Blended Latent Diffusion

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The tremendous progress in neural image generation, coupled with the emergence of seemingly omnipotent vision-language models has finally enabled text-based interfaces for creating and editing images. Handling generic images requires a diverse underlying generative model, hence the latest works utilize diffusion models, which were shown to surpass GANs in terms of diversity. One major drawback of diffusion models, however, is their relatively slow inference time. In this paper, we present an accelerated solution to the task of local text-driven editing of generic images, where the desired edits are confined to a user-provided mask. Our solution leverages a text-to-image Latent Diffusion Model (LDM), which speeds up diffusion by operating in a lower-dimensional latent space and eliminating the need for resource-intensive CLIP gradient calculations at each diffusion step. We first enable LDM to perform local image edits by blending the latents at each step, similarly to Blended Diffusion. Next we propose an optimization-based solution for the inherent inability of LDM to accurately reconstruct images. Finally, we address the scenario of performing local edits using thin masks. We evaluate our method against the available baselines both qualitatively and quantitatively and demonstrate that in addition to being faster, it produces more precise results.

1 INTRODUCTION

In recent years we have witnessed tremendous progress in realistic image synthesis and image manipulation with deep neural generative models. GAN-based models were first to emerge [Brock et al. 2018; Goodfellow et al. 2014; Karras et al. 2019, 2020], soon followed by diffusion-based models [Ho et al. 2020; Nichol and Dhariwal 2021; Sohl-Dickstein et al. 2015]. In parallel, recent vision-language models, such as CLIP [Radford et al. 2021], have paved the way for generating and editing images using a fundamental form of human communication — natural language. The resulting text-guided image generation and manipulation approaches, e.g., [Ding et al. 2021; Nichol et al. 2021; Patashnik et al. 2021; Ramesh et al. 2022; Saharia et al. 2022b; Yu et al. 2022], enable artists to simply convey their intent in natural language, potentially saving hours of painstaking manual work. Figure 1 shows a few examples.

Fig. 1. Applications of our method: (top left) adding a new object in a masked area, guided by a text prompt; (top right) altering a part within an existing object; (middle left) generation of text; (middle right) altering the background in the scene; (bottom left) generating multiple predictions for the same text prompt (“stones”); (bottom right) guiding the result by a combination of text (“paint splashes”) and scribbles. Credits: pxfuel / piqsels

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However, the vast majority of text-guided approaches focus on generating images from scratch or on manipulating existing images globally. The local editing scenario, where the artist is only interested in modifying a part of a generic image, while preserving the remaining parts, has not received nearly as much attention, despite the ubiquity of this use case in practice. We know of only three methods to date that explicitly address the local editing scenario: Blended Diffusion [Avrahami et al. 2022b], GLIDE [Nichol et al. 2021] and DALL-E 2 [Ramesh et al. 2022]. Among these, only Blended Diffusion is publicly available in full.

All three local editing approaches above are based on diffusion models [Ho et al. 2020; Nichol and Dhariwal 2021; Sohl-Dickstein et al. 2015]. While diffusion models have shown impressive results on generation, editing, and other tasks (Section 2), they suffer from long inference times, due to the iterative diffusion process that is applied at the pixel level to generate each result. Some recent works [Bond-Taylor et al. 2021; Esser et al. 2021b; Gu et al. 2021; Hu et al. 2021; Rombach et al. 2022; Valdat et al. 2021] have thus proposed to perform the diffusion in a latent space with lower dimensions and higher-level semantics, compared to pixels, yielding competitive performance on various tasks with much lower training and inference times. In particular, Latent Diffusion Models (LDM) [Rombach et al. 2022] offer this appealing combination of competitive image quality with fast inference, however, this approach targets text-to-image generation from scratch, rather than global image manipulation, let alone local editing.

In this work, we harness the merits of LDM to the task of local text-guided natural image editing, where the user provides the image to be edited, a natural language text prompt, and a mask indicating an area to which the edit should be confined. Our approach is “zero-shot”, since it relies on available pretrained models, and requires no further training. We first show how to adapt the Blended Diffusion approach of Avrahami et al. [2022b] to work in the latent space of LDM, instead of working at the pixel level.

Next, we address the imperfect reconstruction inherent to LDM, due to the use of VAE-based lossy latent encodings. This is especially problematic when the original image contains areas to which human perception is particularly sensitive (e.g., faces or text) or other non-random high frequency details. We present an approach that employs latent optimization to effectively mitigate this issue.

Then, we address the challenge of performing local edits inside thin masks. Such masks are essential when the desired edit is highly localized, but they present a difficulty when working in a latent space with lower spatial resolution. To overcome this issue, we propose a solution that starts with a dilated mask, and gradually shrinks it as the diffusion process progresses.

Finally, we evaluate our method against the baselines both qualitatively and quantitatively, using new metrics for text-driven editing methods that we propose: precision and diversity. We demonstrate that our method is not only faster than the baselines, but also achieves better precision.

In summary, the main contribution of this paper are: (1) Adapting the text-to-image LDM to the task of local text-guided image editing. (2) Addressing the inherent problem of inaccurate reconstruction in LDM, which severely limits the applicability of this method. (3) Addressing the case when the method is fed by a thin mask, based on our investigation of the diffusion dynamics. (4) Proposing new evaluation metrics for quantitative comparisons between local text-driven editing methods.

2 RELATED WORK

Text-to-image synthesis and global editing. Text-to-image synthesis has advanced tremendously in recent years. Seminal works based on RNNs [Mansimov et al. 2016] and GANs [Reed et al. 2016; Xu et al. 2018; Zhang et al. 2017, 2018b], were later superseded by transformer-based approaches [Vaswani et al. 2017]. DALL-E [Ramesh et al. 2021] proposed a two-stage approach: first, train a discrete VAE [Razavi et al. 2019; van den Oord et al. 2017] to learn a rich semantic context, then train a transformer model to autoregressively model the joint distribution over the text and image tokens.

Another line of works is based on CLIP [Radford et al. 2021], a vision-language model that learns a rich shared embedding space for images and text, by contrastive training on a dataset of 400 million (image, text) pairs collected from the internet. Some of them [Crowson 2021; Crowson et al. 2022; Liu et al. 2021; Murdoch 2021; Paiss et al. 2022; Patashnik et al. 2021] combine a pretrained generative model [Brock et al. 2018; Dhariwal and Nichol 2021; Esser et al. 2021a] with a CLIP model to steer the generative model to perform text-to-image synthesis. Utilizing CLIP along with a generative model was also used for text-based domain adaptation [Gal et al. 2022] and text-to-image without training on text data [Ashual et al. 2022; Wang et al. 2022; Zhou et al. 2021]. Make-a-scene [Gafni et al. 2022] first predicts the segmentation mask, conditioned on the text, and then uses the generated mask along with the text to generate the predicted image. SpaText [Avrahami et al. 2022a] extends Make-a-scene to support free-form text prompt per segment. These works do not address our setting of local text-guided image editing.

Diffusion models were also used for various global image-editing applications: ILVR [Choi et al. 2021] demonstrates how to condition a DDPM model on an input image for image translation tasks. Palette [Saharia et al. 2022a] trains a designated diffusion model to perform four image-to-image translation tasks, namely colorization, inpainting, uncropping, and JPEG restoration. SDEedit [Meng et al. 2021] demonstrates stroke painting to image, image compositing, and stroke-based editing. RePaint [Lugmayr et al. 2022] uses a diffusion model for free-form inpainting of images. None of the above methods tackle the problem of local text-driven image editing.

Local text-guided image manipulation. Paint By Word [Bau et al. 2021] was first to address the problem of zero-shot local text-guided image manipulation by combining BigGAN / StyleGAN with CLIP and editing only the part of the feature map that corresponds to the input mask. However, this method only operated on generated images as input, and used a separate generative model per input domain. Later, Blended Diffusion [Avrahami et al. 2022b] was proposed as the first solution for local text-guided editing of real generic images; this approach is further described in Section 3.

Text2LIVE [Bar-Tal et al. 2022] enables editing the appearance of an object within an image, without relying on a pretrained generative model. They mainly focus on changing the colors/textures of an existing object or adding effects such as fire/smoke, and not on
editing a general scene by removing objects or replacing them with new ones, as we do.

More related to our work are the recent GLIDE [Nichol et al. 2021] and DALL-E 2 [Ramesh et al. 2022] works. GLIDE employs a two-stage diffusion-based approach for text-to-image synthesis: the first stage generates a low-resolution version of the image, while the second stage generates a higher resolution version of the image, conditioned on both the low-resolution version and the guiding text. In addition, they fine-tune their model specifically for the task of local editing by a guiding text prompt. Currently, only GLIDE-filtered, a smaller version of their model (300M parameters instead of 5B), which was trained on a smaller filtered dataset, has been released. As we demonstrate in Section 5, GLIDE-filtered often fails to obtain the desired edits. DALL-E 2 performs text-to-image synthesis by mapping text prompts into CLIP image embeddings, followed by decoding such embeddings to images. The DALL-E 2 website [OpenAI 2022] shows some examples of local text-guided image editing; however, this is not the full story in the paper [Ramesh et al. 2022]. Furthermore, neither of their two models has been released. The only available resource is their online demo [OpenAI 2022] that is free for a small number of images, which we use for comparisons (Figure 8).

The concurrent prompt-to-prompt work [Hertz et al. 2022] enables editing of generated images without input masks, given a source text prompt and a target text prompt. In contrast, our method enables editing real images, given only a target prompt and a mask.

In summary, at the time of this writing, the only publicly available models that address our setting are Blended Diffusion and GLIDE-filtered.

3 LATENT DIFFUSION AND BLENDED DIFFUSION

Diffusion models are deep generative models that sample from the desired distribution by learning to reverse a gradual noising process. Starting from a standard normal distribution noise $\mathbf{x}_T$, a series of less-noisy latents, $\mathbf{x}_{T-1}, \ldots, \mathbf{x}_0$, are produced. For more details, please refer to [Ho et al. 2020; Nichol and Dhariwal 2021].

Traditional diffusion models operate directly in the pixel space, hence their optimization often consumes hundreds of GPU days and their inference times are long. To enable faster training and inference on limited computational resources, Rombach et al. [2022] proposed Latent Diffusion Models (LDMs). They first perform perceptual image compression, using an autoencoder (VAE [Kingma and Welling 2013] or VQ-VAE [Esser et al. 2021a; Razavi et al. 2019; Van Den Oord et al. 2017]). Next, a diffusion model is used that operates on the lower-dimensional latent space. They also demonstrate the ability to train a conditional diffusion model on various modalities (e.g., semantic maps, images, or texts), s.t. when they combine it with the autoencoder they create image-to-image / semantic-map-to-image / text-to-image transitions.

Blended Diffusion [Avrahami et al. 2022b] addresses zero-shot text-guided local image editing. This approach utilizes a diffusion model trained on ImageNet [Deng et al. 2009], which serves as a prior for the manifold of the natural images, and a CLIP model [Radford et al. 2021], which navigates the diffusion model towards the desired text-specified outcome. In order to create a seamless result where only the masked region is modified to comply with the guiding text prompt, each of the noisy images progressively generated by the CLIP-guided process is spatially blended with the corresponding noisy version of the input image. The main limitations of this method is its slow inference time (about 25 minutes using a GPU) and its pixel-level noise artifacts (see Figure 2).

In the next section, we leverage the trained LDM text-to-image model of Rombach et al. [2022] to offer a solution for zero-shot text-guided local image editing by incorporating the idea of blending the diffusion latents from Avrahami et al. [2022b] into the LDM latent space (Section 4.1) and mitigating the artifacts inherent to working in that space (Sections 4.2 and 4.3).

4 METHOD

Given an image $x$, a guiding text prompt $d$ and a binary mask $m$ that marks the region of interest in the image, our goal is to produce a modified image $\hat{x}$, s.t. the content $\hat{x} \odot m$ is consistent with the text description $d$, while the complementary area remains close to the source image, i.e., $\hat{x} \odot (1 - m) = \hat{x} \odot (1 - m)$, where $\odot$ is element-wise multiplication. Furthermore, the transition between the two areas of $\hat{x}$ should ideally appear seamless.

In Section 4.1 we start by incorporating Blended Diffusion [Avrahami et al. 2022b] into Latent Diffusion [Rombach et al. 2022] in order to achieve local text-driven editing. The resulting method fails to achieve satisfying results in some cases; specifically, the reconstruction of the complementary area is imperfect, and the method struggles when the input mask $m$ contains thin parts. We solve these issues in Sections 4.2 and 4.3, respectively.

4.1 Blended Latent Diffusion

As explained in Section 3, Latent Diffusion [Rombach et al. 2022] can generate an image from a given text (text-to-image LDM). However, this model lacks the capability of editing an existing image in a local fashion, hence we propose to incorporate Blended Diffusion [Avrahami et al. 2022b] into text-to-image LDM. Our approach is summarized in Algorithm 1, and depicted as a diagram in Figure 3.

LDM performs text-guided denoising diffusion in the latent space learned by a variational auto-encoder $\text{VAE} = (E(x), D(z))$, where $E(x)$ encodes an image $x$ to a latent representation $z$ and $D(z)$ decodes it back to the pixel space. Referring to the part that we wish to modify as foreground ($fg$) and to the remaining part as background ($bg$), we follow the idea of Blended Diffusion and repeatedly blend the two parts in this latent space, as the diffusion progresses. The
inputs will be used to perform the blending.

ALGORITHM 1: Latent Blended Diffusion: given a text-conditioned
Latent Diffusion model \( \text{VAE} = (E(x), D(z)), \text{DiffusionModel} = (\text{noise}(z, t), \text{denoise}(z, d, t)) \)

**Input**: source image \( x \), target text description \( d \), input mask \( m \), diffusion steps \( k \).

**Output**: edited image \( \hat{x} \) that differs from input image \( x \) inside area \( m \) according to text description \( d \)

\[ m_{\text{latent}} = \text{downsample}(m) \]
\[ z_{\text{init}} \sim E(x) \]
\[ z_k \sim \text{noise}(z_{\text{init}}, k) \]
\[ \text{for all } t \text{ from } k \text{ to } 0 \text{ do} \]
\[ z_{fg} \sim \text{denoise}(z_t, d, t) \]
\[ z_{bg} \sim \text{noise}(z_{\text{init}}, t) \]
\[ z_t \leftarrow z_{fg} \odot m_{\text{latent}} + z_{bg} \odot (1 - m_{\text{latent}}) \]
\[ \text{end for} \]
\[ \hat{x} = D(z_0) \]
\[ \text{return } \hat{x} \]

Input image \( x \) is encoded into the latent space using the VAE encoder \( z_{\text{init}} \sim E(x) \). The latent space still has spatial dimensions (due to the convolutional nature of the VAE), however the width and the height are smaller than those of the input image (by a factor of 8). We therefore downsample the input mask \( m \) to these spatial dimensions to obtain the latent space binary mask \( m_{\text{latent}} \), which will be used to perform the blending.

Now, we noise the initial latent \( z_{\text{init}} \) to the desired noise level (in a single step) and manipulate the denoising diffusion process in the following way: at each step, we first perform a latent denoising step, conditioned directly on the guiding text prompt \( d \), to obtain a less noisy foreground latent denoted as \( z_{fg} \), while also noising the original latent \( z_{\text{init}} \) to the current noise level to obtain a noisy background latent \( z_{bg} \). The two latents are then blended using the resized mask, i.e. \( z_{fg} \odot m_{\text{latent}} + z_{bg} \odot (1 - m_{\text{latent}}) \), to yield the latent for the next latent diffusion step. Similarly to Blended Diffusion, at each denoising step the entire latent is modified, but the subsequent blending enforces the parts outside \( m_{\text{latent}} \) to remain the same. While the resulting blended latent is not guaranteed to be coherent, the next latent denoising step makes it so. Once the latent diffusion process terminates, we decode the resultant latent to the output image using the decoder \( D(z) \). A visualization of the diffusion process is available in the supplementary material.

Operating on the latent level, in comparison to operating directly on pixels using a CLIP model, has the following main advantages:

- **Faster inference.** The smaller dimension of the latent space makes the diffusion process much faster. In addition, there is no need to calculate the CLIP-loss gradients at each denoising step. Thus, the entire editing process is faster by an order of magnitude (see Section 5.2).

- **Avoiding pixel-level artifacts.** Pixel-level diffusion sometimes results in pixel values outside the valid range, producing noticeable clipping artifacts. Operating in the latent space avoids such artifacts (Figure 2).

- **Avoiding adversarial examples.** Operating on the latent space with no pixel-level CLIP-loss gradients effectively eliminates the risk of adversarial examples, eliminating the need for the extending augmentations of Avrahami et al. [2022b].

- **Better precision.** Our method achieves better precision than the baselines, both at the batch level and at the final prediction level (Section 5).

However, operating in latent space also introduces some drawbacks, which we will address later in this section:

- **Imperfect reconstruction.** The VAE latent encoding is lossy; hence, the final results are upper-bounded by the decoder’s reconstruction abilities. Even the initial reconstruction, before performing any diffusion, often visibly differs from the input. In images of human faces, or images with high frequencies, even such slight changes may be perceptible (see Figure 4(b)).

- **Thin masks.** When the input mask \( m \) is relatively thin (and its downscaled version \( m_{\text{latent}} \) can become even thinner), the effect of the edit might be limited or non-existent (see Figure 7).
As discussed above, LDM’s latent representation is obtained using a VAE [Kingma and Welling 2013], which is lossy. As a result, the encoded image is not reconstructed exactly, even before any latent diffusion takes place (Figure 4(a)). The imperfect reconstruction may thus be visible in areas outside the mask (Figure 4(b)).

A naïve way to deal with this problem is to stitch the original image and the edited result $\hat{x}$ at the pixel level, using the input mask $m$. However, because the unmasked areas were not generated by the decoder, there is no guarantee that the generated part will blend seamlessly with the surrounding background. Indeed, this naïve stitching produces visible seams, as demonstrated in Figure 4(c).

Alternatively, one could perform seamless cloning between the edited region and the original, e.g., utilizing Poisson Image Editing [Pérez et al. 2003], which uses gradient-domain reconstruction in pixel space. However, this often results in a noticeable color shift of the edited area, as demonstrated in Figure 4(d).

In the GAN inversion literature [Abdal et al. 2019, 2020; Xia et al. 2021; Zhu et al. 2020] it is standard practice to achieve image reconstruction via latent-space optimization. In theory, latent optimization can also be used to perform seamless cloning, as a post-process step: given the input image $x$, the mask $m$, and the edited image $\hat{x}$, along with its corresponding latent vector $z_0$, one could use latent optimization to search for a better vector $z^*$, s.t. the masked area will be similar to the edited image $\hat{x}$ and the unmasked area will be similar to the input image $x$:

$$z^* = \arg\min_{z} \|D(z) \odot m - \hat{x} \odot m\| + \lambda \|D(z) \odot (1-m) - x \odot (1-m)\| \quad (1)$$

using a standard distance metric, such as MSE. $\lambda$ is a hyperparameter that controls the importance of the background preservation, which we set to $\lambda = 100$ for all our results and comparisons. The optimization process is initialized with $z^0 = z_0$. The final image is then inferred from $z^*$ using the decoder: $x^* = D(z^*)$. However, as we can see in Figure 4(e), even though the resulting image is closer to the input image, it is over-smoothed.

The inability of latent space optimization to capture the high-frequency details suggests that the expressivity of the decoder $D(z)$ is limited. This leads us again to draw inspiration from GAN inversion literature — it was shown [Bau et al. 2020; Pan et al. 2021; Roich et al. 2021; Tzaban et al. 2022] that fine-tuning the GAN generator weights per image results in a better reconstruction. Inspired by this approach, we can achieve seamless cloning by fine-tuning the decoder’s weights $\theta$ on a per-image basis:

$$\theta^* = \arg\min_{\theta} \|D_{\theta}(z_0) \odot m - \hat{x} \odot m\| + \lambda \|D_{\theta}(z_0) \odot (1-m) - x \odot (1-m)\| \quad (2)$$

and use these weights to infer the result $x^* = D_{\theta^*}(z_0)$. As we can see in Figure 4(f), this method yields the best result: the foreground region follows $\hat{x}$, while the background preserves the fine details from the input image $x$, and the blending appears seamless.

In contrast to Blended Diffusion [Avrahami et al. 2022b], in our method the background reconstruction is optional. Thus, it is only
needed in cases where the unmasked area contains perceptually important fine-detail content, such as faces, text, structured textures, etc. A few reconstruction examples are shown in Figure 5.

4.3 Progressive Mask Shrinking

When the input mask \( m \) has thin parts, these parts may become even thinner in its downscaled version \( m_{\text{latent}} \), to the point that changing the latent values under \( m_{\text{latent}} \) by the text-driven diffusion process fails to produce a visible change in the reconstructed result. In order to pinpoint the root-cause, we visualize the diffusion process: given a noisy latent \( z_t \) at timestep \( t \), we can estimate \( z_0 \) using a single diffusion step with the closed form formula derived by Song et al. [2020]. The corresponding image is then inferred using the VAE decoder \( D(z_0) \).

Using the above visualization, Figure 6 shows that during the denoising process, the earlier steps generate only rough colors and shapes, which are gradually refined to the final output. The top row shows that even though the guiding text “fire” is echoed in the latents early in the process, blending these latents with \( z_{\text{fg}} \) using a thin \( m_{\text{latent}} \) mask may cause the effect to disappear.

This understanding suggests the idea of progressive mask shrinking: because the early noisy latents correspond to only the rough colors and shapes, we start with a rough, dilated version of \( m_{\text{latent}} \), and gradually shrink it as the diffusion process progresses, s.t. only the last denoising steps employ the thin \( m_{\text{latent}} \) mask when blending \( z_{\text{fg}} \) with \( z_{\text{bg}} \). The process is visualized in Figure 6. For more implementation details and videos visualizing the process, please see the supplementary material.

Figure 7 demonstrates the effectiveness of this method. Nevertheless, this technique struggles in generating fine details (e.g. the “green bracelet” example).

4.4 Prediction Ranking

Due to the stochastic nature of the diffusion process, we can generate multiple predictions for the same inputs, which is desirable because of the one-to-many nature of our problem. As in previous works [Avrahami et al. 2022b; Ramesh et al. 2021; Razavi et al. 2019], we found it beneficial to generate multiple predictions, rank them, and retrieve the best ones. We rank the predictions by the normalized cosine distance between their CLIP embeddings and the CLIP embedding of the guiding prompt \( d \). We also use the same ranking for all of the baselines that we compare our method against, except PaintByWord++ [Bau et al. 2021; Crowson et al. 2022], as it produces a single output per input, and thus no ranking is required.

5 RESULTS

We begin by comparing our method against previous methods, both qualitatively and quantitatively. Next, we demonstrate several of the use cases enabled by our method.

5.1 Comparisons

In Figure 8 we compare the zero-shot text-driven image editing results produced by our method against the following baselines: (1) Local CLIP-guided diffusion [Crowson 2021], (2) PaintByWord++ [Bau et al. 2021; Crowson et al. 2022], (3) Blended Diffusion [Avrahami et al. 2022b], (4) GLIDE [Nichol et al. 2021], (5) GLIDE-masked [Nichol et al. 2021], (6) GLIDE-filtered [Nichol et al. 2021], and (7) DALL-E 2. See Avrahami et al. [2022b] for more details on baselines (1)–(3). The images for the baselines (1)–(5) were taken directly
Fig. 8. Comparison to baselines: A comparison with Local CLIP-guided diffusion [Crowson 2021], PaintByWord++ [Bau et al. 2021; Crowson et al. 2022], Blended Diffusion [Avrahami et al. 2022b], GLIDE [Nichol et al. 2021], GLIDE-masked [Nichol et al. 2021], GLIDE-filtered [Nichol et al. 2021] and DALL-E 2 [Ramesh et al. 2022]. Credits: rihaij @ pixabay / zimt2003 @ pixabay / pxfuel / pratyksh @ pixabay / whitehouse.gov / aranprime @ Unsplash
from the corresponding papers. Note that Nichol et al. [2021] only released GLIDE-filtered, a smaller version of GLIDE, which was trained on a filtered dataset, and this is the only public version of GLIDE. Because the (4) full GLIDE model and (5) GLIDE-masked are not available, we use the results from the paper [Nichol et al. 2021]. The images for (3)–(6) and our method required generating a batch of samples and taking the best one ranked by CLIP. The GLIDE model has about \( \times 3 \) the parameters vs. our model. See the supplementary materials for more details.

Figure 8 demonstrates that baselines (1) and (2) do not always preserve the background of the input image. The edits by GLIDE-filtered (6) typically fail to follow the guiding text. So the comparable baselines are (3) Blended Diffusion, (4) GLIDE, (5) GLIDE-masked, and (7) DALL·E 2. As we can see, our method avoids the pixel-level noises of Blended Diffusion (e.g., the pizza example) and generates better colors and textures (e.g., the dog collar example). Comparing to GLIDE, we see that in some cases GLIDE generates better shadows than our method (e.g., the cat example), however it can add artifacts (e.g., the front right paw of the cat in GLIDE’s prediction). Furthermore, GLIDE’s generated results do not always follow the guiding text (e.g., the golden necklace and blooming tree examples), hence, the authors of GLIDE propose GLIDE-masked, a version of GLIDE that does not take into account the given image — by fully masking the context. Using this approach, they manage to generate in the masked area, but it comes at the expense of the transition quality between the masked region and the background (e.g., the plate in the pizza example and the bone in the dogs example). Our method is able to generate a result that corresponds to the text in all the examples, while being blended into the scene seamlessly.

Inspecting DALL·E 2 results, we see that most of the results either ignore the guiding text (e.g., the dog collar, dog bone, and pizza examples) or only partially follow it (e.g., “golden necklace” generates a regular necklace, “blooming tree” generates a flower, and “blue short pants” generates text on top of the pants). For more examples, please see the supplementary material.

During our experiments, we noticed that the predictions of our method typically contain more results that comply with the guiding text prompt. In order to verify this quantitatively, we generated editing predictions for 50 random images, random masks, and text prompts randomly chosen from ImageNet classes. See Figure 9 for some examples. Then, batch prediction was evaluated using an off-the-shelf ImageNet classifier. We refrained from using CLIP cosine similarity as the precision measure, because it was shown that CLIP operates badly as an evaluator for gradient-based solutions that use CLIP, due to adversarial attacks [Nichol et al. 2021]. We denote this measure as the “precision” of the model. For more details see Section C.1 in the supplementary material. As reported in Table 1, our method indeed outperforms the baselines by a large margin. In addition, we ranked the results in the batch as described in Section 4.4 and calculated the average accuracy by taking only the top image in each batch, to find that our method still outperforms the baselines.

We also assess the average batch diversity, by calculating the pairwise LPIPS [Zhang et al. 2018a] distances between all the masked predictions in the batch that were classified correctly by the classifier. As can be seen in Table 1, our method has the second-best diversity, but it is outperformed by Local CLIP-guided diffusion by a large margin, which we attribute to the fact that this method changes the entire image (does not preserve the background) and thus the content generated in the masked area is much less constrained.

In addition, we conducted a user study on Amazon Mechanical Turk (AMT) [Amazon 2022] to assess the visual quality and text-matching of our results. Each of the 50 random predictions that were used in the quantitative evaluation was presented to a human evaluator next to a result from one of the baselines. The evaluator was asked to choose which of the two results has a better (1) visual quality and (2) matches the text more closely. The evaluators could also indicate that neither image is better than the other. As seen in Table 1 (right), the majority (≥ 50%) of evaluators prefer the visual quality and the text matching of our method over the other methods. A binomial statistical significance test, reported in Table 2 in the supplementary material, suggests that these results are statistically significant. The results of GLIDE-filtered [Nichol et al. 2021] were preferred in terms of visual quality, however these results typically fail to change the input image or make negligible changes: thus, although the result looks natural, it does not reflect the desired edit. See Figure 9 and the supplementary material for more examples and details. We chose to use a two-way question system in order to make the task clearer to the evaluators by providing only two images without the input image and mask.

### 5.2 Inference Time Comparison

We compare the inference time of various methods on an A10 NVIDIA GPU in Table 2. We show results for Blended Diffusion and GLIDE-filtered (the available smaller model, which is probably faster than the full unpublished model). Both of these methods require generating multiple predictions (batch) and taking the best one in order to achieve good results. The recommended batch size for Blended Diffusion is 64, whereas GLIDE-filtered and our method use a batch size of 24.

Our method supports generation with or without optimizing for background preservation (Section 4.2), and we report both options in Table 2. The background optimization introduces an additional inference time overhead, however, it is up to the user to decide whether this additional step is necessary (e.g., when editing images with human faces). Our method outperforms the baselines on the

| Method                  | Batch Precision | Batch Diversity | Best Result Precision | Human Visual Quality | Human Text Matching |
|-------------------------|-----------------|-----------------|-----------------------|----------------------|---------------------|
| Blended Diffusion       | 10.4%           | 0.106           | 36%                   | 64%                  | 35%                 |
| Local CLIP-guided diffusion | 10.49%   | 0.419           | 38%                   | 74%                  | 62%                 |
| PaintByWord++           | -               | 0%              | -                     | -                    | -                   |
| GLIDE-filtered          | 1.87%           | 0.114           | 4%                    | 26%                  | 86%                 |
| Ours                    | 28.66%          | 0.115           | 54%                   | -                    | -                   |

Table 1. Quantitative comparison. In terms of precision, our method outperforms the baselines, both at the batch level and at the best result level. In terms of diversity, only the Local CLIP-guided diffusion baseline achieves a better score, due to its tendency to change the entire image significantly (lack of background preservation). The two rightmost columns report the percentage of human evaluators that preferred our method over the baseline. Our method outperforms the baselines in terms of visual quality and text matching except the visual quality of GLIDE-filtered, which mostly leaves the input untouched.
Table 2. Inference time comparison: Our method outperforms all other methods when using batch processing. This stems from the fact that we perform diffusion in the latent space, and because our background preservation optimization is only required for the top-ranked result. Batch sizes marked with * are below the size recommended by the respective authors (lower batch precision), but are reported for comparison purposes.

| Method                  | Batch Size | Single Image (sec) | Full Batch (sec) | Per Image in Batch (sec) |
|-------------------------|------------|--------------------|------------------|--------------------------|
| Blended Diffusion       | 64         | 27                 | 1472             | 23                       |
| Blended Diffusion       | 24*        | 27                 | 552              | 23                       |
| Local CLIP-guided diffusion | 64       | 27                 | 1472             | 23                       |
| Local CLIP-guided diffusion | 24*      | 27                 | 552              | 23                       |
| PaintByWord++           | -          | 78                 | -                | -                        |
| GLIDE-filtered          | 24         | 7                  | 89               | 3.7                      |
| Ours (without background opt.) | 24       | 6                  | 53               | 2.2                      |
| Ours (with background opt.) | 24       | 25                 | 72               | 3                        |

standard case of batch inference, even when accounting for the background preservation optimization. The acceleration in comparison to Blended Diffusion and Local CLIP-guided diffusion is \( \times 10 \) with equal batch sizes and \( \times 20 \) with the recommended batch sizes, which stems from the fact that our generation process is done in the lower dimensional latent space, and the background preservation optimization need only be done on the selected result. The acceleration in comparison to PaintByWord++ and GLIDE-filtered is \( \times 1.47 \) and \( \times 1.23 \), respectively.

5.3 Use Cases

Our method is applicable in a variety of editing scenarios with generic real-world images, several of which we demonstrate here.

**Text-driven object editing.** using our method one can easily add new objects (Figure 1(top left)) or modify or replace existing ones (Figure 1(top right)), guided by a text prompt. In addition, we have found that the method is capable of injecting visually plausible text into images, as demonstrated in Figure 1(middle left).

**Background replacement.** rather than inserting or editing the foreground object, another important use case is text-guided background replacement, as demonstrated in Figure 1(middle right).

**Scribble-guided editing.** The user can scribble a rough shape on a background image, provide a mask (covering the scribble) to indicate the area that is allowed to change, and provide a text prompt. Our method transforms the scribble into a natural object while attempting to match the prompt, as demonstrated in Figure 1(bottom left).

For all of the use cases mentioned above, our method is inherently capable of generating multiple predictions for the same input, as discussed in Section 4.4 and demonstrated in Figure 1(bottom right). Due to the one-to-many nature of the task, we believe it is desirable to present the user with ranked (Section 4.4) multiple outcomes, from which they may choose the one that best suits their needs. Alternatively, the highest ranked result can be chosen automatically. For more results, see Section A in the supplementary.

Fig. 9. Precision & Diversity Experiment: Two examples of random input images and masks, and the corresponding results of different methods, used in our quantitative evaluation. GLIDE-filtered [Nichol et al. 2021] typically fails to modify the image according to the guiding text prompt; hence, the typical result looks similar to the input image, and therefore looks natural. For more examples please refer to the supplementary material. Credits: piqsels

Fig. 10. Limitations: Top row: our CLIP-based ranking takes into account only the masked area, Thus, the results are sometimes only piece-wise realistic, and the image does not look realistic as a whole. Bottom row: the model has a text bias - it may try to create movie posters/book covers with text instead or in addition to generating the actual object. Credits: pxfuel
Although our method is significantly faster than prior works, it still takes over a minute on an A10 GPU to generate a ranked batch of predictions, due to the diffusion process. This limits the applicability of our method on lower-end devices. Hence, accelerating the inference time further is still an important research avenue.

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In addition, we found our method to be somewhat sensitive to its inputs. Figure 11 demonstrates that small changes to the input prompt (first row), to the input mask (second row), or to the input image (third row) may result in small output changes. Credits: pxfuel

6 LIMITATIONS & CONCLUSIONS

Although our method is significantly faster than prior works, it still takes over a minute on an A10 GPU to generate a ranked batch of predictions, due to the diffusion process. This limits the applicability of our method on lower-end devices. Hence, accelerating the inference time further is still an important research avenue.

As in Blended Diffusion, the CLIP-based ranking only takes into account the generated masked area. Without a more holistic view of the image, this ranking ignores the overall realism of the output image, which may result in images where each area is realistic, but the image does not look realistic overall, e.g., Figure 10(top). Thus, a better ranking system would prove useful.

Furthermore, we observe that LDM’s amazing ability to generate texts is a double-edged sword: the guiding text may be interpreted by the model as a text generation task. For example, Figure 10(bottom) demonstrates that instead of generating a big mountain, the model tries to generate a movie poster named “big mountain”.

In addition, we found our method to be somewhat sensitive to its inputs. Figure 11 demonstrates that small changes to the input prompt, to the input mask, or to the input image may result in small output changes. For more examples and details, please read Section D in the supplementary material.

Even without solving the aforementioned open problems, we have shown that our system can be used to locally edit images using text. Our results are realistic enough for real-world editing scenarios, and we are excited to see what users will create with the source code that we will release upon publication.
