffer from low resolution and motion blur, which harm the generation quality. Nevertheless, they provide object pairs which naturally differ in lighting, geometry, view and even provide non-rigid pose variations. As a result, they are also used in the second stage. Illustrated by Fig. 3, each training pair comes from one video with instance-level segmentation labels. Two distinct frames are randomly sampled; one serves as the target image, while the object is extracted from the other frame as the augmented input.

Object-centric datasets offer a significantly larger scale than video segmentation datasets and provide more intricate object details. However, they are only used in the first stage due to the limited background information available in these datasets. During training, each pair  $I_{v1}, I_{v2}$  are also randomly sampled from the same video with  $|v1 - v2| \leq n$ , where  $n$  is the temporal sampling window. Empirically, we observe a loss in the generation quality as  $n$  increases, and  $n = 7$  strikes a balance between fidelity and quality.

### 3.4. Training Strategies

All previous (or concurrent) training-free methods [6, 53, 58, 60] use a *frozen* transformer-based image encoder, either using DINOv2 or CLIP. However, freezing the encoder will limit their capability in extracting the object details: i) CLIP only encodes the semantic features of the object; ii) DINOv2 is trained on a dataset that is constructed based on image retrieval, allowing objects that are not entirely identical to be treated as the same instance. To overcome this challenge, we fine-tune the encoder specifically for compositing, ensuring the extraction of instance-level features.

Due to the extensive scale of the aforementioned encoders, they are prone to overfitting. The implementation of appropriate training strategies can effectively stabilize the training process and improve identity preservation. To this end, we design a novel training scheme: Sequential Collaborative Training.

More specifically, the object compositing stage is further divided into two phases: 1) in the first  $n$  epochs, we assign the adapter a larger learning rate of  $4 \times 10^{-5}$ , and assign the UNet a smaller learning rate of  $4 \times 10^{-6}$ ; 2) in the next  $n$  epochs, we swap the learning rate of these two components (and the training finishes). This strategy focuses on training one component at each phase, with the other component simultaneously trained at a lower rate to adapt to the changed domain; the generator is trained in the end to ensure the

Datasets	Pixabay	VIPSeg	YoutubeVOS	PPR10K
Training	116,820	51,743	42,868	6,020
Validation	6,490	5,487	3,690	102

Table 1. Statistics of the datasets used in the second stage.

synthesis quality.

## 4. Experiments

### 4.1. Training Details

The first stage is trained on 1,409,545 pairs and validated on 11,175 pairs from MVImgNet, which takes 5 epochs to finish. The learning rate associated with DINOv2 (ViT-g/14 with registers) is  $4 \times 10^{-6}$ , and the batch size is 256. The image embedding is dropped at a rate of 0.05.

The second stage is fine-tuned on a mixture of image datasets and video datasets, including a training set of 217,451 pairs and a validation set of 15,769 pairs (listed in Tab. 1), where we apply [26] to obtain the segmentation masks as labels. It is trained for 15 epochs with a batch size of 256. The embedding is dropped at a rate of 0.1.

In both stages, the images are resized to  $512 \times 512$ . During inference, the DDIM sampler generates the composite image after 50 denoising steps using a CFG [16] scale of 3.0. The model is trained on 8 NVIDIA A100 GPUs. The model is built on Stable Diffusion v1.4 ([43]).

### 4.2. Evaluation Benchmark

**Datasets** are collected from Pixabay and DreamBooth [44] for testing. More specifically, Pixabay testing set has 1,000 high-resolution images and has no overlap with the training set. A foreground object is selected from each image and perturbed through the data augmentation pipeline as in Sec. 3.3. The DreamBooth testing set consists of 25 unique objects with various views. Combined with 59 background images that are manually chosen, 113 pairs are generated for this test set. This dataset is challenging since most objects are of complex texture or structure. We also conduct a user study on this dataset.

**Metrics** measuring fidelity and realism are adopted to evaluate the effectiveness of different models in terms of identity preservation and background harmonization. We utilize CLIP-score [14], DINO-score, and DreamSim [8] as the measurements of generation fidelity. To obtain more precise comparison results, we always crop the output images so that the generated object is located in the center of the image. FID [15] is employed to measure the realism which indicates the compositing quality.

### 4.3. Quantitative Evaluation

To demonstrate the effectiveness of our model, we test our model and three baseline methods (Paint-by-Example [58],

Method	FID ↓	CLIP-score ↑	DINO-score ↑	DreamSim ↓
PbE	-	71.5000	31.3765	0.4954
OS	-	73.6250	32.9739	0.4297
T-I	-	75.1250	39.2863	0.3661
Ours	-	<b>77.0625</b>	<b>43.4463</b>	<b>0.2898</b>
PbE	23.2663	93.6250	85.2260	0.1907
OS	22.4934	94.9375	90.3853	0.1422
T-I	63.9730	88.3125	73.2155	0.3219
Ours	<b>16.4487</b>	<b>96.1875</b>	<b>94.705</b>	<b>0.0831</b>

Table 2. Quantitative comparison with prior works. IMPRINT and the baselines are tested on two datasets for realism and ID-preserving measurement: DreamBooth (top) and the Pixabay test set (bottom). The results on both datasets demonstrate the advance of our model in both ID-preserving and realistic harmonization with the background.

	Ours	OS	Ours	PbE	Ours	T-I
Realism	<b>50.68</b>	49.32	<b>62.84</b>	37.16	<b>53.38</b>	46.62
Fidelity	<b>80.41</b>	19.59	<b>86.49</b>	13.51	<b>73.65</b>	26.35

Table 3. User study results. We design two questions to measure the realism and fidelity of the generation. In both questions, the user is presented side-by-side comparisons of our generated image and another image randomly chosen from one of the baselines. The results in the table show user preference percentage. Our model not only achieves better realism, but also outperforms the baselines in ID-preserving by a large margin.

ObjectStitch [53], and TF-ICON [35]) on the two aforementioned test sets. The same inputs (a mask and a reference object) are used in all models. For fair comparison, we further fine-tune Paint-by-Example (PbE) on our second-stage training set.

When testing on TF-ICON, we employ the parameter set in "same domain" mode, as suggested by the official implementation. It also requires a text prompt as an additional input, so we apply BLIP2 [27], a state-of-the-art vision-language model to generate captions for the images. Moreover, the captions for the DreamBooth test set are manually refined to improve the performance. As shown in Tab. 2, IMPRINT achieves the best performance in both realism and fidelity. See the Appendix for quantitative comparisons with AnyDoor.

#### 4.4. Qualitative Evaluation

Qualitative comparisons are shown in Fig. 4, comparing our model against prior methods. Although PbE and ObjectStitch show natural compositing effects, they often fail to capture the finer details of the objects. When the object has complex texture or structure, their generated object becomes less recognizable and even suffers from artifacts. In contrast, TF-ICON shows better consistency between the input and output, especially in keeping surface textures and captions. However, the background adaptation ability is

also strictly restricted. As can be observed, TF-ICON has less variation in color and geometry changes, which results in a degradation in compositing effects. We further compare to AnyDoor with both qualitative and quantitative assessments (see the Appendix). The results show that IMPRINT achieves better ID-preservation and shows the flexibility in adapting to the background in terms of color and geometry.

We also show the synthesis results of the first stage in Fig. 5. Using the ID-preserving representation, our model is able to generate high-fidelity objects with large view variations. This process requires no extra condition such as camera parameters.

#### 4.5. User Study

We also conduct a user study using Amazon Mechanical Turk, comparing our method against the three baselines on the challenging DreamBooth dataset. The user study consists of side-by-side comparisons of our result and a randomly chosen result from the baselines. We design two questions: 1) Which image is more realistic? (the input objects are hidden from the users) 2) Which image is more similar to the reference object? Each question has 111 comparisons. We received more than 880 votes from over 130 users. The results are shown in Tab. 3. In terms of realism, our model outperforms PbE and TF-ICON, while comparable with ObjectStitch. We also evaluate the visual similarity. The preference rate in the table demonstrates that our method has a significant advantage over the baselines.

#### 4.6. Additional Visual Results of Shape-control

Shape-guided generation introduces a lot more flexibility for image editing, as the user now gains control over the shape, view and pose of the objects, and the transformation can be either rigid or non-rigid. Fig. 6 illustrates the diverse usage of image editing given a mask as guidance.

#### 4.7. Ablation Study

When pursuing better identity preservation and background harmonization in the field of generative object compositing, we gain valuable experience in a wide range of techniques that contribute to this task. In Tab. 4, we provide a complete analysis and insights of all the factors, as well as demonstrate the effectiveness of our proposed method. The same metrics are utilized as explained in Sec. 4.2.

**Training strategies.** In setting 2, we also optimize CLIP encoder. The results of settings 1 and 2 show that the optimized CLIP can capture better object identity. However, this improvement comes at the cost of variation. Setting 5 and 6 also demonstrate improved identity and less variation. For this reason, the encoder backbone is frozen in our second stage.

**Dataset.** Dataset is another component that significantly affects the performance. After adding the video datasets,

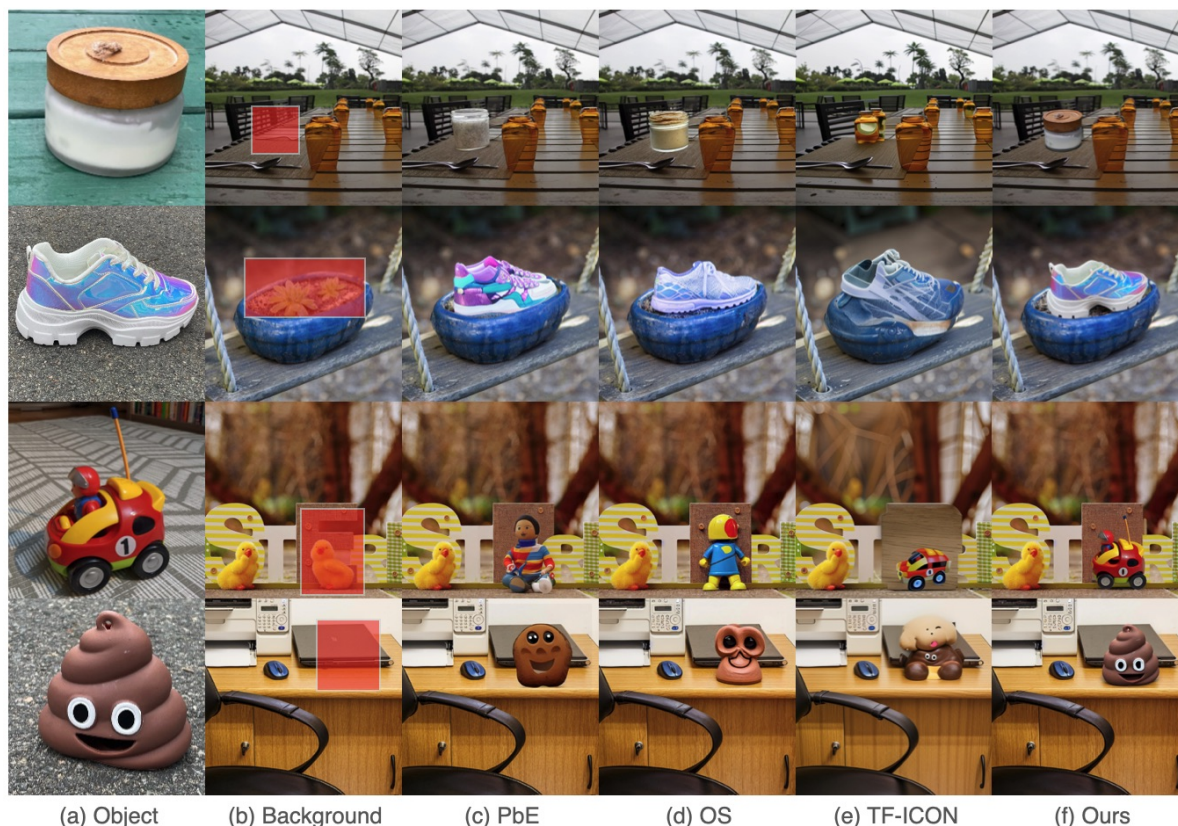


Figure 4. Qualitative comparison on the DreamBooth test set. Paint-by-Example and ObjectStitch lose most object details and only maintain categorical information. TF-ICON tends to copy the pose of the input subject. The comparison highlights the advantage of IMPRINT in keeping identity and making geometric changes.

No.	(PRE)	Encoder	Adapter	(PRE) Tune encoder	(PRE) Tune UNet	Tune encoder	Video data	MVImgNet	FID ↓	DINO score ↑
1	✗	CLIP	✓	-	-	✗	✗	✗	22.493	90.385
2	✗	CLIP	✓	-	-	✓	✗	✗	19.538	92.695
3	✗	CLIP	✓	-	-	✓	✓	✗	17.847	94.216
4	✗	DINOv2	✗	-	-	✗	✓	✗	20.748	92.512
5	✗	DINOv2	✓	-	-	✗	✓	✗	20.131	92.846
6	✗	DINOv2	✓	-	-	✓	✓	✗	17.477	94.164
7	✗	DINOv2	✓	-	-	✓	✓	✓	17.947	94.023
8	✓	DINOv2	✓	✓	✗	✗	✓	✗	17.847	93.908
9	✓	DINOv2	✓	✗	✓	✗	✓	✗	19.286	93.273
10	✓	DINOv2	✓	✓	✓	✗	✓	✗	<b>16.449</b>	<b>94.705</b>

Table 4. Ablation study on our methodologies and other common components. *PRE* means whether the setting has our pretraining stage; *MVImgNet* and *video data* mean whether they are used in the compositing stage.

the model develops a stronger capability in engraving the details (setting 2 and 3). Nevertheless, if there are too many training pairs from object-centric datasets (*MVImgNet*), the generation quality will degrade (setting 6 and 7) since the background information is insufficient.

**Architecture.** Inspired by [53], we also use an adapter to connect the encoder with the generator. Setting 4 and 5 indicates that using the adapter will boost the overall performance in both realism and fidelity. We also observed the model converges faster when using the adapter.

**Pretraining.** In our framework, the first stage pretraining is a key component in improving ID-preservation and harmonization effects. To demonstrate the effectiveness, we test the original DINOv2 and our finetuned DINOv2 on a Objaverse test set. In this evaluation, the encoders generate embeddings for diverse views of 20 objects from various categories. The embeddings are then clustered and visualized in t-SNE figures (Fig. 8). This figure shows that the finetuned encoder produces better clustering results, demonstrating that our ID-preserving representation effectively encodes

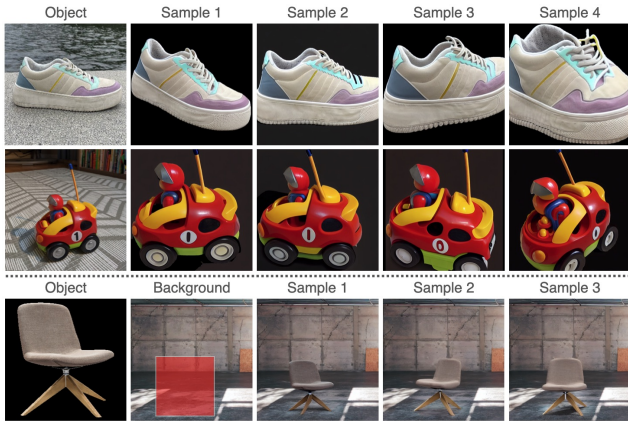


Figure 5. Top: Results of context-agnostic ID-preserving pretraining (after the first stage); IMPRINT generates view pose changes while memorizing the details of the object. Bottom: Diverse poses of the object after the second stage.

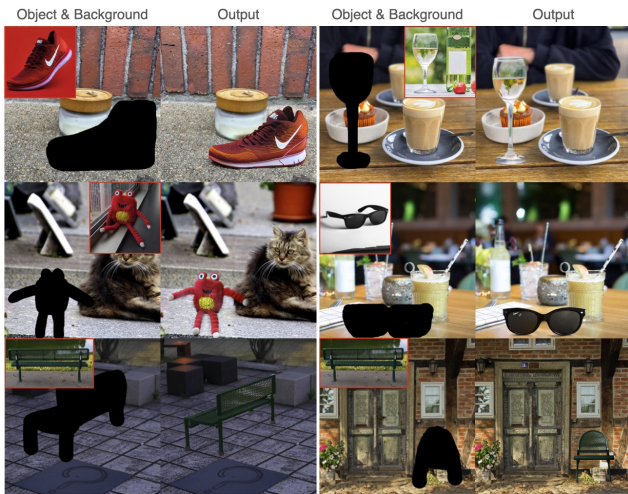


Figure 6. More shape-control results. IMPRINT introduces more user control by using a user-provided mask as input. Inspired by [55], we define four types of mask (including bounding box). In addition to compositing, our model also performs edits on the input object. Depending on the shape of the coarse mask, IMPRINT can operate different types of editing, including changing the view of an object, and applying non-rigid transformation on the object.

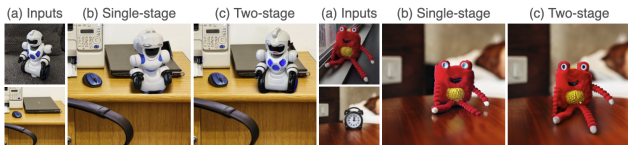


Figure 7. Ablation study on our two-stage training scheme. In (b) MVImgNet is added to the training set and simply trains the whole network in one stage. Compared with two-stage training, single-stage has a notable degradation in quality and loses more details.

the key details of the objects. We further ablate on the first stage training using setting 7 (where there is only the com-

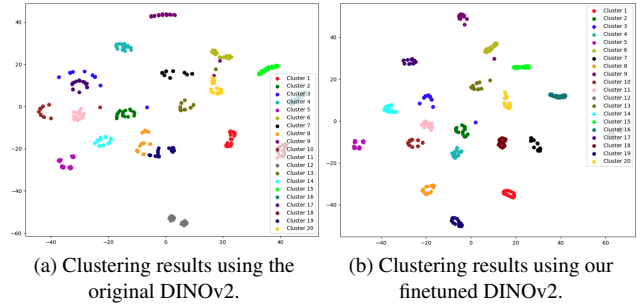


Figure 8. Ablation study on our first stage training. We use DINOv2 (before and after the first stage) to predict embeddings of different views of 20 Objaverse objects. The embeddings are then clustered using the same algorithm and visualized using t-SNE figures. The improved clustering results demonstrate that the embeddings produced by finetuned DINOv2 have higher quality.

positing stage) and 10 (two-stage). Without the first stage, there is a notable drop in the compositing quality (Fig. 7). Additionally, we assess the effect of freezing some components (*i.e.*, UNet or DINOv2) during the pretraining. Compared with Setting 10, setting 8 and 9 exhibit a drop in both harmonization and ID-preservation, validating the effectiveness of our training scheme.

## 5. Conclusion, Limitation and Future Work

In this paper, we propose IMPRINT, a novel two-stage framework that achieves state-of-the-art performance in identity preservation and background harmonization for generative object compositing. We design a new pretraining scheme where the model learns a view-invariant identity-preserving representation that efficiently captures the details of the object. By decoupling the task into an identity-preserving stage and a harmonization stage, IMPRINT can generate large color and geometry variations to better align with the background. Through visual and numerical comparison results, we show that IMPRINT significantly outperforms the previous methods in this task. Furthermore, we add shape guidance as an additional user control. Although IMPRINT effectively addresses both identity preservation and background alignment, it has several limitations. When the required view change is too large, there could be a notable drop in identity preservation, which can be improved by exploring and incorporating a 3D model or NERF representation into our model. Another limitation is that the model may degrade consistency of small texts or logos. Potential ideas to improve this are to employ more accurate latent auto-encoder to avoid loss of information in the latent space and learn object encoders at higher resolution to encode small local details more accurately.

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