
Mitigating Occlusions in Virtual Try-On via A Simple-Yet-Effective Mask-Free Framework

Chenghu Du¹ Shengwu Xiong² Junyin Wang¹ Yi Rong^{1*} Shili Xiong^{1,3*}

¹School of Computer Science and Artificial Intelligence, Wuhan University of Technology

²Interdisciplinary Artificial Intelligence Research Institute, Wuhan College

³Shanghai Artificial Intelligence Laboratory

{duch, xiongsw, wjy199708, yrong}@whut.edu.cn slxiong.illinois@gmail.com

<https://du-chenghu.github.io/OccFree-VTON/>

Abstract

This paper investigates the occlusion problems in virtual try-on (VTON) tasks. According to how they affect the try-on results, the occlusion issues of existing VTON methods can be grouped into two categories: (1) Inherent Occlusions, which are the ghosts of the clothing from reference input images that exist in the try-on results. (2) Acquired Occlusions, where the spatial structures of the generated human body parts are disrupted and appear unreasonable. To this end, we analyze the causes of these two types of occlusions, and propose a novel mask-free VTON framework based on our analysis to deal with these occlusions effectively. In this framework, we develop two simple-yet-powerful operations: (1) The background pre-replacement operation prevents the model from confusing the target clothing information with the human body or image background, thereby mitigating inherent occlusions. (2) The covering-and-eliminating operation enhances the model's ability of understanding and modeling human semantic structures, leading to more realistic human body generation and thus reducing acquired occlusions. Moreover, our method is highly generalizable, which can be applied in in-the-wild scenarios, and our proposed operations can also be easily integrated into different generative network architectures (e.g., GANs and diffusion models) in a plug-and-play manner. Extensive experiments on three VTON datasets validate the effectiveness and generalization ability of our method. Both qualitative and quantitative results demonstrate that our method outperforms recently proposed VTON benchmarks.

1 Introduction

Virtual Try-On (VTON) technology [1, 2, 3, 4, 5, 6, 7, 8, 9] aims to synthesize the user's desired clothing from a garment image onto human models or real-person images. It provides customers with a convenient and efficient try-on experience that greatly reduces the time and effort required in traditional offline shopping modes. Therefore, VTON has gained substantial interest in recent years, particularly in the fields of fashion, e-commerce, and entertainment.

One of the main problems in building a VTON model lies in the unpaired nature of the training data. While the target clothing image and the corresponding ground-truth image of a person wearing this clothing are provided, the input reference image that contains the same person but wearing a different clothing is typically unavailable. According to the strategies adopted to address this issue, current VTON methods can be roughly divided into two categories: (1) Mask-based methods [10, 11, 5, 12, 7, 8, 13] consider VTON as a self-supervised image inpainting problem. They first

*Corresponding authors.



Figure 1: **Visualization of the occlusion issues in VTON and the effectiveness of the proposed method.** It illustrates the inherent occlusion (Cyan regions) caused by imprecise inpainting masks and acquired occlusion (Red regions) resulting from erroneous human structural representations.

mask the clothing-relevant regions in the ground-truth image, and then attempt to recover these regions based on the target clothing image. In contrast, (2) Mask-free methods [1, 2, 3, 14, 15, 16] directly synthesize pseudo reference images (*e.g.*, via generative model) as the input for VTON model training, thus eliminating the requirement of generating inpainting masks in inference phase.

However, during the training stage, these two types of methods both rely on the inpainting masks to accurately remove the clothing regions or generate appropriate pseudo reference inputs, respectively. *As a result, the imprecise masks that cannot fully cover the clothing regions will incorrectly remain a portion of the target clothing areas in the masked (or pseudo) input images.* Such remained regions can be misidentified as the human body or background and be mistakenly preserved. Therefore, training with these samples will establish incorrect associations between the target clothing information and the human body or background pixels. This will finally lead to a sub-optimal model that outputs the try-on results containing ghosts of the clothing from reference input images, which are recognized as **Inherent Occlusions** [17] (see the top row in Fig. 1). In addition, existing VTON approaches may also suffer from another type of **Acquired Occlusions**, which is typically caused by erroneous human structural representations (HSRs) that misguide the learning and inference processes of the generator. Consequently, the spatial structures of human body parts in the try-on results will be disrupted and appear unreasonable, as shown in the bottom row of Fig. 1.

In this study, we propose a simple-yet-effective approach that is able to deal with both inherent and acquired occlusions in a unified mask-free VTON framework. On the one hand, to tackle inherent occlusions, we design a **background pre-replacement** operation that replaces the image regions outside the combination of the inpainting mask and the person identity mask in each training sample with either a pure background or a random scene image. In this way, the remained target clothing areas will be filled with background pixels, thus allowing the learned model to differentiate the clothing information from the background more effectively. On the other hand, since HSRs mainly affect the generative quality of human body parts, the acquired occlusions caused by erroneous HSRs mostly occur in situations where the human body generation is required, *i.e.*, when trying on clothes with smaller body coverage to the reference image with a larger clothing area. To this end, we develop a **covering-and-eliminating** operation to mimic these situations so that the related robustness can be improved. Specifically, it first produces pseudo reference images with a different clothing that completely covers the original target clothing. Then, our model is trained to eliminate these coverings and reconstruct the underlying human body areas. During this process, the model's understanding of human semantic structures will be enhanced under the accurate supervision of real ground-truths, thereby mitigating the negative effects of incorrect HSRs. Extensive experiments on three VTON datasets validate the effectiveness of our framework, surpassing recently proposed benchmarks both qualitatively and quantitatively. The main contributions of this paper are summarized as follows:

- We analyze the causes of both inherent and acquired occlusions, and propose a novel mask-free VTON framework that can effectively handle these two types of occlusions.
- We design a background pre-replacement operation to prevent the model from mistaking the target clothing information as the human body or image background during the training process, thus mitigating inherent occlusions.
- We design a covering-and-eliminating operation to generate pseudo reference images that mimic the situations where acquired occlusions mostly occur. Under the supervision of real

ground-truths, eliminating the larger clothing in these reference images and reconstructing the human body will improve the model's ability of modeling human semantic structures.

- We validate the effectiveness of our method through extensive experiments and demonstrate its scalability to be compatible with different generative network architectures.

2 Related Work

Virtual Try-Ons. Recent work has achieved impressive results in virtual try-ons. For instance, Xie *et al.* [4] then proposed GP-VTON, which warps garments based on the characteristics of each area of garments, advancing garment alignment to the current peak of fully generalizable performance. However, it heavily relies on human parsing, and mask errors lead to a series of failed results. To address this, Du *et al.* [15] designed a cyclic architecture USC-PFN that successfully eliminates the negative impact of masks during inference. Recently, methods based on diffusion models have achieved notable results. For instance, DCI-VTON [5], based on the PbE architecture [11], pioneered the possibility of achieving high-quality virtual try-ons. Subsequently, methods like LaDI-VTON [10], StableVITON [7], and AnyDoor [13] have focused on the diffusion model structure to enhance generation quality. However, it has been demonstrated that even elementary Latent Diffusion Models are capable of producing high-quality results. Therefore, optimizing the final output results seems to be more effective than improving the network structure. Recently, Chong *et al.* [9] proposed CatVTON. They found that training only the self-attention layers of the diffusion model can achieve model convergence at an extremely low computational cost. This undoubtedly provides a more efficient research path for subsequent studies. Since then, it seems that the design of model architecture is a laborious and unprofitable task. Based on this, we propose a framework that focuses on the needs of the task itself rather than the design of model structure. It can easily solve the occlusion problem that all current methods have failed to address, and provides a new shortcut for future research on more robust and practical virtual try-on.

Occlusion. This is a long-standing challenge in virtual try-on, as the unpaired nature of training data and the imprecise segmentation masks often lead to two types of occlusions (inherent occlusion and acquired occlusion). Early works used 3D models [18] or dense pose [19] to infer missing regions, while recent methods adopt inpainting networks conditioned on segmentation masks [17]. Despite these advances, most existing methods treat occlusion as a passive artifact to be inpainted, rather than actively modeling the interaction between visible and occluded regions. We propose a simple-yet-effective mask-free framework that eliminates both types of occlusions via two key operations: background pre-replacement and covering-and-eliminating, which enhances the model's understanding of human semantic structures.

3 Preliminary

Given a VTON dataset $\{(\mathbf{g}_i, \mathbf{p}_i)\}_i \in \mathbf{D}$, where $\mathbf{g}_i \in \mathbb{R}^{3 \times H \times W}$ represents source clothing images and $\mathbf{p}_i \in \mathbb{R}^{3 \times H \times W}$ denotes reference person images depicting individuals wearing the corresponding clothing from $\mathbf{g}_i$. Due to the unpaired nature of the training data, *i.e.* the input $\mathbf{p}_i$ that contains the same person but wearing a different clothing is typically unavailable, prior methods [4, 5, 7, 8] typically leverage a mask-based inpainting model $\mathcal{M}_\phi$ parameterized by ϕ , which formulate VTON as an optimization problem by minimizing the following training objective:

$$\phi^* = \arg \min_{\phi} \mathcal{L}_{\text{dist}} \left(\mathbf{p}_i, \mathcal{M}_\phi(\mathbf{m}_{\text{agn}_i}, \mathbf{p}_{\text{agn}_i}, \mathbf{g}_i) \right), \quad (1)$$

where $\mathbf{m}_{\text{agn}_i} \in \{0, 1\}^{H \times W}$ is a inpainting mask, which represents the area of the clothing to be changed on $\mathbf{p}_i$ as well as the adjacent skin regions. $\mathbf{p}_{\text{agn}_i} = \mathbf{p}_i \odot (1 - \mathbf{m}_{\text{agn}_i})$ represents an inpainting person. Both are shown in Fig. 1, column 2. $\mathcal{L}_{\text{dist}}(\cdot)$ denotes a suitable loss function, *e.g.*, ℓ_1 and MSE losses. To compensate for the missing structural information (*e.g.*, arm shape) in $\mathbf{m}_{\text{agn}_i}$ region, additional human structural representations $\mathbf{r}_i$ (*e.g.*, densepose map [19]) of $\mathbf{p}_i$ are typically introduced as supplementary conditions to guide the synthesis of limbs and clothing. However, the low quality of $\mathbf{m}_{\text{agn}_i}$ and $\mathbf{r}_i$ usually hinders inpainting methods from obtaining the ideal semantic information to accurately translate the desired human body regions [1, 2], resulting in defective appearance **occlusion**, as depicted in Fig. 1.

Table 1: **Comparison of occlusion handling capabilities** between mask-based and mask-free VTONs. $\mathcal{M}_\phi$ and $\mathcal{M}_\psi$ correspond to mask-based and mask-free models. $\mathbf{D}_{\text{syn}}$ and $\mathbf{D}_{\text{real}}$ denote synthetic (by pre-trained $\mathcal{M}_\phi$) and real datasets. $\mathbf{D}_{\text{syn}}^*$ is generated from well-trained $\mathcal{M}_\psi$.

Model	Training Data	Mask-Free	Inherent Occlusion	Acquired Occlusion
$\mathcal{M}_\phi$	$\mathbf{D}_{\text{real}}$	✗	✗	✗
$\mathcal{M}_\psi$	$\mathbf{D}_{\text{syn}}, \mathbf{D}_{\text{real}}$	✓	✗	✗
$\mathcal{M}_\theta$	$\mathbf{D}_{\text{syn}}^*, \mathbf{D}_{\text{real}}$	✓	✓	<i>partial</i>

To mitigate the negative impacts of $\mathbf{m}_{\text{agn}_i}$ and $\mathbf{r}_i$, a mask-free architecture is proposed [1, 2, 3]. It uses the pre-trained well-performed, mask-based inpainting model $\mathcal{M}_\phi^*$ to generate a pseudo reference image $\mathbf{t}_{\text{un}_i} \in \mathbb{R}^{3 \times H \times W}$ ($\mathbf{p}_i$ wearing random clothing $\mathbf{g}_{\text{un}_i}$), thus replacing the functions of $\mathbf{m}_{\text{agn}_i}$ and $\mathbf{r}_i$, to form data triplets $(\mathbf{t}_{\text{un}_i}, \mathbf{g}_i, \mathbf{p}_i)$ for the full-supervised training of a mask-free $\mathcal{M}_\psi$ parameterized by ψ . It can also be formulated as minimizing the following training objective:

$$\psi^* = \arg \min_{\psi} \mathcal{L}_{\text{dist}} \left(\mathbf{p}_i, \mathcal{M}_\psi \left(\underbrace{\mathcal{M}_\phi^*(\mathbf{m}_{\text{agn}_i}, \mathbf{p}_{\text{agn}_i}, \mathbf{g}_{\text{un}_i}, \mathbf{r}_i)}_{\text{Pseudo Reference Image } \mathbf{t}_{\text{un}_i}}, \mathbf{g}_i \right) \right). \quad (2)$$

Since $\mathbf{m}_{\text{agn}_i}$ and $\mathbf{r}_i$ are no longer required as input conditions at $\mathcal{M}_\psi$, it seems that this architecture can thoroughly block the negative impact of $\mathbf{m}_{\text{agn}_i}$ and $\mathbf{r}_i$ on the results. However, as can be seen from Eq. (2), the pseudo reference image $\mathbf{t}_{\text{un}_i}$ related to defective $\mathbf{m}_{\text{agn}_i}$ and $\mathbf{r}_i$ that is not responsible in $\mathcal{M}_\phi^*$ can still be transferred to $\mathcal{M}_\psi$ during training, which can still cause **occlusion** in the results.

4 Occlusion Analysis

As can be seen from Fig. 1, occlusion manifests in different forms, but it is mainly caused by $\mathbf{m}_{\text{agn}}$ and $\mathbf{r}$ (subscript i is omitted for brevity). We refer to the occlusion caused by $\mathbf{m}_{\text{agn}}$ as "**inherent occlusion**," while the occlusion caused by $\mathbf{r}$ is called "**acquired occlusion**."

• **Inherent Occlusion.** The inherent occlusion stems from the *erroneous parsing of the clothing-relevant region* in $\mathbf{p}$, leading to an imprecise inpainting mask $\mathbf{m}_{\text{agn}}$ that missegments the human body, background, and clothing regions of $\mathbf{p}$. For mask-based methods, $\mathbf{m}_{\text{agn}}$ serves as the guiding condition for the inpainting model $\mathcal{M}_\phi$ (in Eq. (1)) to determine the area $\mathbf{p}_{\text{agn}} = \mathbf{p} \odot (1 - \mathbf{m}_{\text{agn}})$ that is to be preserved before and after trying on. Therefore, the residual source clothing areas in $\mathbf{p}_{\text{agn}}$ were treated as immutable and preserved unconditionally by $\mathcal{M}_\phi$. While ensuring accurate inpainting masks for both training data and inference samples might seem like a solution, the diversity of people, clothing, and scenes worldwide makes it impossible to guarantee consistently accurate masks during large-scale data training and inference. Therefore, this also directly sows the seeds of trouble for mask-free methods. In mask-free methods, the mask-based inpainting model $\mathcal{M}_\phi$ must provide a pseudo-reference (person) image $\mathbf{t}_{\text{un}}$ for model $\mathcal{M}_\psi$ (in Eq. (2)) to form a data triplet $\{(\mathbf{t}_{\text{un}}, \mathbf{g}), \mathbf{p}\}$, enabling fully supervised training for $\mathcal{M}_\psi$. This reconstructs $\mathbf{p}$ without needing the inpainting mask $\mathbf{m}_{\text{agn}}$. However, $\mathbf{t}_{\text{un}}$ contains residual areas from $\mathbf{p}$, which are mistakenly treated as background during reconstruction and mapped unchanged into the results. This creates incorrect associations between the target clothing and the human body or background pixels, ultimately leading to sub-optimal models that output try-on results with ghosts of the clothing from reference images. Consequently, during inference, when dealing with complex postures or rare clothing styles in person image $\mathbf{p}$, the mask-free $\mathcal{M}_\psi$ still misrecognizes boundaries between the human body and background, resulting in inherent occlusion.

• **Acquired Occlusion.** The acquired occlusion stems from *erroneous parsing of the human structure*, resulting in an inaccurate human structural representations (HSRs) $\mathbf{r}$ that misguide the learning and inference processes of the generator. For example, if a human parsing (semantic segmentation) map with a missing arm is used to translate into a human image, it is evident that the arm in the resulting image will also be missing. Therefore, as one of the conditional inputs, the quality of HSRs determines the quality of the generated human regions. In mask-based and mask-free methods, the manner in which acquired occlusion is produced is the same as that of inherent occlusion. The only difference is that acquired occlusion directly affects the model's understanding of human semantic

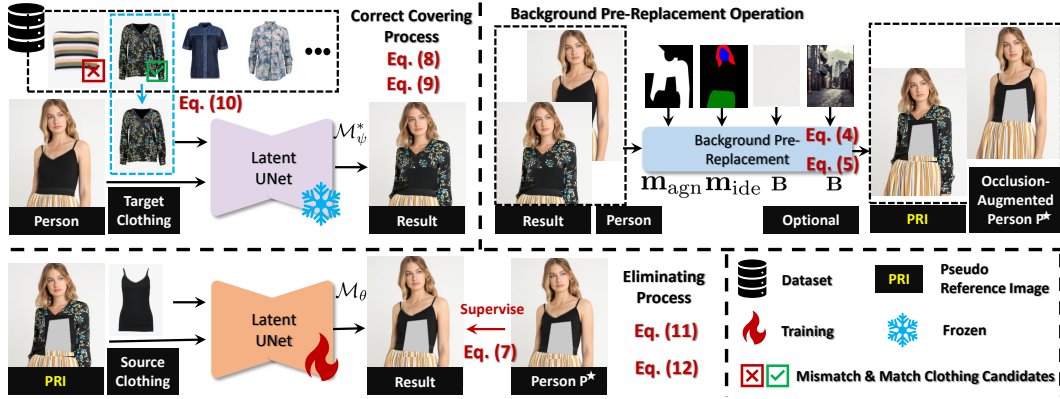


Figure 2: **Overview of our proposed framework.** It includes two operations: the covering and eliminating processes to integrate clothing with a person image, and the background pre-replacement operation to create a pseudo reference image by substituting the original background.

structures, thereby translating into disruptions and rendering the spatial structure of clothing and body parts unreasonable.

Based on the above analysis, we summarize the occlusion handling capabilities of mask-based and mask-free VTON methods in Tab. 1. It can be seen that they are all directly or indirectly affected by $\mathbf{m}_{\text{agn}}$ and $\mathbf{r}$. Motivated by the desire to break through the limitations faced by the aforementioned VTON methods, our goal is to design a new framework with a robust VTON model $\mathcal{M}_\theta$ to fundamentally mitigate the two types of occlusion issues.

5 Proposed Framework

To address the two types of occlusion problems, we propose a novel VTON framework (see Fig. 2) that aims to achieve high-quality occlusion-free VTON through a simple-yet-effective method.

5.1 How to Eliminate Inherent Occlusion ?

To eliminate inherent occlusion, a potential and feasible solution is to simultaneously *remove the residual regions from both the inputs and the supervision signals during training*. This prevents the model from mistakenly identifying these residual regions as part of the background or human body. However, detecting and segmenting the residual regions still involves the unreliability of segmentation errors. Therefore, we attempt to **replace the entire background that contains the residual regions**.

Background Pre-Replacement. To this end, we propose a background pre-replacement operation to intercept the residual regions that may propagate during the training process from the source. Given a data group $(\mathbf{p}, \mathbf{m}_{\text{agn}}, \mathbf{m}_{\text{ide}}) \in \mathbf{D}_{\text{real}}$, where $\mathbf{m}_{\text{ide}} \in \{0, 1\}^{H \times W^2}$ is a person identity mask from human parsing, *e.g.*, the head, hands, and feet. As shown in Figs. 2, we segment out the residual background mask $\mathbf{m}_{\text{RB}} \in \{0, 1\}^{H \times W}$ from $\mathbf{m}_{\text{agn}}$ via Eq. (3):

$$\mathbf{m}_{\text{RB}} = 1 - (\mathbf{m}_{\text{agn}} + \mathbf{m}_{\text{ide}} \odot (1 - \mathbf{m}_{\text{agn}})), \quad (3)$$

where $\odot$ represents the element-wise (Hadamard) product. In this case, $(1 - \mathbf{m}_{\text{RB}}) \odot \mathbf{p}$ contains not only the *background* but also *residual clothing regions*. Then, we use a background map $\mathbf{B} \in \mathbb{R}^{3 \times H \times W}$ to replace $(1 - \mathbf{m}_{\text{RB}}) \odot \mathbf{p}$ with a completely pure background, thereby completely severing the connection between the background and the human body region, expressed in Eq. (4):

$$\mathbf{p}^* = \mathbf{m}_{\text{RB}} \odot \mathbf{p} + (1 - \mathbf{m}_{\text{RB}}) \odot \mathbf{B}, \quad (4)$$

where $\mathbf{p}^*$ is the background-replaced version of $\mathbf{p}$. Thus, $\mathbf{p}$ ensures that there are no residuals in the supervision signal. For the input side, mask-based methods, which require the input of $\mathbf{m}_{\text{agn}}$, are

²The implementation method is shown in the **Technical Appendices** (Sec. C)

unable to effectively eliminate occlusions. Therefore, we use $\mathbf{m}_{\text{RB}}$ to process its result $\mathbf{t}_{\text{un}}$, thereby removing the residuals in the input of the mask-free model, as shown in Eq. (5):

$$\mathbf{t}_{\text{un}}^* = \mathbf{m}_{\text{RB}} \odot \mathbf{t}_{\text{un}} + (1 - \mathbf{m}_{\text{RB}}) \odot \mathbf{B}. \quad (5)$$

For specific improvements to the mask-free methods, please refer to Eq. (22). In summary, our design aims to enable the model to accurately **distinguish** between the human body and background from $\mathbf{p}$.

In-the-Wild Scenes. Currently, the datasets in use often feature meaningless and low-diversity scenarios. For instance, the backgrounds in the VITON [20] and VITON-HD [21] datasets are irregularly grayish-white, and most backgrounds in the DressCode dataset [22] are just monotonous wall colors. To enable the model to focus on changes in the inpainting region without being distracted by the diverse backgrounds found in real-world scenarios, the background map $\mathbf{B}$ can be designed to be *random* in-the-wild scene images generated by a pre-trained well-performed T2I (Text-to-Image) model [23, 24]: $\mathbf{B} = \text{T2I}(\mathbf{c}, \epsilon)$ ³, where $\mathbf{c}$ is the prompt and ϵ is random Gaussian noise. Alternatively, $\mathbf{B}$ can be designed as *random* single value matrix: $\mathbf{B} = \text{random}(0, 1) \in \mathbb{R}^{3 \times H \times W}$ for the pure background scenes.

5.2 How to Eliminate Acquired Occlusion ?

To address acquired occlusion as much as possible, one potential solution is *to significantly enhance the model's ability to understand human semantic structures*. To this end, a straightforward idea is **to first produce pseudo reference images with a different clothing that completely covers the original target clothing in $\mathbf{p}$. Then, our model is trained to eliminate these coverings and reconstruct the underlying human body areas**. During this process, the model's understanding of human semantic structures will be enhanced under the accurate supervision of real ground-truths, thereby mitigating the acquired occlusions of incorrect HSRs.

Covering and Eliminating Processes. We introduce an ideal architecture that can achieve the desired processes with a de-occlusion model $\mathcal{M}_\theta$, parameterized by θ , by minimizing the following training objectives:

$$\theta^* = \arg \min_{\theta} \mathcal{L}_{\text{dist}} \left(\mathbf{p}^*, \underbrace{\mathcal{M}_\theta \left(\underbrace{\mathcal{M}_\theta(\mathbf{p}^*, \mathbf{g}_{\text{un}})}_{\text{Covering Process}}, \mathbf{g} \right)}_{\text{Eliminating Process}} \right). \quad (6)$$

It can be observed that the architecture completely discards HSRs and instead acquires human structural information by learning to parse the human body within $\mathbf{p}^*$ itself. However, due to the absence of corresponding ground truth for $(\mathbf{p}^*, \mathbf{g}_{\text{un}})$, this architecture fails to converge. Moreover, since the mask-free model does not have the interference of $\mathbf{m}_{\text{agn}}$ and $\mathbf{r}$ present in the mask-based model, we positively believe that *the cover results of mask-free model $\mathcal{M}_\psi^*$ can serve as the more beneficial pseudo reference images $\mathbf{p}_{\text{un}}$* . To leverage this, we directly use the results of $\mathcal{M}_\psi^*$ to optimize $\mathcal{M}_\theta$. Therefore, Eq. (6) is rewritten as Eq. (7):

$$\theta^* = \arg \min_{\theta} \mathcal{L}_{\text{dist}}(\mathbf{p}^*, \mathcal{M}_\theta(\mathbf{p}_{\text{un}}, \mathbf{g})), \text{ where } \mathbf{p}_{\text{un}} = \text{BPR}(\mathcal{M}_\psi^*(\mathbf{p}, \mathbf{g}_{\text{un}})), \quad (7)$$

where BPR is background pre-replacement operations. However, the given $\mathbf{g}_{\text{un}}$ is random, whereas the $\mathbf{g}_{\text{un}}$ we expect here should have an area larger than that of the clothing $\mathbf{g}$ worn by $\mathbf{p}^*$.

Correct Covering Process. For simplicity and readability, we first analyze the **upper** clothing ($\mathbf{g}, \mathbf{g}_{\text{un}}$) here, while other cases, such as dresses, are discussed in the **Technical Appendices** (Sec. C.2). To obtain the desired $\mathbf{g}_{\text{un}}$, inspired by [6], we design a functional function $\mathcal{A}(\cdot)$ to determine the size of the clothing $\mathbf{g}$ on $\mathbf{p}^*$ and the size of the clothing $\mathbf{g}_{\text{un}}$. Although directly comparing sizes is intuitive and effective, for upper clothing, there may be cases where the sleeves of $\mathbf{g}_{\text{un}}$ are longer than those of $\mathbf{g}$, but the neckline is lower than that of $\mathbf{g}$. This makes it impossible to accurately judge the size and achieve complete coverage. Therefore, we conduct a more accurate indirect comparison by separately comparing the arm length and neckline size of $\mathbf{p}^*$ and $\mathbf{p}_{\text{un}}$. To this end, we trained a

³The implementation method is shown in the **Technical Appendices** (Sec. C)



Figure 3: **Qualitative results** on the VITON-HD dataset. The baseline methods consist of seven SOTA diffusion-based methods. **Red** dashed boxes highlight the limitations of each method.

parser S , which can generate human parsing (semantic segmentation) maps $\mathbf{m}^t \in \mathbb{R}^{18 \times H \times W}$ for 18 human semantic categories, thereby segmenting the human body region with specified semantics,

$$\mathbf{m}^t = S(\mathbf{p}_{\text{un}}), \text{ where } S^* = \arg \min_S \|\mathbf{m}^s - S(\mathbf{p}^*)\|_2^2, \quad (8)$$

here, $\mathbf{m}^s \in \mathbf{D}_{\text{real}}$ is the human parsing map of $\mathbf{p}^*$. Therefore, $\mathcal{A}(\cdot)$ is formulated as Eq. (9):

$$\mathcal{A}(\mathbf{m}_j^s, \mathbf{m}_j^t) = \sum_{w=1}^W \sum_{h=1}^H (\mathbf{m}_j^t - \mathbf{m}_j^s \odot \mathbf{m}_j^t)_{w,h}, \quad (9)$$

where j denotes the specified semantics, *e.g.*, neck, arms. To ensure that only $\mathbf{g}_{\text{un}}$ with a size absolutely larger than $\mathbf{g}$ participates in the training of the stage represented by Eq. (7), we introduce a gating coefficient γ . Following [6], when the arm and neck sizes of $\mathbf{p}_{\text{un}}$ are both smaller than those of $\mathbf{p}^*$, we set $\gamma = 1$ (represents that backpropagation can be performed). In this case, $\mathbf{g}_{\text{un}}$ can fully cover the original clothing of $\mathbf{p}^*$, expressed as Eq. (10):

$$\gamma = \begin{cases} 1, & \text{if } \mathcal{A}(\mathbf{m}_{\text{arm}}^s, \mathbf{m}_{\text{arm}}^t) \geq 0 \text{ and } \mathcal{A}(\mathbf{m}_{\text{neck}}^s, \mathbf{m}_{\text{neck}}^t) \geq 0, \\ 0, & \text{otherwise.} \end{cases} \quad (10)$$

where $\mathbf{m}_{\text{arm}} \in \{0, 1\}^{H \times W}$ and $\mathbf{m}_{\text{neck}} \in \{0, 1\}^{H \times W}$ represent the semantic layers of the arms and the neck, respectively. By performing the occlusion elimination task represented in Eq. (7), the model can effectively learn to eliminate the acquired occlusions and achieve a favorable convergence. However, there exists a *distribution shift* between the pseudo reference image $\mathbf{p}_{\text{un}}$ and the real data $\mathbf{p}$, which will bound the performance of $\mathcal{M}_\theta$.

Correct Distribution Shift. To correct the distribution shift, we perform the reconstruction task with a probability of $\eta = 10\%$ during training, thereby expanding the model's perception of the real distribution. This process is represented as Eq. (11):

$$\theta^* = \arg \min_{\theta} \mathcal{L}_{\text{dist}}(\mathbf{p}, \mathcal{M}_\theta(\mathbf{p}, \mathbf{g})). \quad (11)$$

5.3 Plug-and-Play De-occlusion for Generative Models

There are now many types of generative networks, such as the classic GANs [25] and diffusion models [23]. *The de-occlusion approach we discussed above can be fully applied to both.* However, for diffusion models, due to their unique Markov process, the implementation process differs slightly from that of GANs. We implemented $\mathcal{M}_\theta$ using the diffusion model in this work, and the overall loss corresponding to Eqs. (7) and (11) is expressed as Eq. (12):

$$\min_{\theta} \begin{cases} \gamma \cdot \mathcal{L}_{\text{LDM}}(\mathcal{M}_\theta(\mathbf{p}_{\text{un}}, \mathbf{g}), \mathbf{p}^*), & \text{if } p > \eta, \\ \mathcal{L}_{\text{LDM}}(\mathcal{M}_\theta(\mathbf{p}, \mathbf{g}), \mathbf{p}), & \text{otherwise.} \end{cases} \quad (12)$$

where $p = \text{random}(0, 1)$ denotes the probability value generated randomly. Limited by space, specific implementation details are illustrated in **Technical Appendices** (Sec. B).

Table 2: **Quantitative comparisons on the VITON-HD and DressCode datasets.** For LPIPS, FID, and KID, the lower the better. For SSIM, the higher the better. "Mask-Free" denotes whether the inpainting mask m_{agn} and human structural representation (HSR) r are used during *inference*. **Bold** denotes the best result. Underline represents second best.

Train / Test Methods	Publication	Backbone	Mask-Free	VITON-HD				DressCode Upper			
				SSIM _p ↑	LPIPS _p ↓	FID _{up} ↓	KID _{up} ↓	SSIM _p ↑	LPIPS _p ↓	FID _{up} ↓	KID _{up} ↓
VITON-HD [21]	CVPR'21	ResUnet	✗	0.862	0.117	12.117	3.23	n/a	n/a	n/a	n/a
HR-VITON [26]	ECCV'22	ResUnet	✗	0.878	0.105	11.265	2.73	0.936	0.065	13.82	2.71
GP-VTON [4]	CVPR'23	ResUnet	✗	0.884	0.081	9.701	1.26	0.769	0.270	20.11	8.17
LaDI-VTON [10]	MM'23	SD1.5	✗	0.864	0.096	9.480	1.99	0.915	0.063	14.26	3.33
PbE [11]	CVPR'23	SD1.5	✗	0.802	0.143	11.939	3.85	0.897	0.078	15.33	4.64
DCI-VTON [5]	MM'23	SD1.5	✗	0.880	0.080	8.998	1.19	0.937	0.042	11.92	1.89
StableVTON [7]	CVPR'24	SD1.5	✗	0.864	0.084	9.465	1.40	n/a	n/a	n/a	n/a
StableGarment [27]	arXiv'24	SD1.5	✗	0.803	0.104	17.115	8.85	n/a	n/a	n/a	n/a
Anydoor [13]	CVPR'24	SD1.5	✗	0.821	0.099	10.850	2.46	0.899	0.119	14.83	3.05
IDM-VTON [28]	ECCV'24	SDXL	✗	0.850	<u>0.060</u>	9.842	1.12	0.880	0.056	9.54	4.32
LDE-VTON [16]	AAAI'25	SD1.5	✗	0.884	0.081	9.640	1.21	n/a	n/a	n/a	n/a
CatVTON [9]	ICLR'25	SD1.5	✗	0.870	0.061	9.287	1.17	0.902	<u>0.045</u>	<u>7.40</u>	2.62
BooW-VTON [14]	CVPR'25	SDXL	✓	0.862	0.108	8.809	0.82	0.919	0.062	11.03	0.86
Ours	This Work	SD1.5	✓	0.889	0.057	<u>8.854</u>	<u>0.96</u>	0.923	0.042	6.58	<u>1.72</u>

- n/a: official code or data is inaccessible.

6 Experiments and Analysis

Implementation. Our model is built on the Diffusers framework⁴ with Stable Diffusion v1.5 as the backbone and initialized from the official CatVTON checkpoint [9]. It is fine-tuned for 100 epochs on six NVIDIA RTX 4090 GPUs under Ubuntu 22.04 LTS. Training employs $T = 1,000$ denoising steps with a linear noise schedule, the AdamW [29] optimizer ($\beta_1 = 0.5$, $\beta_2 = 0.999$) in fp32 precision, a batch size of 8, and a learning rate of 1×10^{-5} .

Datasets and Metrics. We conduct experiments on three challenging datasets: **VITON** [20], **VITON-HD** [21], and **DressCode** [22]. **VITON** dataset contains 16,253 image groups, each with a resolution of 256×192 . It is divided into a training set of 14,221 groups and a testing set of 2,032 groups. **VITON-HD** dataset, with a resolution of 512×384 , comprises 13,679 image groups and is split into a training set of 11,647 groups and a testing set of 2,032 groups. **DressCode** dataset, also with a resolution of 512×384 , includes 15,363 image groups and is divided into a training set of 12,863 groups and a testing set of 2,500 groups.

All evaluations and visualizations are performed using the test set. For metrics, under paired setting (p, g), we employ the **SSIM** (Structural Similarity Index Measure) [33] to assess the pixel-level similarity between the generated and ground-truth images. Meanwhile, we utilize **LPIPS** (Learned Perceptual Image Patch Similarity) [34] to measure the perceptual similarity, which captures the semantic and high-level features of the images. For evaluating the overall distribution of generated images compared to real images, under unpaired setting (p, g_{un}), we calculate the **FID** (Fréchet Inception Distance) [35] and **KID** (Kernel Inception Distance) [36], which provide insights into how well our method can produce images that match the real-world data distribution.

Baselines. We utilize 21 state-of-the-art (SOTA) methods for comprehensive evaluation.

• **GAN-based Methods:** PF-AFN [2], RT-VTON [30], DAFlow [31], DressCode [22], POVNet [32], USC-PFN [15], VITON-HD [21], HR-VITON [26], and GP-VTON [4].

Table 3: **Quantitative comparisons on the VITON dataset.**

Methods	Publication	Mask-Free	SSIM _p ↑	FID _{up} ↓
PF-AFN [2]	CVPR'21	✓	0.89	10.21
RT-VTON [30]	CVPR'22	✗	n/a	11.66
DAFlow [31]	ECCV'22	✗	0.88	12.05
DressCode [22]	CVPR'22	✗	0.89	13.71
POVNet [32]	TPAMI'23	✗	0.89	13.37
USC-PFN [15]	NeurIPS'23	✓	0.91	10.47
PbE [11]	CVPR'23	✗	0.83	12.56
TPD [12]	CVPR'24	✗	0.89	<u>9.58</u>
LDE-VTON [16]	AAAI'25	✗	<u>0.91</u>	9.86
Ours	This Work	✓	0.91	9.23

- n/a: official code or data is inaccessible.

⁴<https://github.com/huggingface/diffusers>



Figure 4: **Qualitative results** on the DressCode dataset. The baseline methods consist of four SOTA diffusion-based methods. **Red** dashed boxes highlight the limitations of each method.

• **Diffusion-based Methods:** LaDI-VTON [10], PbE [11], DCI-VTON [5], TPD [12], StableVITON [7], OOTDiffusion [8], AnyDoor [13], StableGarment [27], IDM-VTON [28], LDE-VTON [16], CatVTON [9], and BooW-VTON [14].

6.1 Comparison with Baseline Methods

We conducted a quantitative comparison of our method against 21 baseline methods, as shown in Tab. 3. On the low-resolution dataset VITON [20], our method outperforms existing technologies in terms of FID, while achieving comparable results to the SOTA methods in terms of SSIM. This is mainly because the residual parts of the source person are favorable for the SSIM metric (for reconstruction). As shown in Tab. 2, on the two high-resolution datasets VITON-HD [21] and DressCode [22], our method slightly underperforms the SOTA BooW-VTON in some metrics. One significant reason for this is that BooW-VTON utilizes a more powerful SDXL backbone [24].

Apart from this, our method outperforms existing technologies in most cases and also secures the highest overall ranking. This demonstrates that our method can effectively address occlusion issues while generalizing well to try-on scenarios with various clothing styles.

For a visual assessment⁵, we present qualitative comparison on VITON-HD [21] and DressCode [22]. As shown in Figs. 3 and 4. It can be seen that regardless of the style of the dataset, our framework can handle both types of occlusions with ease, especially the significant inherent occlusions. Our method can almost completely eliminate this issue, which demonstrates the generalization and universality of the proposed approach. Furthermore, as shown in Fig. 5, we applied our training framework to GANs. The occlusion-free results obtained confirm that our framework can be generalized to any generative network type (GANs or diffusion models, *etc.*).

6.2 Ablation Studies

We study the effectiveness of each design choice in our framework and draw the following conclusions: **(#1) Correct Covering Process.** We replaced g_{un} in Eq. (7) with both a randomly selected g_{un} and one that had been filtered through our strategy, in order to verify the effectiveness of our filtering approach. As shown in Fig. 6 and Tab. 4, using a randomly selected g_{un} still resulted in significant acquired occlusion. However, after applying our filtering strategy to the baseline (CatVTON [9]), the phenomenon of acquired occlusion was largely eliminated. This indicates that enhancing the model's ability to eliminate occlusions in covered samples can improve the model's capability to parse human structures. **(#2) Background Pre-Replacement.** Without background pre-replacement,



Figure 5: **Applying our training framework to GANs.**

⁵More visualization results are shown in the **Technical Appendices** (Sec. D) and **Supplementary Material**



Figure 6: **Visual ablation studies** of different components in our approach. Zooming in for more details. **Red** dashed boxes highlight the limitations of each configuration.

the try-on results of configuration #2 in Fig. 6 exhibited significant inherent occlusion. However, after introducing $\mathbf{m}_{RB}$ to replace the background of $\mathbf{p}$, the inherent occlusion was eliminated, thereby demonstrating the effectiveness of the background pre-replacement. **(#3) Correct Distribution Shift.** We verified its effectiveness by separately adding and removing the correct distribution shift process. As can be seen from Fig. 6 and Tab. 4, when the correct distribution shift is removed, some samples exhibit synthetic bias, which is caused by the erroneous distribution of some defective $\mathbf{p}_{un}$ misleading the model training process. Therefore, when it is added, this part of the defect is significantly improved. **(#4) In-the-Wild Scenes.** Firstly, Tab. 4 presents our background replacement method for datasets with pure backgrounds. Additionally, we verified the generalization of replacing the background of $\mathbf{p}$ with $\mathbf{B}$ in real-world scenarios, *i.e.*, testing the model trained on the pure background VITON-HD dataset with the DressCode dataset. The results in Fig. 6 show that our method can better handle person images with diverse background styles, indicating that using the synthesized $\mathbf{B}$ can significantly enhance the model’s ability to distinguish between the human body and background.

7 Conclusion

In this work, we present a novel mask-free VTON framework to address the inherent and acquired occlusion problems that plague existing VTON methods. Our framework introduces two key operations: the background pre-replacement operation and the covering-and-eliminating operation. The background pre-replacement operation effectively mitigates inherent occlusions by preventing the model from confusing target clothing information with the human body or image background. The covering-and-eliminating operation enhances the model’s ability to understand and model human semantic structures, thereby reducing acquired occlusions. Our method is highly generalizable and can be easily integrated into various generative network architectures, such as GANs and diffusion models, in a plug-and-play manner. Extensive experiments on three VTON datasets validate the effectiveness and generalization ability of our proposed framework.

Acknowledgments

This work was in part supported by the National Key Research and Development Program of China (Grant No. 2022ZD0160604), the National Natural Science Foundation of China (NSFC, Grant No. 62176194), the Key Research and Development Program of Hubei Province (Grant No. 2023BAB083), the Project of Sanya Yazhou Bay Science and Technology City (Grant Nos. SCKJ-JYRC-2022-76, SKJC-2022-PTDX-031), the Project of Sanya Science and Education Innovation Park of Wuhan University of Technology (Grant No. 2021KF0031), and the Huawei Kunpeng-Ascend Innovation Incentive Programme. This work was also supported in part by both computing resources from the Wuhan Supercomputing Center and the Wuhan Artificial Intelligence Computing Center.

Table 4: **Ablation studies on VITON-HD.**

Configuration	SSIM _p ↑	LPIPS _{up} ↓	FID _{up} ↓	KID _{up} ↓
Baseline	0.870	0.061	9.287	1.17
#1	0.883	0.059	8.902	1.11
#2	0.882	0.060	8.863	1.04
#3	0.887	0.058	8.859	0.98
#4	0.889	0.057	8.854	0.96

References

- [1] Thibaut Issenhuth, Jérémie Mary, and Clément Calauzenes. Do not mask what you do not need to mask: a parser-free virtual try-on. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XX 16*, pages 619–635. Springer, 2020.
- [2] Yuying Ge, Yibing Song, Ruimao Zhang, Chongjian Ge, Wei Liu, and Ping Luo. Parser-free virtual try-on via distilling appearance flows. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 8485–8493, 2021.
- [3] Sen He, Yi-Zhe Song, and Tao Xiang. Style-based global appearance flow for virtual try-on. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 3470–3479, 2022.
- [4] Zhenyu Xie, Zaiyu Huang, Xin Dong, Fuwei Zhao, Haoye Dong, Xijin Zhang, Feida Zhu, and Xiaodan Liang. Gp-vton: Towards general purpose virtual try-on via collaborative local-flow global-parsing learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 23550–23559, June 2023.
- [5] Junhong Gou, Siyu Sun, Jianfu Zhang, Jianlou Si, Chen Qian, and Liqing Zhang. Taming the power of diffusion models for high-quality virtual try-on with appearance flow. In *Proceedings of the 31st ACM International Conference on Multimedia*, pages 7599–7607, 2023.
- [6] Chenghu Du, Junyin Wang, Yi Rong, Shuqing Liu, Kai Liu, and Shengwu Xiong. Cyclelton: A cycle mapping framework for parser-free virtual try-on. *Proceedings of the AAAI Conference on Artificial Intelligence*, 38(2):1618–1625, 2024.
- [7] Jeongho Kim, Gyojung Gu, Minho Park, Sunghyun Park, and Jaegul Choo. Stablelton: Learning semantic correspondence with latent diffusion model for virtual try-on. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 1–10, 2024.
- [8] Yuhao Xu, Tao Gu, Weifeng Chen, and Arlene Chen. Ootdiffusion: Outfitting fusion based latent diffusion for controllable virtual try-on. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 39, pages 8996–9004, 2025.
- [9] Zheng Chong, Xiao Dong, Haoxiang Li, Shiyue Zhang, Wenqing Zhang, Xujie Zhang, Hanqing Zhao, Dongmei Jiang, and Xiaodan Liang. Catvton: Concatenation is all you need for virtual try-on with diffusion models. *arXiv preprint arXiv:2407.15886*, 2024.
- [10] Davide Morelli, Alberto Baldrati, Giuseppe Cartella, Marcella Cornia, Marco Bertini, and Rita Cucchiara. Ladi-vton: Latent diffusion textual-inversion enhanced virtual try-on. In *Proceedings of the 31st ACM International Conference on Multimedia*, pages 8580–8589, 2023.
- [11] Binxin Yang, Shuyang Gu, Bo Zhang, Ting Zhang, Xuejin Chen, Xiaoyan Sun, Dong Chen, and Fang Wen. Paint by example: Exemplar-based image editing with diffusion models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 18381–18391, 2023.
- [12] Xu Yang, Changxing Ding, Zhibin Hong, Junhao Huang, Jin Tao, and Xiangmin Xu. Texture-preserving diffusion models for high-fidelity virtual try-on. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 7017–7026, 2024.
- [13] Xi Chen, Lianghua Huang, Yu Liu, Yujun Shen, Deli Zhao, and Hengshuang Zhao. Anydoor: Zero-shot object-level image customization. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 6593–6602, 2024.
- [14] Xuanpu Zhang, Dan Song, Pengxin Zhan, Tianyu Chang, Jianhao Zeng, Qingguo Chen, Weihua Luo, and Anan Liu. Boow-vton: Boosting in-the-wild virtual try-on via mask-free pseudo data training. *arXiv preprint arXiv:2408.06047*, 2024.
- [15] Chenghu Du, Shuqing Liu, Shengwu Xiong, et al. Greatness in simplicity: Unified self-cycle consistency for parser-free virtual try-on. *Advances in Neural Information Processing Systems*, 36, 2024.
- [16] Chenghu Du, Junyin Wang, Feng Yu, and Shengwu Xiong. Latent diffusion-enhanced virtual try-on via optimized pseudo-label generation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 39, pages 2780–2788, 2025.
- [17] Zhijing Yang, Junyang Chen, Yukai Shi, Hao Li, Tianshui Chen, and Liang Lin. Occlumix: Towards de-occlusion virtual try-on by semantically-guided mixup. *IEEE Transactions on Multimedia*, 25:1477–1488, 2023.

- [18] Bharat Lal Bhatnagar, Garvita Tiwari, Christian Theobalt, and Gerard Pons-Moll. Multi-garment net: Learning to dress 3d people from images. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, October 2019.
- [19] Rıza Alp Güler, Natalia Neverova, and Iasonas Kokkinos. Densepose: Dense human pose estimation in the wild. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 7297–7306, 2018.
- [20] Xintong Han, Zuxuan Wu, Zhe Wu, Ruichi Yu, and Larry S Davis. Viton: An image-based virtual try-on network. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 7543–7552, 2018.
- [21] Seunghwan Choi, Sunghyun Park, Minsoo Lee, and Jaegul Choo. Viton-hd: High-resolution virtual try-on via misalignment-aware normalization. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 14131–14140, 2021.
- [22] Davide Morelli, Matteo Fincato, Marcella Cornia, Federico Landi, Fabio Cesari, and Rita Cucchiara. Dress code: High-resolution multi-category virtual try-on. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 2231–2235, 2022.
- [23] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 10684–10695, 2022.
- [24] Dustin Podell, Zion English, Kyle Lacey, Andreas Blattmann, Tim Dockhorn, Jonas Müller, Joe Penna, and Robin Rombach. Sdxl: Improving latent diffusion models for high-resolution image synthesis. *arXiv preprint arXiv:2307.01952*, 2023.
- [25] Ian J Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. *Advances in neural information processing systems*, 27, 2014.
- [26] Sangyun Lee, Gyojung Gu, Sunghyun Park, Seunghwan Choi, and Jaegul Choo. High-resolution virtual try-on with misalignment and occlusion-handled conditions. In *Computer Vision—ECCV 2022: 17th European Conference, Tel Aviv, Israel, October 23–27, 2022, Proceedings, Part XVII*, pages 204–219. Springer, 2022.
- [27] Rui Wang, Hailong Guo, Jiaming Liu, Huaxia Li, Haibo Zhao, Xu Tang, Yao Hu, Hao Tang, and Peipei Li. Stablegarment: Garment-centric generation via stable diffusion. *arXiv preprint arXiv:2403.10783*, 2024.
- [28] Yisol Choi, Sangkyung Kwak, Kyungmin Lee, Hyungwon Choi, and Jinwoo Shin. Improving diffusion models for authentic virtual try-on in the wild. In *European Conference on Computer Vision*, pages 206–235. Springer, 2024.
- [29] Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization. *arXiv preprint arXiv:1711.05101*, 2017.
- [30] Han Yang, Xinrui Yu, and Ziwei Liu. Full-range virtual try-on with recurrent tri-level transform. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 3460–3469, 2022.
- [31] Shuai Bai, Huiling Zhou, Zhikang Li, Chang Zhou, and Hongxia Yang. Single stage virtual try-on via deformable attention flows. In *Computer Vision—ECCV 2022: 17th European Conference, Tel Aviv, Israel, October 23–27, 2022, Proceedings, Part XV*, pages 409–425. Springer, 2022.
- [32] Kedan Li, Jeffrey Zhang, and David Forsyth. Povnet: Image-based virtual try-on through accurate warping and residual. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 45(10):12222–12235, 2023.
- [33] Kalpana Seshadrinathan and Alan C Bovik. Unifying analysis of full reference image quality assessment. In *2008 15th IEEE International Conference on Image Processing*, pages 1200–1203. IEEE, 2008.
- [34] Richard Zhang, Phillip Isola, Alexei A Efros, Eli Shechtman, and Oliver Wang. The unreasonable effectiveness of deep features as a perceptual metric. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 586–595, 2018.
- [35] Martin Heusel, Hubert Ramsauer, Thomas Unterthiner, Bernhard Nessler, and Sepp Hochreiter. Gans trained by a two time-scale update rule converge to a local nash equilibrium. *Advances in neural information processing systems*, 30, 2017.

- [36] Mikołaj Bińkowski, Danica J Sutherland, Michael Arbel, and Arthur Gretton. Demystifying mmd gans. *arXiv preprint arXiv:1801.01401*, 2018.
- [37] Jascha Sohl-Dickstein, Eric Weiss, Niru Maheswaranathan, and Surya Ganguli. Deep unsupervised learning using nonequilibrium thermodynamics. In *International conference on machine learning*, pages 2256–2265. PMLR, 2015.
- [38] Jonathan Ho, Ajay Jain, and Pieter Abbeel. Denoising diffusion probabilistic models. *Advances in neural information processing systems*, 33:6840–6851, 2020.
- [39] Alexander Quinn Nichol and Prafulla Dhariwal. Improved denoising diffusion probabilistic models. In *International conference on machine learning*, pages 8162–8171. PMLR, 2021.
- [40] Bochao Wang, Huabin Zheng, Xiaodan Liang, Yimin Chen, Liang Lin, and Meng Yang. Toward characteristic-preserving image-based virtual try-on network. In *Proceedings of the European conference on computer vision (ECCV)*, pages 589–604, 2018.
- [41] Ruiyun Yu, Xiaoqi Wang, and Xiaohui Xie. Vtnfp: An image-based virtual try-on network with body and clothing feature preservation. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 10511–10520, 2019.
- [42] Xintong Han, Xiaojun Hu, Weilin Huang, and Matthew R Scott. Clothflow: A flow-based model for clothed person generation. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 10471–10480, 2019.
- [43] Matiur Rahman Minar, Thai Thanh Tuan, Heejune Ahn, Paul Rosin, and Yu-Kun Lai. Cp-vton+: Clothing shape and texture preserving image-based virtual try-on. In *CVPR Workshops*, volume 3, pages 10–14, 2020.
- [44] Surgan Jandial, Ayush Chopra, Kumar Ayush, Mayur Hemani, Balaji Krishnamurthy, and Abhijeet Halwai. Sievenet: A unified framework for robust image-based virtual try-on. In *Proceedings of the IEEE/CVF winter conference on applications of computer vision*, pages 2182–2190, 2020.
- [45] Han Yang, Ruimao Zhang, Xiaobao Guo, Wei Liu, Wangmeng Zuo, and Ping Luo. Towards photo-realistic virtual try-on by adaptively generating-preserving image content. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 7850–7859, 2020.
- [46] Guoqiang Liu, Dan Song, Ruofeng Tong, and Min Tang. Toward realistic virtual try-on through landmark guided shape matching. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pages 2118–2126, 2021.
- [47] Chongjian Ge, Yibing Song, Yuying Ge, Han Yang, Wei Liu, and Ping Luo. Disentangled cycle consistency for highly-realistic virtual try-on. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 16928–16937, 2021.
- [48] Ayush Chopra, Rishabh Jain, Mayur Hemani, and Balaji Krishnamurthy. Zflow: Gated appearance flow-based virtual try-on with 3d priors. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 5433–5442, 2021.
- [49] Kedan Li, Min Jin Chong, Jeffrey Zhang, and Jingen Liu. Toward accurate and realistic outfits visualization with attention to details. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 15546–15555, 2021.

Appendix

For a thorough understanding and visualization of our proposed framework, we compile a comprehensive appendix.

- Section **A**: Preliminary: Diffusion Models.
- Section **B**: Algorithmic Representation of Proposed Method During Training and Inference.
- Section **C**: Comprehensive Technical Appendices.
- Section **D**: More Visualization Results Comparing with Baseline Methods.
- Section **E**: Limitations, Failure Cases, and Future Work Discussion.
- Section **F**: Societal Impact Discussion.

A Preliminary: Diffusion Models

Diffusion models [37, 38, 39], as probabilistic generative models, encompass a two-step process: diffusion and its reverse. The diffusion phase adheres to a Markov chain defined by $q(z_t|z_{t-1}) = \mathcal{N}(z_t; \sqrt{1-\beta_t}z_{t-1}, \beta_t\mathbf{I})$, spanning T iterations with a noise schedule $\{\beta_t\}_{t=1}^T$. This schedule incrementally corrupts the initial data, $z_0 \sim q(z_0)$, with Gaussian noise. Each noisy latent state z_t at any timestep t can be sampled directly through a closed-form sampling function:

$$z_t := \sqrt{\bar{\alpha}_t}z_0 + \sqrt{1-\bar{\alpha}_t}\epsilon, \quad \epsilon \sim \mathcal{N}(0, \mathbf{I}), \quad (13)$$

where t is uniformly sampled from $\{1, \dots, T\}$. The noise level is determined by $\alpha_t = 1 - \beta_t$, and $\bar{\alpha}_t = \prod_{s=1}^t \alpha_s$. The reverse process starts with a noisy data $z_T \sim \mathcal{N}(0, \mathbf{I})$ at step T and gradually denoises it using known real distributions $q(z_{t-1}|z_t)$ for each step:

$$p_\theta(z_{t-1}|z_t) = \mathcal{N}(z_{t-1}; \mu_\theta(z_t, t), \Sigma_\theta(z_t, t)). \quad (14)$$

To achieve this, a denoising autoencoder $\epsilon_\theta(\cdot)$ is trained to remove noise ϵ from z_t to reconstruct z_0 by optimizing the following objective:

$$\min_{\theta} \mathbb{E}_{z_0, \epsilon, t} \|\epsilon_\theta(z_t, t) - \epsilon\|_2^2. \quad (15)$$

B Training and Inference Procedures

The training and inference procedures of our proposed VTON framework are designed to address the inherent and acquired occlusion issues while ensuring high-quality occlusion-free virtual try-on results. The detailed procedures are outlined in Algorithm 1. The training process iterates until convergence, optimizing the model parameters θ to achieve high-quality occlusion-free virtual try-on. Additionally, for diffusion models, our training objective for Eq. (7) is formulated as follows:

$$\min_{\theta} \mathbb{E}_{z_0, \epsilon_x \sim \mathcal{N}(0, \mathbf{I}), t \sim \mathcal{U}(1, T)} \left[\|\epsilon_x - \epsilon_\theta(z_t, \text{Cat}_S(\mathbf{z}_{\text{p}_{\text{un}}}, \mathbf{z}_{\text{g}}), t)\|_2^2 \right], \quad (16)$$

where

$$\mathbf{z}_t = \sqrt{\bar{\alpha}_t}\epsilon_x - \sqrt{1-\bar{\alpha}_t}\text{Cat}_S(\mathbf{z}_{\text{p}^*}, \mathbf{z}_{\text{g}}), \quad \epsilon_x \sim \mathcal{N}(0, \mathbf{I}) \in \mathbb{R}^{4 \times \frac{H}{8} \times \frac{W}{4}}, \quad (17)$$

$\mathbf{z}_{\text{p}_{\text{un}}} \in \mathbb{R}^{4 \times \frac{H}{8} \times \frac{W}{8}} = \mathcal{E}_{\text{VAE}}(\mathbf{p}_{\text{un}})$, $\mathbf{z}_{\text{g}} \in \mathbb{R}^{4 \times \frac{H}{8} \times \frac{W}{8}} = \mathcal{E}_{\text{VAE}}(\mathbf{g})$, $\mathbf{z}_{\text{p}^*} \in \mathbb{R}^{4 \times \frac{H}{8} \times \frac{W}{8}} = \mathcal{E}_{\text{VAE}}(\mathbf{p}^*)$. $\text{Cat}_S(\cdot)$ denotes the concatenation operation along the **spatial** dimension. $\mathcal{E}$ is the encoder of KL-regularized autoencoder with its default latent-space downsampling factor $f = 8$. In addition, our training objective for Eq. (11) is formulated as follows:

$$\min_{\theta} \mathbb{E}_{z_0, \epsilon_x \sim \mathcal{N}(0, \mathbf{I}), t \sim \mathcal{U}(1, T)} \left[\|\epsilon_x - \epsilon_\theta(z_t, \text{Cat}_S(\mathbf{z}_{\text{p}}, \mathbf{z}_{\text{g}}), t)\|_2^2 \right], \quad (18)$$

where

$$\mathbf{z}_t = \sqrt{\bar{\alpha}_t}\epsilon_x - \sqrt{1-\bar{\alpha}_t}\text{Cat}_S(\mathbf{z}_{\text{p}}, \mathbf{z}_{\text{g}}), \quad \epsilon_x \sim \mathcal{N}(0, \mathbf{I}) \in \mathbb{R}^{4 \times \frac{H}{8} \times \frac{W}{4}}, \quad (19)$$

$\mathbf{z}_{\text{p}} \in \mathbb{R}^{4 \times \frac{H}{8} \times \frac{W}{8}} = \mathcal{E}_{\text{VAE}}(\mathbf{p})$.

During the inference phase, the pre-trained well-performed try-on model $\mathcal{M}_\theta^*$ is used to generate virtual try-on results.

Algorithm 1: Training and Inference Procedures

Input: Dataset $\mathbf{D}_{\text{real}}$, pre-trained T2I model, pre-trained parser S , pre-trained model $\mathcal{M}_{\psi}^*$ **Output:** Trained model $\mathcal{M}_{\theta}^*$

```
1 Training Procedure:
2 repeat
3   Obtain the input sample:
4    $(\mathbf{g}, \mathbf{g}_{\text{un}}, \mathbf{p}) \sim \mathbf{D}_{\text{real}}$  // Target clothing image, random clothing image, and
      reference person image from the dataset
5   Obtain the segmentation masks:
6    $\mathbf{m}_{\text{agn}} \sim \mathbf{D}_{\text{real}}$  // inpainting mask from the dataset
7    $\mathbf{m}_{\text{ide}} \sim \mathbf{D}_{\text{real}}$  // Identity layers (e.g., head, hands, feet) from the
      dataset
8   Generate the background-replaced person image:
9    $\mathbf{m}_{\text{RB}} \leftarrow 1 - (\mathbf{m}_{\text{agn}} + \mathbf{m}_{\text{ide}} \odot (1 - \mathbf{m}_{\text{agn}}))$ ; // Compute the residual
      background mask.
10   $\mathbf{B} \leftarrow \text{T2I}(c, \epsilon)$ ; // Generate a random background image using a
      pre-trained T2I model.
11   $\mathbf{p}^* \leftarrow \mathbf{m}_{\text{RB}} \odot \mathbf{p} + (1 - \mathbf{m}_{\text{RB}}) \odot \mathbf{B}$ ; // Replace the background.
12  Check the size of the clothing:
13   $\mathbf{m}_{\text{t}} \leftarrow S(\mathbf{p}^*)$ ; // Generate the human parsing map of the person image
      using a pre-trained parser  $S$ .
14   $\gamma \leftarrow \begin{cases} 1, & \text{if } \mathcal{A}(\mathbf{m}_{\text{s}}^{\text{neck}}, \mathbf{m}_{\text{t}}^{\text{neck}}) \geq 0 \text{ and } \mathcal{A}(\mathbf{m}_{\text{s}}^{\text{arm}}, \mathbf{m}_{\text{t}}^{\text{arm}}) \geq 0, \\ 0, & \text{otherwise.} \end{cases}$ ; // Check if the
      clothing can fully cover the original one.
15  Compute the pseudo reference image:
16   $\mathbf{p}_{\text{un}} \leftarrow \mathcal{M}_{\psi}^*(\mathbf{p}^*, \mathbf{g}_{\text{un}})$ ; // Generate the pseudo reference image using the
      teacher model.
17  Perform the de-occlusion task:
18  if  $\gamma = 1$  then
19     $\nabla_{\theta} \mathcal{L}_{\text{DM}}(\mathcal{M}_{\theta}(\mathbf{p}_{\text{un}}, \mathbf{g}), \mathbf{p}^*)$ ; // Minimize the loss between the generated
      image and the pseudo reference image.
20  end
21  Correct the distribution shift:
22   $p \sim \text{Uniform}(0, 1)$ ; // Generate a random probability value.
23  if  $p < \eta$  then
24     $\nabla_{\theta} \mathcal{L}_{\text{DM}}(\mathcal{M}_{\theta}(\mathbf{p}, \mathbf{g}), \mathbf{p})$ ; // Minimize the loss between the generated
      image and the real image.
25  end
26 until converged;
27 Inference Procedure:
   Input: Target clothing image  $\mathbf{g}_{\text{un}}$ , reference person image  $\mathbf{p}$ 
   Output: Virtual try-on result  $\mathbf{p}_{\text{try}}$ 
28 Generate the virtual try-on result:
29  $\mathbf{p}_{\text{try}} \leftarrow \mathcal{M}_{\theta}^*(\mathbf{p}, \mathbf{g}_{\text{un}})$ ; // Generate the virtual try-on result.
30 return  $\mathbf{p}_{\text{try}}$ 
```

C Technical Appendices

C.1 Improve Traditional Mask-Free Method

For traditional mask-free methods, such as WUTON [1], PF-AFN [2], and LDE-VTON [16], solving inherent occlusions can be achieved with just a few simple steps. First, we generate teacher knowledge through a pre-trained well-performed teacher (inpainting) model $\mathcal{M}_{\phi}^*$:

$$\mathbf{t}_{\text{un}} = \mathcal{M}_{\phi}^*(\mathbf{m}_{\text{agn}}, \mathbf{p}_{\text{agn}}, \mathbf{g}_{\text{un}}, \mathbf{r}). \quad (20)$$

Then, we use $\mathbf{m}_{\text{RB}}$ to perform *background pre-replacement* on $\mathbf{t}_{\text{un}}$:

$$\mathbf{t}_{\text{un}}^* = \mathbf{m}_{\text{RB}} \odot \mathbf{B} + (1 - \mathbf{m}_{\text{RB}}) \odot \mathbf{t}_{\text{un}}. \quad (21)$$

Finally, $\mathbf{t}_{\text{un}}^*$ is paired with $\mathbf{p}^*$, where $\mathbf{p}^*$ can be used as the input, while $\mathbf{t}_{\text{un}}^*$ serves as the pseudo reference image. The distillation process is then carried out by training a student network $\mathcal{M}_\psi$:

$$\psi^* = \arg \min_{\psi} \mathcal{L}_{\text{dist}} \left(\mathbf{t}_{\text{un}}^*, \mathcal{M}_\psi(\mathbf{p}^*, \mathbf{g}_{\text{un}}) \right). \quad (22)$$

Alternatively, $\mathbf{t}_{\text{un}}^*$ can be used as the input, while $\mathbf{p}^*$ is used as the ground truth to train the student network $\mathcal{M}_\psi$:

$$\psi^* = \arg \min_{\psi} \mathcal{L}_{\text{dist}} \left(\mathbf{p}^*, \mathcal{M}_\psi(\mathbf{t}_{\text{un}}^*, \mathbf{g}) \right). \quad (23)$$

C.2 Size Comparison for Other Types of Clothing

To ensure that only $\mathbf{g}_{\text{un}}$ with a size absolutely larger than $\mathbf{g}$ participates in the training of the stage represented by Eq. (7), in addition to the execution process for upper clothing described in the main text, the following are the execution processes for the remaining two types of clothing.

Lower Clothing. For lower clothing, when the leg size of $\mathbf{p}_{\text{un}}$ is smaller than those of $\mathbf{p}^*$, we set $\gamma = 1$. In this case, $\mathbf{g}_{\text{un}}$ can fully cover the original lower clothing of $\mathbf{p}^*$, expressed as Eq. (24):

$$\gamma = \begin{cases} 1, & \text{if } \mathcal{A}(\mathbf{m}_{\text{leg}}^s, \mathbf{m}_{\text{leg}}^t) \geq 0, \\ 0, & \text{otherwise,} \end{cases} \quad (24)$$

where $\mathbf{m}_{\text{leg}} \in \{0, 1\}^{H \times W}$ represents the semantic layer of the legs. For the person identity mask $\mathbf{m}_{\text{ide}}$, we obtained the layers "hair," "shoes," "hat," "sunglasses," "scarf," "bag," "head," "upper_clothes," and "arms" from human parsing as the sub-layers that compose $\mathbf{m}_{\text{ide}}$. The code is represented as:

```
1 m_ide = (parse_array == label_map["hair"]).astype(np.float32) + \
2 (parse_array == label_map["left_shoe"]).astype(np.float32) + \
3 (parse_array == label_map["right_shoe"]).astype(np.float32) + \
4 (parse_array == label_map["hat"]).astype(np.float32) + \
5 (parse_array == label_map["sunglasses"]).astype(np.float32) + \
6 (parse_array == label_map["scarf"]).astype(np.float32) + \
7 (parse_array == label_map["bag"]).astype(np.float32) + \
8 (parse_array == label_map["head"]).astype(np.float32) + \
9 (parse_array == label_map["upper_clothes"]).astype(np.float32) + \
10 (parse_array == label_map["left_arm"]).astype(np.float32) + \
11 (parse_array == label_map["right_arm"]).astype(np.float32)
```

Dresses. For dresses, when the arm, neck, and leg sizes of $\mathbf{p}_{\text{un}}$ are smaller than those of $\mathbf{p}^*$, we set $\gamma = 1$. In this case, $\mathbf{g}_{\text{un}}$ can fully cover the original dresses of $\mathbf{p}^*$, expressed as Eq. (25):

$$\gamma = \begin{cases} 1, & \text{if } \mathcal{A}(\mathbf{m}_{\text{neck}}^s, \mathbf{m}_{\text{neck}}^t) \geq 0 \text{ and } \mathcal{A}(\mathbf{m}_{\text{arm}}^s, \mathbf{m}_{\text{arm}}^t) \geq 0 \text{ and } \mathcal{A}(\mathbf{m}_{\text{leg}}^s, \mathbf{m}_{\text{leg}}^t) \geq 0, \\ 0, & \text{otherwise.} \end{cases} \quad (25)$$

For $\mathbf{m}_{\text{ide}}$, we obtained the layers "hair," "shoes," "hat," "sunglasses," "scarf," "bag," and "head," from human parsing as the sub-layers that compose $\mathbf{m}_{\text{ide}}$. The code is represented as:

```
1 m_ide = (parse_array == label_map["hair"]).astype(np.float32) + \
2 (parse_array == label_map["left_shoe"]).astype(np.float32) + \
3 (parse_array == label_map["right_shoe"]).astype(np.float32) + \
4 (parse_array == label_map["hat"]).astype(np.float32) + \
5 (parse_array == label_map["sunglasses"]).astype(np.float32) + \
6 (parse_array == label_map["scarf"]).astype(np.float32) + \
7 (parse_array == label_map["bag"]).astype(np.float32) + \
8 (parse_array == label_map["head"]).astype(np.float32)
```

Upper Clothing. For m_{ide} , we obtained the layers "hair," "shoes," "hat," "sunglasses," "scarf," "bag," "head," "skirt," "pants," "dress" "belt" and "legs" from human parsing as the sub-layers that compose m_{ide} . The code is represented as:

```
1 m_ide = m_ide + # m_ide of dresses
2   (parse_array == label_map["skirt"]).astype(np.float32) + \
3   (parse_array == label_map["pants"]).astype(np.float32) + \
4   (parse_array == label_map["dress"]).astype(np.float32) + \
5   (parse_array == label_map["belt"]).astype(np.float32) + \
6   (parse_array == label_map["left_leg"]).astype(np.float32) + \
7   (parse_array == label_map["right_leg"]).astype(np.float32)
```

C.3 How to obtain B in Eq. (4)?

The background map B can be designed to be random scene images generated by a pre-trained well-performed T2I (Text-to-Image) model [23, 24]: $B = T2I(c, \epsilon)$, where c is the prompt and ϵ is random Gaussian noise. In our implementation, T2I utilizes the pre-trained SD1.5 implemented by the diffusers library in Huggingface⁶. By simply inputting a prompt c related to any scene, the desired scene image B can be obtained.

Alternatively, B can be designed as random single value matrix: $B = \text{random}(0, 1) \in \mathbb{R}^{3 \times H \times W}$. This approach is simpler and more practical because we only require the model to focus on the human body in the image, without needing the model to understand what the background in the image is. Its code is implemented as follows:

```
1 mRB = 1 - (agnostic_mask + m_ide * (1-agnostic_mask))
2 B = torch.rand(1) # A random floating-point number between 0 and 1
3 image = (1 - mRB) * image + mRB * B
```

The reason for choosing a random floating-point number between 0 and 1 is that the normalized human image's original background color values generally range from 0 to 1, which allows B to better adapt to real sample distributions.

D More Results

We first supplement some quantitative results of classic methods on the VITON dataset [20] in Tab. 3, as shown in Table 5. In addition, we qualitatively compare our proposed method with several state-of-the-art (SOTA) methods.

D.1 Results of VITON-HD

We conducted qualitative comparisons between our method and baseline methods on the VITON-HD dataset [21], with a resolution of 512×384 . Figs. 7 and 8 illustrate the visual comparison of try-on results between our method, DCI-VTON [5], StableVITON [7], IDM-VTON [28], StableGarment [27], LDE-VTON [16], and CatVTON [9]. It is evident that our method can handle occlusion problem of higher-resolution images in different methods, resulting in more realistic try-on results.

D.2 Results of DressCode

Furthermore, we have also included additional visual comparisons between our method and baseline methods (IDM-VTON [28], StableGarment [27], and CatVTON [9]) on DressCode dataset [22] to

Table 5: **Supplementary quantitative results of early virtual try-on methods on the VITON dataset in Tab. 3.** "Mask-Free" denotes whether the mask and structural representation are used during inference. **Bold** denotes the best result. Underline represents second best.

Methods	Publication	Mask-Free	SSIM _p ↑	FID _{up} ↓
VITON [20]	CVPR'18	✗	0.74	55.71
CP-VTON [40]	ECCV'18	✗	0.72	24.45
VTNFP [41]	ICCV'19	✗	0.80	n/a
Cloth-flow [42]	CVPR'19	✗	0.84	14.43
CP-VTON+ [43]	CVPRW'20	✗	0.75	21.04
SieveNet [44]	WACV'20	✗	0.77	n/a
ACGPN [45]	CVPR'20	✗	0.84	16.64
LM-VTON [46]	AAAI'21	✗	0.85	17.18
DCTON [47]	CVPR'21	✗	0.83	14.82
ZFlow [48]	ICCV'21	✗	0.88	15.17
OVNet [49]	CVPR'21	✗	0.85	15.78
Ours	This Work	✓	0.91	9.23

- n/a: official code or data is inaccessible.

⁶<https://huggingface.co/docs/diffusers/training/text2image>

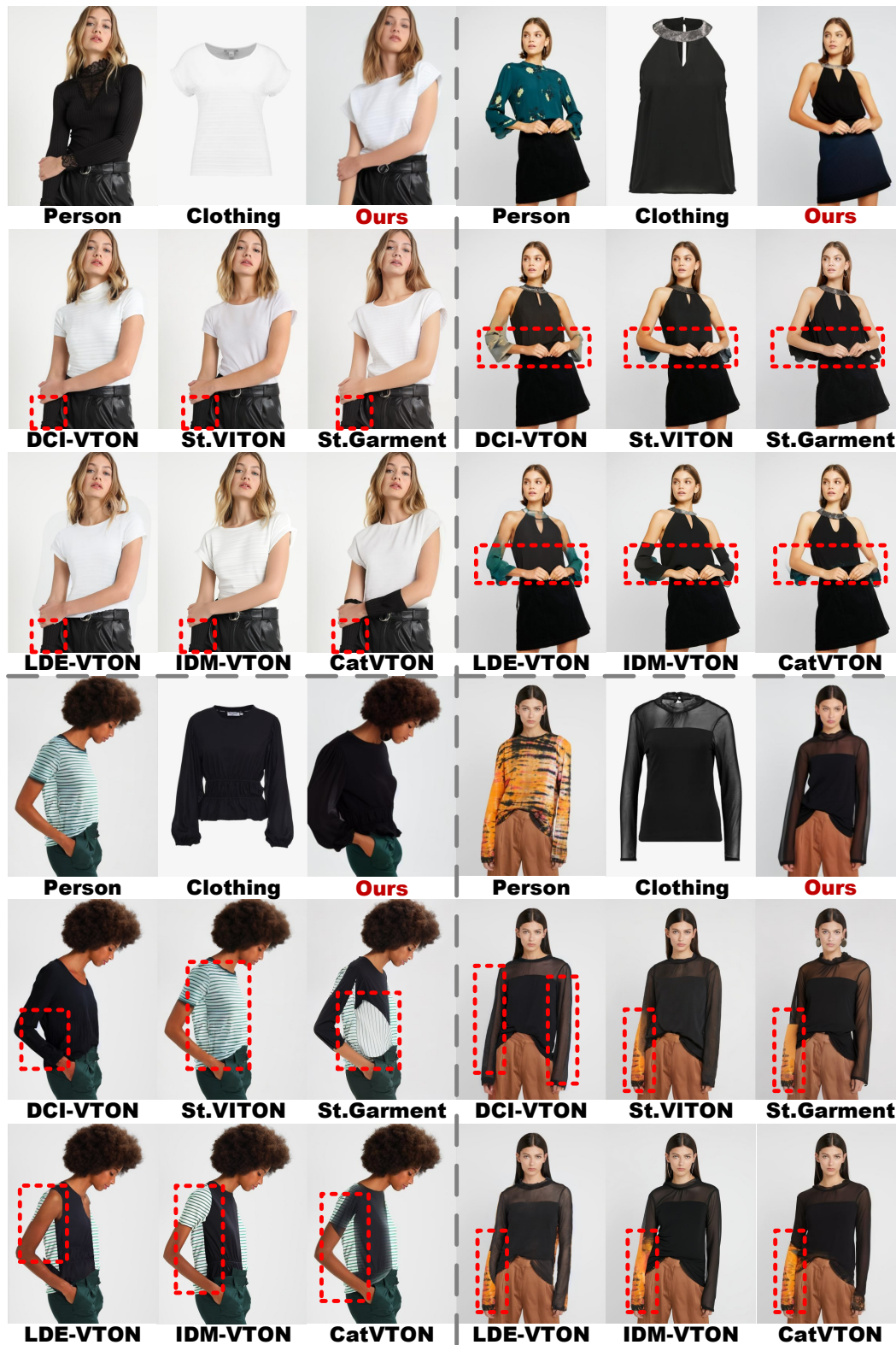


Figure 7: **Qualitative results** on the VITON-HD dataset. The baseline methods consist of six SOTA diffusion-based methods. **Red** dashed boxes highlight the limitations of each method.

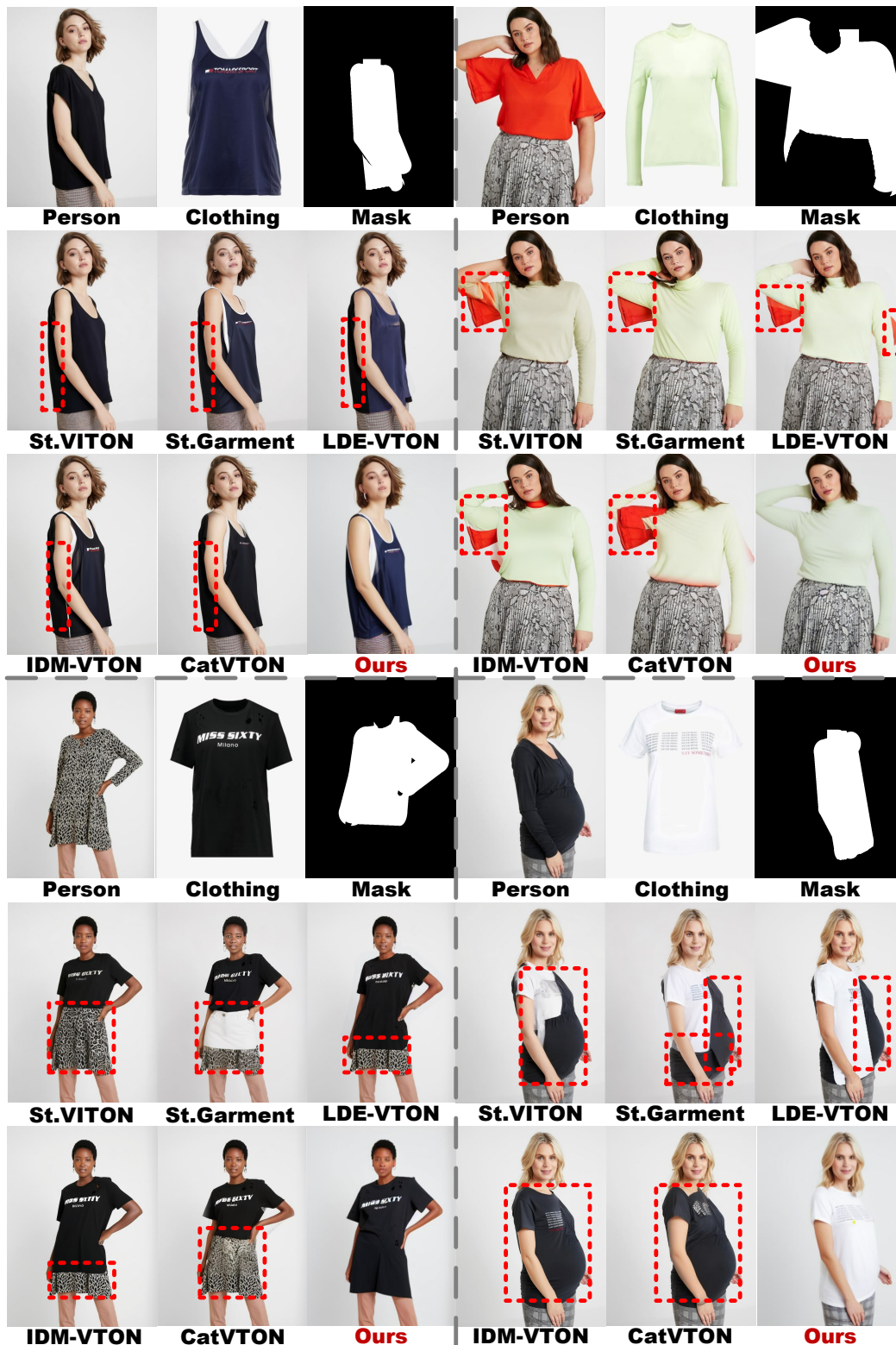


Figure 8: **Qualitative results** on the VITON-HD dataset. The baseline methods consist of five SOTA diffusion-based methods. Red dashed boxes highlight the limitations of each method.



Figure 9: **Qualitative results** on the DressCode dataset (**Dresses**). The baseline methods consist of three SOTA diffusion-based methods. **Red** dashed boxes highlight the limitations of each method.



Figure 10: **Qualitative results** on the DressCode dataset (**Upper**). The baseline methods consist of three SOTA diffusion-based methods. **Red** dashed boxes highlight the limitations of each method.





Figure 12: **Qualitative results** in in-the-wild scenarios.

demonstrate its superiority, as shown in Figs. 9 (Dresses), 10 (Upper Clothing), and 11 (Lower Clothing).

D.3 In-the-Wild Results

To validate the robustness and generalization of the model in real-world, open-domain scenarios, we tested a set of in-the-wild samples. In the actual implementation, we migrated our de-occlusion architecture to [8] to leverage the powerful garment-image understanding capability of ReferenceNet. After fine-tuning, the visualized results are shown in Fig. 12.

E Limitation and Future Work

Despite significant advancements in addressing occlusion issues for virtual try-on, this work still faces limitations, particularly regarding dataset quality. Current datasets, whether synthetic or real, may fail to capture the full range of human appearances, clothing styles, and occlusion scenarios, thus limiting model performance. Furthermore, our method may yield failed results when encountering clothing shapes that are objectively unlearnable, as shown in Fig. 13. In the currently available datasets, the lower body area indicated by the red dashed box in the swimsuit is covered by pants after trying it on. However, in real life, people generally do not wear other pants or skirts when wearing this kind of swimsuit. Due to the inconsistency between this ground truth and real-life situations, biases have been introduced in the try-on process for different clothing samples. The model cannot learn to synthesize this area, resulting in a failed try-on of the lower body area. However, this limitation is due to the lack of diversity in the dataset, rather than a flaw in the framework we designed. We believe that this issue can be resolved in the future by using a much larger number of training samples. Future work should focus on enriching dataset diversity and mitigating biases to enhance model robustness and applicability.



Figure 13: **Example of a failed virtual try-on of our method.**

F Discussion of Societal Impacts

The societal impacts of virtual try-on technology are multifaceted, offering significant benefits in terms of enhanced shopping experiences, fashion innovation, and environmental sustainability. However, these advancements also bring challenges related to privacy, digital divide, ethical considerations, and economic disruption. Addressing these challenges requires a collaborative effort from technologists, policymakers, and stakeholders across the retail and fashion industries to ensure that the benefits of virtual try-on technology are realized equitably and responsibly.

By engaging in ongoing discussions and implementing appropriate measures, we can harness the potential of virtual try-on technology to create a more inclusive, convenient, and sustainable future for fashion and retail.

NeurIPS Paper Checklist

1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

Answer: [Yes]

Justification: The main claims made in the abstract and introduction accurately reflect the paper's contributions and scope.

Guidelines:

- The answer NA means that the abstract and introduction do not include the claims made in the paper.
- The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
- The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
- It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [Yes]

Justification: We discuss the limitations of the work in the section of limitation.

Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. Theory assumptions and proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [NA]

Justification: This paper does not involve theoretical results.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. Experimental result reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [Yes]

Justification: We provide detailed information about experiments in the appendix and provide the source code that can reproduce reported results.

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general, releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
 - (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
 - (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
 - (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
 - (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: We will release of code and data.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so “No” is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. Experimental setting/details

Question: Does the paper specify all the training and test details (e.g., data splits, hyper-parameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [Yes]

Justification: We specify all the training and test details in the main text and appendix.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

7. Experiment statistical significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [No]

Justification: We follow the convention in prior works and report the performance number on the standard benchmarks.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).

- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. Experiments compute resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [Yes]

Justification: We provided sufficient information on the computer resources in the main text.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. Code of ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics <https://neurips.cc/public/EthicsGuidelines>?

Answer: [Yes]

Justification: The research conducted in the paper conformed, in every respect, with the NeurIPS Code of Ethics.

Guidelines:

- The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. Broader impacts

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [Yes]

Justification: Discuss both potential positive societal impacts and negative societal impacts of the work in the appendix.

Guidelines:

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.

- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. Safeguards

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [NA]

Justification: We don't need those for our model.

Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. Licenses for existing assets

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [Yes]

Justification: We properly credited the creators or original owners of assets (e.g., code, data, models), used in the paper and conformed the license and terms.

Guidelines:

- The answer NA means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, paperswithcode.com/datasets has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.

- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. **New assets**

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [\[Yes\]](#)

Justification: All new assets are well documented.

Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and research with human subjects**

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [\[NA\]](#)

Justification: Our paper does not involve study participants.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional review board (IRB) approvals or equivalent for research with human subjects**

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [\[NA\]](#)

Justification: Our paper does not involve study participants.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

16. **Declaration of LLM usage**

Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

Answer: [NA]

Justification: The core method development in this research does not involve LLMs as any important, original, or non-standard components.

Guidelines:

- The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
- Please refer to our LLM policy (<https://neurips.cc/Conferences/2025/LLM>) for what should or should not be described.