

Blended Diffusion for Text-driven Editing of Natural Images

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Abstract

Natural language offers a highly intuitive interface for image editing. In this paper, we introduce the first solution for performing local (region-based) edits in generic natural images, based on a natural language description along with an ROI mask. We achieve our goal by leveraging and combining a pretrained language-image model (CLIP), to steer the edit towards a user-provided text prompt, with a denoising diffusion probabilistic model (DDPM) to generate natural-looking results. To seamlessly fuse the edited region with the unchanged parts of the image, we spatially blend noised versions of the input image with the local text-guided diffusion latent at a progression of noise levels. In addition, we show that adding augmentations to the diffusion process mitigates adversarial results. We compare against several baselines and related methods, both qualitatively and quantitatively, and show that our method outperforms these solutions in terms of overall realism, ability to preserve the background and matching the text. Finally, we show several text-driven editing applications, including adding a new object to an image, removing/replacing/altering existing objects, background replacement, and image extrapolation.

1. Introduction

It is said that “a picture is worth a thousand words”, but recent research indicates that only a few words are often sufficient to describe one. Recent works that leverage the tremendous progress in vision-language models and data-driven image generation have demonstrated that text-based interfaces for image creation and manipulation are now finally within reach [12, 23, 29, 30, 38, 39, 41, 47, 51, 57].

The most impressive results in text-driven image manipulation leverage the strong generative capabilities of modern GANs [6, 19, 25–27]. However, GAN-based approaches are typically limited to images from a restricted domain, on which the GAN was trained. Furthermore, in order to manipulate real images, they must be first *inverted* into the GAN’s latent space. Although many GAN inversion techniques have recently emerged [1–3, 44, 48, 52, 59], it was also shown that there is a trade-off between the reconstruc-

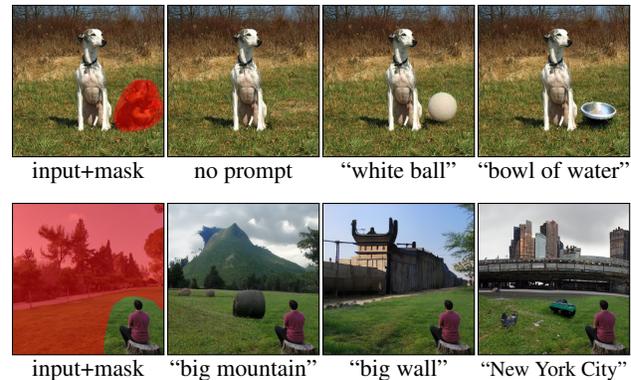


Figure 1. **Text-driven object/background replacement:** Given an input image and a mask, we modify the masked area according to a guiding text prompt, without affecting the unmasked regions.

tion accuracy and the editability of the inverted images [48]. Restricting the image manipulation to a specific region in the image is another challenge for existing approaches [4].

In this work, we present the first approach for region-based editing of *generic* real-world natural images, using natural language text guidance¹. Specifically, we aim at a text-driven method that (1) can operate on real images, rather than generated ones, (2) is not restricted to a specific domain, such as human faces or bedrooms, (3) modifies only a user-specified region, while preserving the rest of the image, (4) yields globally coherent (seamless) editing results, and (5) capable of generating multiple results for the same input, because of the one-to-many nature of the task. Several examples of such edits are shown in Figure 1.

The demanding image editing scenario described above has not received much attention in the deep-learning era. In fact, the most closely related works are classical approaches, such as seamless cloning [14, 37] and image completion [21], none of which are text-driven. A more recent related work is zero-shot semantic image painting [4] in which arbitrary simple textual descriptions can be attributed to the desired location within an image. However, this method does not operate on real images (requirement 1), does not preserve the background of the image (require-

¹Code is available at: <https://omriavrahami.com/blended-diffusion-page/>

ment 3), and does not generate multiple outputs for the same input (requirement 5).

To achieve our goals, we utilize two off-the-shelf pretrained models: Denoising Diffusion Probabilistic Models (DDPM) [11, 24, 35] and Contrastive Language-Image Pre-training (CLIP) [40]. DDPM is a class of probabilistic generative models that has recently been shown to surpass the image generation quality of state-of-the-art GANs [11]. We use DDPM as our generative backbone in order to ensure natural-looking results. The CLIP model is contrastively trained on a dataset of 400 million (image, text) pairs collected from the internet to learn a rich shared embedding space for images and text. We use CLIP in order to guide the manipulation to match the user-provided text prompt.

We show that a naïve combination of DDPM and CLIP to perform text-driven local editing fails to preserve the image background, and in many cases, leads to a less natural result. Instead, we propose a novel way to leverage the diffusion process, which blends the CLIP-guided diffusion latents with *suitably noised versions of the input image*, at each diffusion step. We show that this scheme produces natural-looking results that are coherent with the unaltered parts of the input. We further show that using *extending augmentations* at each step of the diffusion process reduces adversarial results. Our method utilizes pretrained DDPM and CLIP models, without requiring additional training.

In summary, our main contributions are: (1) We propose the first solution for general-purpose region-based image editing, using natural language guidance, applicable to real, diverse images. (2) Our background preservation technique guarantees that unaltered regions are perfectly preserved. (3) We demonstrate that a simple augmentation technique significantly reduces the risk of adversarial results, allowing us to use gradient-based diffusion guidance.

2. Related Work

Text-to-image synthesis. Recently, we’ve witnessed significant advances in text-to-image generation. Initial RNN-based works [32] were quickly superseded by generative adversarial approaches, such as the seminal work by Reed et al. [43]. The latter was further improved by multi-stage architectures [54, 55] and an attention mechanism [53].

DALL-E [41] introduced a GAN-free two stage approach: first, a discrete VAE [42, 49] is trained to reduce the context for the transformer. Next, a transformer [50] is trained autoregressively to model the joint distribution over the text and image tokens.

Several recent projects [8, 9, 33] utilize a pretrained generative model [6, 11, 13] using a pretrained CLIP model [40] to steer the generated result towards the desired target description. These methods are mainly used to create abstract artworks from text descriptions and lack the ability to edit parts of a real image, while preserving the rest.

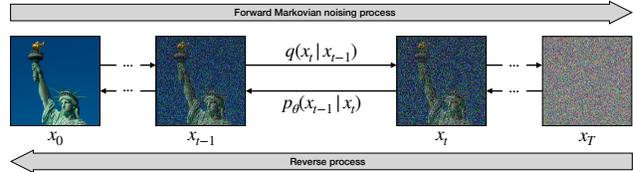


Figure 2. **Denoising diffusion.** Starting from a sample x_0 , a forward Markovian noising process produces a series of noisy images by gradually adding Gaussian noise $q(x_t | x_{t-1})$, until obtaining a nearly isotropic Gaussian noise sample x_T . The reverse process transforms a Gaussian noise sample x_T into x_0 by repeated denoising using a learned posterior $p_\theta(x_{t-1} | x_t)$.

While text-to-image is a challenging and interesting task, in this work we focus on text-driven image manipulation, where edits are restricted to a user-specified region.

Text-driven image manipulation. Several recent works utilize CLIP in order to manipulate real images. StyleCLIP [36] use pretrained StyleGAN2 [27] and CLIP models to modify images based on text prompts. To manipulate real images (rather than generated ones), they must first be encoded to the latent space [48]. This approach cannot handle generic real images, and is restricted to domains for which high-quality generators are available. In addition, StyleCLIP operates on images in a *global* fashion, without providing spatial control over which areas should change.

More closely related to ours is the work of Bau et al. [4], where arbitrary simple textual descriptions can be attributed to a desired location within an image. Their GAN-based approach has several limitations: (1) although they attempt to preserve the background, it may still change, as can be seen in Figure 5; (2) their solution is mainly demonstrated in the restricted domain of bedrooms, and mainly for color and texture editing tasks. A few examples of general images are shown, but the results are less natural or lack background preservation (see Figure 5). (3) Their model is able to operate only on generated images and is not applicable out-of-the-box to arbitrary natural images. GAN-inversion techniques [1–3, 44, 48, 52, 59] can be used to edit real images, but it was shown [48] that there is a trade-off between the edibility and the distortion of the reconstructed image.

Concurrently with our work, Liu et al. [31] and Kim et al. [28] propose ways to utilize a diffusion model in order to perform *global* text-guided image manipulations. In addition, GLIDE [34] is a concurrent work that utilizes the diffusion model for text-to-image synthesis, as well as local image editing using text guidance. In order to do so, they train a designated diffusion model for these tasks.

3. Denoising Diffusion Probabilistic Models

Denoising diffusion probabilistic models (DDPMs) learn to invert a parameterized Markovian image noising process.

Starting from isotropic Gaussian noise samples, they transform them to samples from a training distribution, gradually removing the noise by an iterative diffusion process (Fig. 2). DDPMs have recently been shown to generate high-quality images [11, 24, 35]. Below, we provide a brief overview of DDPMs, for more details please refer to [24, 35, 45]. We follow the formulations and notations in [35].

Given a data distribution $x_0 \sim q(x_0)$, a forward noising process produces a series of latents x_1, \dots, x_T by adding Gaussian noise with variance $\beta_t \in (0, 1)$ at time t :

$$q(x_1, \dots, x_T | x_0) = \prod_{t=1}^T q(x_t | x_{t-1}) \quad (1)$$

$$q(x_t | x_{t-1}) = \mathcal{N}(\sqrt{1 - \beta_t} x_{t-1}, \beta_t \mathbf{I})$$

When T is large enough, the last latent x_T is nearly an isotropic Gaussian distribution.

An important property of the forward noising process is that any step x_t may be sampled directly from x_0 , without the need to generate the intermediate steps,

$$q(x_t | x_0) = \mathcal{N}(\sqrt{\bar{\alpha}_t} x_0, (1 - \bar{\alpha}_t) \mathbf{I}) \quad (2)$$

$$x_t = \sqrt{\bar{\alpha}_t} x_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon,$$

where $\epsilon \sim \mathcal{N}(0, \mathbf{I})$, $\alpha_t = 1 - \beta_t$ and $\bar{\alpha}_t = \prod_{s=0}^t \alpha_s$.

To draw a new sample from the distribution $q(x_0)$ the Markovian process is reversed. That is, starting from a Gaussian noise sample, $x_T \sim \mathcal{N}(0, \mathbf{I})$, a reverse sequence is generated by sampling the posteriors $q(x_{t-1} | x_t)$, which were shown to also be Gaussian distributions [16, 45].

However, $q(x_{t-1} | x_t)$ is unknown, as it depends on the unknown data distribution $q(x_0)$. In order to approximate this function, a deep neural network p_θ is trained to predict the mean and the covariance of x_{t-1} given x_t as input. Then x_{t-1} may be sampled from the normal distribution defined by these parameters,

$$p_\theta(x_{t-1} | x_t) = \mathcal{N}(\mu_\theta(x_t, t), \Sigma_\theta(x_t, t)). \quad (3)$$

Rather than inferring $\mu_\theta(x_t, t)$ directly, Ho et al. [24] propose to predict the noise $\epsilon_\theta(x_t, t)$ that was added to x_0 in order to obtain x_t , according to Equation (2). Then $\mu_\theta(x_t, t)$ may be derived using Bayes' theorem:

$$\mu_\theta(x_t, t) = \frac{1}{\sqrt{\bar{\alpha}_t}} \left(x_t - \frac{\beta_t}{\sqrt{1 - \bar{\alpha}_t}} \epsilon_\theta(x_t, t) \right) \quad (4)$$

For more details please see [24].

Ho et al. [24] kept $\Sigma_\theta(x_t, t)$ constant, but it was later shown [35] that it is better to learn it by a neural network that interpolates between the upper and lower bounds for the fixed covariance proposed by Ho et al.

Dhariwal and Nichol [11] show that diffusion models can achieve image sample quality superior to the current state-of-the-art generative models. They improved the results

of [24], in terms of FID score [22], by tuning the network architecture and by incorporating guidance using a classifier pretrained on noisy images. For more details please see the supplementary and the original paper [11].

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 as close as possible to the source image, i.e., $x \odot (1 - m) \approx \hat{x} \odot (1 - m)$, 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 adapting the DDPM approach described above to incorporate local text-driven editing by adding a guiding loss comprised of a masked CLIP loss and a background preservation term. The resulting method still falls short of satisfying our requirements, and we proceed to present a new text-driven blended diffusion method in Section 4.2, which guarantees background preservation and improves the coherence of the edited result. Section 4.2.2 introduces an augmentation technique that we employ in order to avoid adversarial results.

4.1. Local CLIP-guided diffusion

Dhariwal and Nichol [11] use a classifier pretrained on noisy images to guide generation towards a target class. Similarly, a pretrained CLIP model may be used to guide diffusion towards a target prompt. Since CLIP is trained on clean images (and retraining it on noisy images is impractical), we need a way of estimating a clean image x_0 from each noisy latent x_t during the denoising diffusion process. Recall that the process estimates at each step the noise $\epsilon_\theta(x_t, t)$ that was added to x_0 to obtain x_t . Thus, x_0 may be obtained from $\epsilon_\theta(x_t, t)$ via Equation (2):

$$\hat{x}_0 = \frac{x_t}{\sqrt{\bar{\alpha}_t}} - \frac{\sqrt{1 - \bar{\alpha}_t} \epsilon_\theta(x_t, t)}{\sqrt{\bar{\alpha}_t}} \quad (5)$$

Now, a CLIP-based loss \mathcal{D}_{CLIP} may be defined as the cosine distance between the CLIP embedding of the text prompt and the embedding of the estimated clean image \hat{x}_0 :

$$\mathcal{D}_{CLIP}(x, d, m) = D_c(CLIP_{img}(x \odot m), CLIP_{txt}(d)) \quad (6)$$

where D_c denotes cosine distance. A similar approach is used in CLIP-guided diffusion [8], where a linear combination of x_t and \hat{x}_0 is used to provide global guidance for the diffusion. The guidance can be made local, by considering only the gradients of \mathcal{D}_{CLIP} under the input mask. In this manner, we effectively adapt CLIP-guided diffusion [8] to the local (region-based) editing setting.

Algorithm 1 Local CLIP-guided diffusion, given a diffusion model $(\mu_\theta(x_t), \Sigma_\theta(x_t))$ and CLIP model

Input: source image x , target text description d , input mask m , diffusion steps k , background preservation coefficient λ
Output: edited image \hat{x} that differs from input image x inside area m according to text description d
 $x_k \sim \mathcal{N}(\sqrt{\alpha_k}x_0, (1 - \alpha_k)\mathbf{I})$
for all t from k to 1 **do**
 $\mu, \Sigma \leftarrow \mu_\theta(x_t), \Sigma_\theta(x_t)$
 $\hat{x}_0 \leftarrow \frac{x_t}{\sqrt{\alpha_t}} - \frac{\sqrt{1-\alpha_t}\epsilon_\theta(x_t, t)}{\sqrt{\alpha_t}}$
 $\hat{x}_{0, aug} \leftarrow \text{ExtendingAugmentations}(\hat{x}_0, N)$
 $\mathcal{L} \leftarrow \mathcal{D}_{CLIP}(\hat{x}_{0, aug}, d, m) + \lambda \mathcal{D}_{bg}(x, \hat{x}_{0, aug}, m)$
 $x_{t-1} \sim \mathcal{N}(\mu + \Sigma \nabla_{\hat{x}_0} \mathcal{L}, \Sigma)$
end for
return x_0

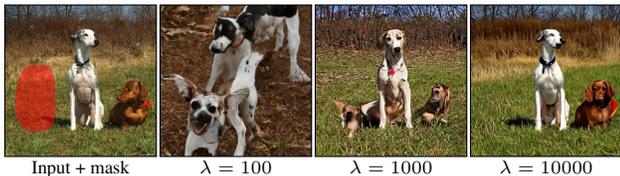


Figure 3. **Effect of λ in local CLIP-guided diffusion.** Given an input image with a mask, and the prompt “a dog”: with λ set too low ($\lambda = 100$), the entire image changes completely, while if λ is too high ($\lambda = 10000$), the model fails to change the foreground (and the background preservation is not perfect). Using an intermediate value ($\lambda = 1000$) the model changes the foreground while resembling the original background (zoom for more details).

The above process starts from an isotropic Gaussian noise and has no background constraints. Thus, although \mathcal{D}_{CLIP} is evaluated inside the masked region, it affects the entire image. In order to steer the surrounding region towards the input image, a background preservation loss \mathcal{D}_{bg} is added to guide the diffusion outside the mask:

$$\mathcal{D}_{bg}(x_1, x_2, m) = d(x_1 \odot (1 - m), x_2 \odot (1 - m))$$

$$d(x_1, x_2) = \frac{1}{2}(\text{MSE}(x_1, x_2) + \text{LPIPS}(x_1, x_2)) \quad (7)$$

where MSE is the L_2 norm of the pixel-wise difference between the images, and LPIPS is the Learned Perceptual Image Patch Similarity metric [56].

The diffusion guidance loss is thus set to the weighted sum $\mathcal{D}_{CLIP}(\hat{x}_0, d, m) + \lambda \mathcal{D}_{bg}(x, \hat{x}_0, m)$, and the resulting method is summarized in Algorithm 1.

In practice, we have found that an inherent trade-off exists between the two guidance terms above, as demonstrated in Figure 3. Note that even in the intermediate case of $\lambda = 1000$ the result is far from perfect: the background is only roughly preserved and the foreground is severely limited. We overcome this issue in the next section.

4.2. Text-driven blended diffusion

The forward noising process implicitly defines a progression of image manifolds, where each manifold consists of

Algorithm 2 Text-driven blended diffusion: given a diffusion model $(\mu_\theta(x_t), \Sigma_\theta(x_t))$, and CLIP model

Input: source image x , target text description d , input mask m , diffusion steps k , number of extending augmentations N
Output: edited image \hat{x} that differs from input image x inside area m according to text description d
 $x_k \sim \mathcal{N}(\sqrt{\alpha_k}x_0, (1 - \alpha_k)\mathbf{I})$
for all t from k to 0 **do**
 $\mu, \Sigma \leftarrow \mu_\theta(x_t), \Sigma_\theta(x_t)$
 $\hat{x}_0 \leftarrow \frac{x_t}{\sqrt{\alpha_t}} - \frac{\sqrt{1-\alpha_t}\epsilon_\theta(x_t, t)}{\sqrt{\alpha_t}}$
 $\hat{x}_{0, aug} \leftarrow \text{ExtendingAugmentations}(\hat{x}_0, N)$
 $\nabla_{text} \leftarrow \frac{1}{N} \sum_{i=1}^N \nabla_{\hat{x}_{0, aug}} \mathcal{D}_{CLIP}(\hat{x}_{0, aug}, d, m)$
 $x_{fg} \sim \mathcal{N}(\mu + \Sigma \nabla_{text}, \Sigma)$
 $x_{bg} \sim \mathcal{N}(\sqrt{\alpha_t}x_0, (1 - \alpha_t)\mathbf{I})$
 $x_{t-1} \leftarrow x_{fg} \odot m + x_{bg} \odot (1 - m)$
end for
return x_{-1}

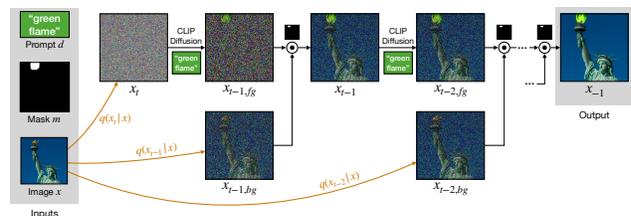


Figure 4. **Text-driven blended diffusion.** Given input image x , input mask m , and a text prompt d , we leverage the diffusion process to edit the image locally and coherently. We denote with \odot the element-wise blending of two images using the input mask m .

noisier images. Each step of the reverse, denoising diffusion process, projects a noisy image onto the next, less noisy, manifold. To create a seamless result where the masked region complies with a guiding prompt, while the rest of the image is identical to the original input, we spatially blend each of the noisy images progressively generated by the CLIP-guided process with the *corresponding noisy version* of the input image. Our key insight is that, while in each step along the way, the result of blending the two noisy images is not guaranteed to be coherent, the denoising diffusion step that follows each blend, restores coherence by projecting onto the next manifold. This process is depicted in Figure 4 and summarized in Algorithm 2.

4.2.1 Background preserving blending

A naïve way to preserve the background is to let the CLIP-guided diffusion process generate an image \hat{x} without any background constraints (by setting $\lambda = 0$ in Algorithm 1). Next, replace the generated background with the original one, taken from the input image: $\hat{x} \odot m + x \odot (1 - m)$. The obvious problem is that combining the two images in this manner fails to produce a coherent, seamless result. See the supplementary for an example.

In their pioneering work, Burt and Adelson [7] show that

two images can be blended smoothly by separately blending each level of their Laplacian pyramids. Inspired by this technique, we propose to perform the blending at different noise levels along the diffusion process. Our key hypothesis is that at each step during the diffusion process, a noisy latent is projected onto a manifold of natural images noised to a certain level. While blending two noisy images (from the same level) yields a result that likely lies outside the manifold, the next diffusion step projects the result onto the next level manifold, thus ameliorating the incoherence.

Thus, at each stage, starting from a latent x_t , we perform a single CLIP-guided diffusion step, that denoises the latent in a direction dependent on the text prompt, yielding a latent denoted $x_{t-1,fg}$. In addition, we obtain a noised version of the background $x_{t-1,bg}$ from the input image using Equation (2). The two latents are now blended using the mask: $x_{t-1} = x_{t-1,fg} \odot m + x_{t-1,bg} \odot (1 - m)$, and the process is repeated (see Figure 4 and Algorithm 2).

In the final step, the entire region outside the mask is replaced with the corresponding region from the input image, thus strictly preserving the background.

4.2.2 Extending augmentations

Adversarial examples [20,46] is a well known phenomenon that may occur when optimizing an image *directly on its pixel values*. For example, a classifier can be easily fooled to classify an image incorrectly by slightly altering its pixels in the direction of their gradients with respect to some wrong class. Adding such adversarial noise will not be perceived by a human, but the classification will be wrong.

Similarly, gradual changes of pixel values by CLIP-guided diffusion, might result in reducing the CLIP loss without creating the desired high-level semantic change in the image. We find that this phenomenon frequently occurs in practice. Bau et al. [4] also experienced this issue and addressed it using a non-gradient method that is based on evolution strategy.

We hypothesized that this problem can be mitigated by performing several augmentations on the intermediate result estimated at each diffusion step, and calculating the gradients using CLIP on each of the augmentations separately. This way, in order to “fool” CLIP, the manipulation must do so on all the augmentations, which is harder to achieve without a high-level change in the image. Indeed, we find that a simple augmentation technique mitigates this problem: given the current estimated result \hat{x}_0 , instead of taking the gradients of the CLIP loss directly, we compute them with respect to several projectively transformed copies of this image. These gradients are then averaged together. We term this strategy as “extending augmentation”. The effect of these augmentations is studied in Section 5.2. We’ve added extending augmentations to our method (Algorithm 2) as

well as to the Local CLIP GD baseline (Algorithm 1) for all the comparisons in this paper.

4.2.3 Result ranking

Algorithm 2 can generate multiple outputs for the same input; this is a desirable feature because our task is one-to-many by its nature. Similarly to [41,42], we found it beneficial to generate multiple predictions, rank them and choose those with the higher scores. For the ranking, we utilize the CLIP model using the same \mathcal{D}_{CLIP} from Equation (6) on the final results, without the extending augmentations.

5. Results

We begin by comparing our method to previous methods and baselines both qualitatively and quantitatively. Next, we demonstrate the effect of our use of extending augmentations. Finally, we demonstrate several applications enabled by our method.

5.1. Comparisons

In Figure 5 we compare the text-driven edits performed by our method to those performed using (1) *PaintByWord* [4]; (2) local CLIP-guided diffusion, as described in Algorithm 1, with $\lambda = 1000$; and (3) VQGAN-CLIP + Paint By Word [4,9]. For the latter, we adapt VQGAN-CLIP [9] to support masks using the same \mathcal{D}_{CLIP} loss from Equation (6). In addition, we find that results can be improved by optimizing only part of the VQGAN [13] latent space that corresponds to the edited area, similarly to the process in Bau et al. [4]. Because VQGAN includes a pre-trained decoder, we can easily use this method on real images. We denote this method *PaintByWord++*.

Since the implementation of Bau et al. [4] is not currently available, we perform this comparison using the examples included in their paper. Note that since *PaintByWord* operates only on GAN-generated images, all the input images in this comparison are synthetic and somewhat unnatural. In order to achieve better results on places, Bau et al. [4] used two different models: one that is trained on MIT Places [58] and the other on ImageNet [10]. In contrast, our method can operate on real images and uses a single DPPM model that was trained on ImageNet.

The results shown in Figure 5 demonstrate that although *PaintByWord* and the other two baselines all encourage background preservation, the background is not always preserved and some global changes occur in almost all cases. Furthermore, in each of the rows (1)–(3) there are some results that appear unrealistic. In contrast, our method preserves the background perfectly, and the edits appear natural and coherent with the surrounding background.

In order to obtain quantitative results, we conducted a preliminary user study comparing between the different re-

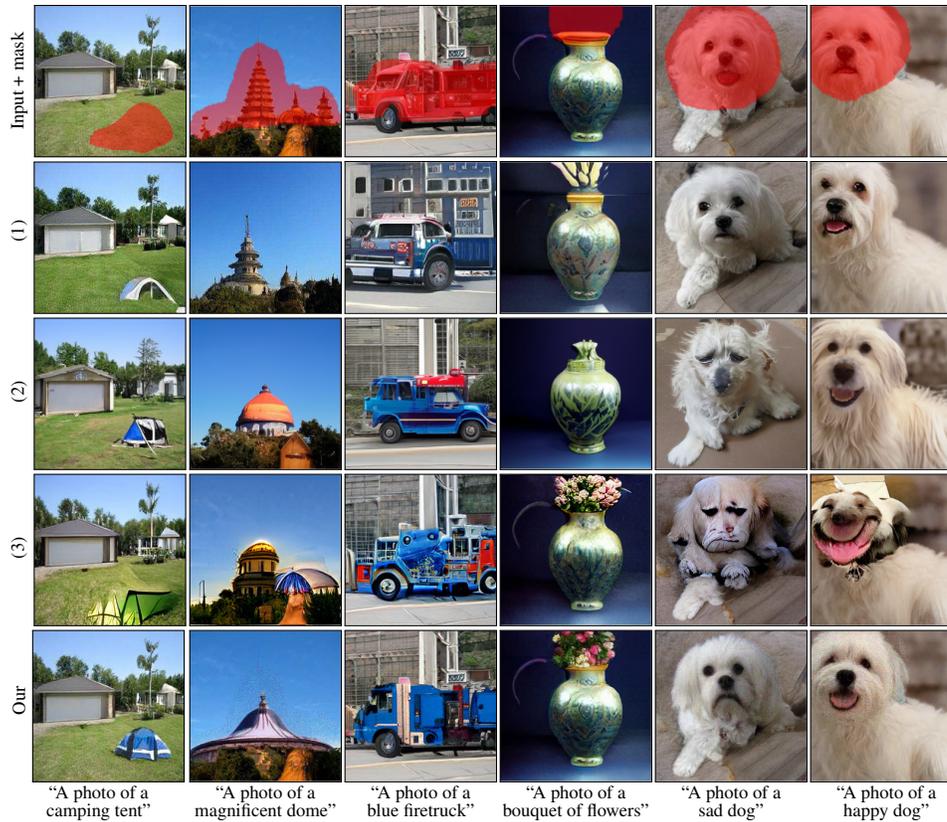


Figure 5. **Comparison using examples from *Paint By Word* [4].** We use the GAN-generated input images, and user-provided masks and text prompts from Bau et al. [4], as well as their results (1). In the next two rows, we show results of two other baselines: (2) Local CLIP GD [8] and (3) *PaintByWord++* [4, 9]. Our results (bottom row) exhibit more realistic objects. Moreover, our method perfectly preserves the background region of the input image, while other methods change it.

Method	Realism \uparrow	Background \uparrow	Text match \uparrow
<i>PaintByWord</i> [4]	3.31 ± 1.38	3.25 ± 1.33	3.14 ± 1.31
Local CLIP GD [8]	3.50 ± 1.19	3.11 ± 1.24	3.86 ± 1.32
<i>PaintByWord++</i> [4, 9]	1.94 ± 1.36	3.37 ± 1.30	3.01 ± 1.38
Ours	3.93 ± 1.08	4.73 ± 0.61	4.63 ± 0.77

Table 1. **User study results:** Participants were presented with the inputs and results shown in Figure 5 and were asked to rate each result on a Likert scale of 1-5 according to the following criteria: overall result realism, background preservation, and correspondence between the text prompt and the outcome. The mean and standard deviation are shown for each method and criterion.

sults shown in Figure 5. Participants were asked to rate each result in terms of realism, background preservation, and correspondence to the text prompt. Table 1 shows that our method outperforms the three baselines in all of these aspects. Please see the supplementary for more details.

In Figure 6 we further compare our method to local CLIP-guided diffusion and *PaintByWord++*, this time using real images as input. Again, the results demonstrate the inability of the baseline methods to preserve the background, and exhibit lack of coherence between the edited region and

its surroundings, in contrast to the results of our method.

5.2. Ablation of extending augmentations

In order to assess the importance of the extending augmentation technique described Section 4.2.2, we disable the extending augmentations completely from our method (Algorithm 2). Figure 7 demonstrates the importance of the augmentations: the same random seed is used in two runs, one with and the other without augmentations. We can see that the images generated with the use of augmentations are more visually plausible and are more coherent than the ones generated without the augmentations.

5.3. Applications

Our method is applicable to generic real-world images and may be used for a variety of applications. Below we demonstrate a few.

Text-driven object editing: we are able to add, remove or alter any of the existing objects in an image. Figure 8 demonstrates the ability to add a new object to an image. Note that the method is able to generate a variety of plausible outcomes. Rather than completely replacing an object,

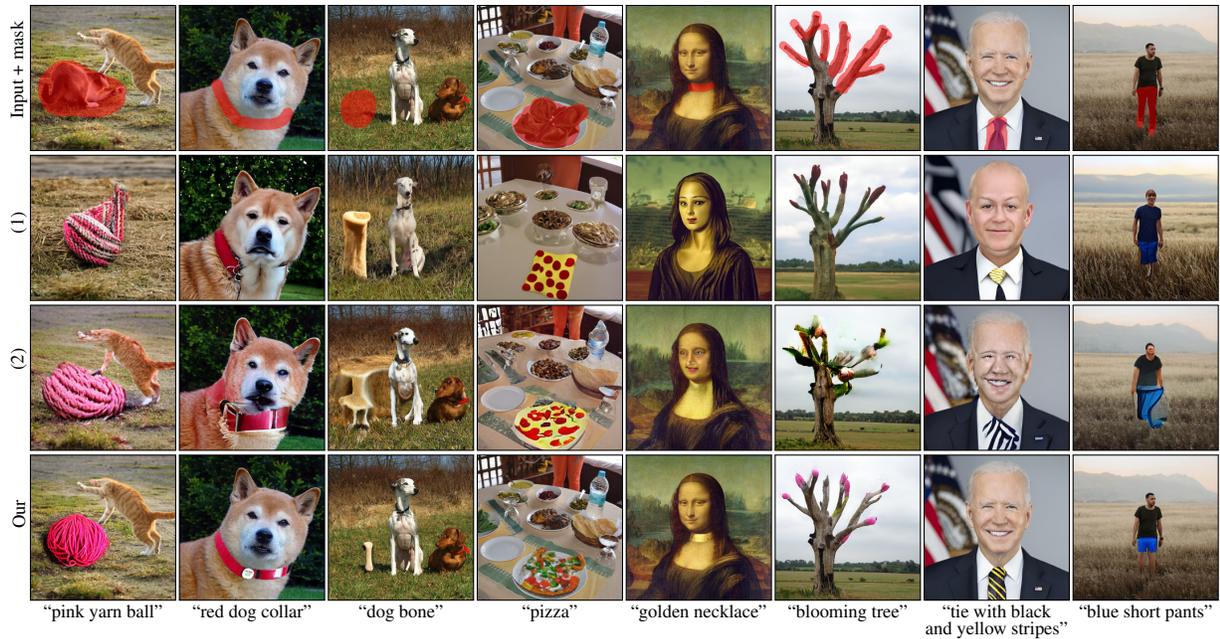


Figure 6. **Comparison to baselines on real images:** A comparison with (1) Local CLIP-guided diffusion [8] and (2) *PaintByWord++* [4,9]. Both baselines fail to preserve the background and produce results that are less natural/coherent, in contrast to the results of our method.

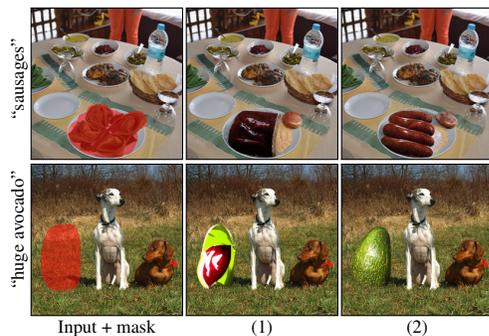


Figure 7. **Extending augmentations ablation:** Using the same random seed and inputs, we compared the generated results (1) without extending augmentations and (2) with them. The augmentations make the resulting images more natural and coherent with the background. See supplementary material for more examples.

only a part of it may be replaced, guided by a text prompt, as shown in the bottom row of Figure 8. Figure 1 demonstrates the ability to remove an object or replace it with a new one. Removal is achieved by not providing any text prompt, and it is equivalent to traditional image inpainting, where no text or other guidance is involved.

Background replacement: rather than editing the foreground object, it is also possible to replace the background using text guidance, as demonstrated in Figure 1. Additional examples for foreground and background editing are included in supplementary results.

Scribble-guided editing: Due to the noising process of diffusion models, another image, or a user-provided scribble,

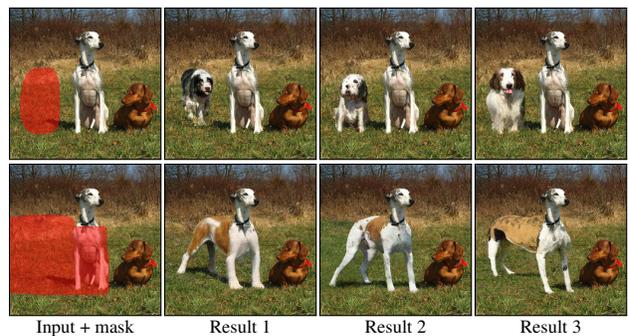


Figure 8. **Multiple outcomes:** Given the same guiding text (top row: “a dog”, bottom row: “body of a standing dog”) our method generates multiple plausible results.

ble, may be used as a guide. For example, the user may scribble a rough shape on a background image, provide a mask (covering the scribble) to indicate the area that is allowed to change, as well as a text prompt. Our method will transform the scribble into a natural object while attempting to match the prompt, as demonstrated in Figure 9.

Text-guided image extrapolation is the ability to extend an image beyond its boundaries, guided by a textual description, s.t. the resulting change is gradual. Figure 10 demonstrates this ability: the user provides an image and two text prompts, each prompt is used to extrapolate the image in one direction. The resulting image can be arbitrarily wide (and mix multiple prompts). More details are provided in the supplementary material.

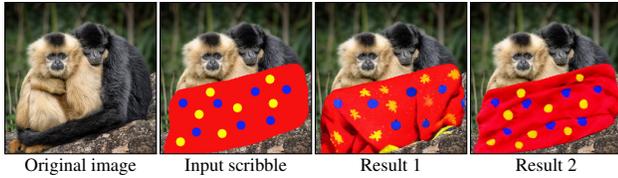


Figure 9. **Scribble-guided editing:** Users scribble a rough shape of the object they want to insert, mark the edited area, and provide a guiding text - “blanket”. The model uses the scribble as a general shape and color reference, transforming it to match the guiding text. Note that the scribble patterns can also change.

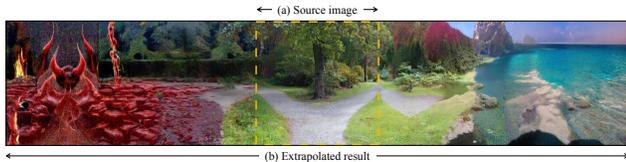


Figure 10. **Text-guided image extrapolation:** The user provides an input image and two text descriptions: “hell” and “heaven”. The model extrapolates the image to the left using the “hell” prompt and to the right using the “heaven” prompt.

6. Limitations and Future Work

The main limitation of our work is its inference time. Because of the sequential nature of DDPMs, generating a single image takes about 30 seconds on a modern GPU as described in the supplementary. In addition, we generate several samples and choose the top-ranked ones, as described in Section 4.2.3. This limits the applicability of our method for real-time applications and weak end-user devices (e.g. mobile devices). Further research in accelerating diffusion sampling is needed to address this problem.

In addition, the ranking method presented in Section 4.2.3 is not perfect because it takes into account only the edited area without the entire context of the image. So, bad results that contain only part of the desired object, may still get a high score, as demonstrated in Figure 11 (1). A better ranking system will enable our method to produce more compelling and coherent results.

Furthermore, because our model is based on CLIP, it inherits its weaknesses and biases. It was shown [18] that CLIP is susceptible to *typographic attacks* - exploiting the model’s ability to read text robustly, they found that even photographs of hand-written text can often fool the model. Figure 11 (2) demonstrates that this phenomenon can occur even when generating images: instead of generating an image of a “rubber toy” our method generates a sign with the word “rubber”.

One avenue for further research is training a version of CLIP that is agnostic to Gaussian noise. This may be done by training a version of CLIP that gets as an input a noisy image, a noise level, and the description text, and embeds the image and the text to a shared embedding space using

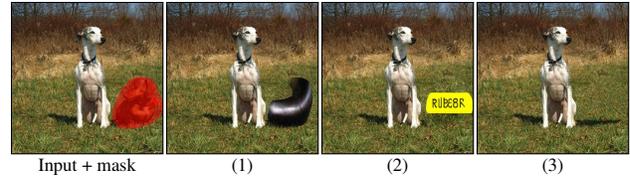


Figure 11. **Failure cases:** Examples of failure cases given source image, mask and description “rubber toy”: (1) partial object — ranking by the edited area only may cause partial object to get a high score, (2) typographic bias — the model can generate a sign with the word “rubber” on it, (3) missing object and unnatural shadows — sometimes the method adds a shadow that is not coherent with the scene and does not correspond to the text.

contrastive loss. The noising process during training should be the same as in Equation (2).

Yet another avenue for research is extending our problem to other modalities such as a general-purpose text editor for 3D objects or videos.

7. Societal Impact

Photo manipulations are almost as old as the photo creation process itself [15]. Such manipulations can be used for art, entertainment, aesthetics, storytelling, and other legitimate use cases, but at the same time can also be used to tell lies via photos, for bullying, harassment, extortion, and may have psychological consequences [17]. Indeed, our method can be used for all of the above. For example, it can be misused to add credibility to fake news, which is a growing concern in the current media climate. It may also erode trust in photographic evidence and allow real events and real evidence to be brushed off as fake [5].

While our work does not enable anything that was out of reach for professional image editors, it certainly adds to the ease-of-use of the manipulation process, thus allowing users with limited technical capabilities to manipulate photos. We are passionate about our research, not only due to the legitimate use-cases, but also because we believe such research must be conducted openly in academia and not kept secret. We will provide our code for the benefit of the academic community, and we are actively working on the complement of this work: image and video forensic methods.

8. Conclusions

We introduced a novel solution to the problem of text-driven editing of natural images and demonstrated its superiority over the baselines. We believe that editing natural images using free text is a highly intuitive interaction, that will be further developed to a level which will make it an indispensable tool in the arsenal of every content creator.

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