ADIR: Adaptive Diffusion for Image Reconstruction

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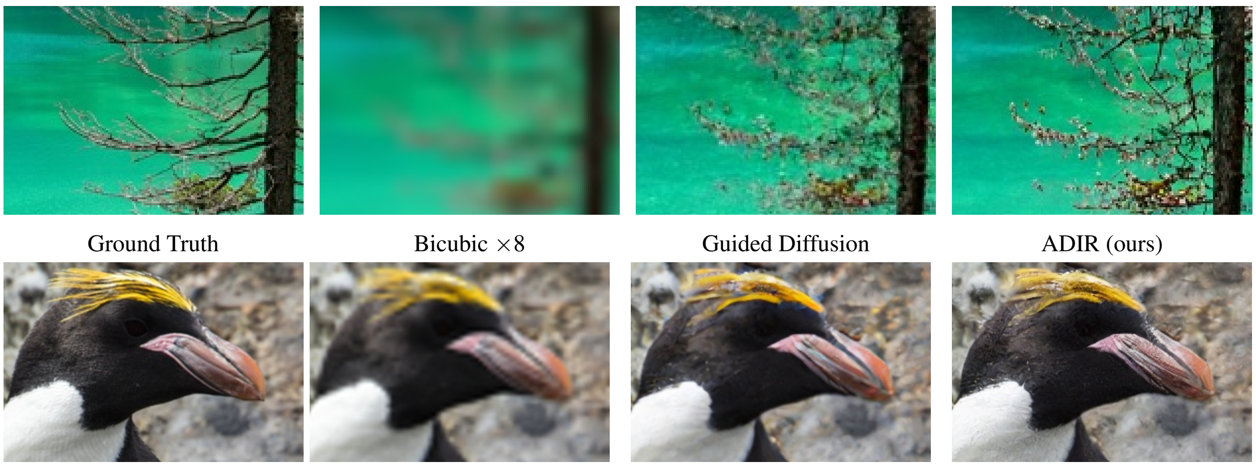


Figure 1: Super-resolution with scale factors 4 and 8, using Stable Diffusion Rombach et al. (2022), Guided Diffusion Dhariwal & Nichol (2021), and our method ADIR. The adaptability of ADIR allows reconstructing finer details.

Abstract

In recent years, denoising diffusion models have demonstrated outstanding image generation performance. The information on natural images captured by these models is useful for many image reconstruction applications, where the task is to restore a clean image from its degraded observations. In this work, we propose a conditional sampling scheme that exploits the prior learned by diffusion models while retaining agreement with the measurements. We then combine it with a novel approach to adapting pre-trained diffusion denoising networks to their input. We examine two adaptation strategies: the first uses only the degraded image, while the second, which we advocate, is performed using images that are "nearest neighbors" of the degraded image, retrieved from a diverse dataset with an off-the-shelf visual-language model. To evaluate our method, we test it on two state-of-the-art publicly available diffusion models, Stable Diffusion and Guided Diffusion. We show that our proposed 'adaptive diffusion for image reconstruction' (ADIR) approach achieves a significant improvement in image reconstruction tasks. Our code will be available online upon publication.

1 Introduction

Image reconstruction problems appear in a wide range of applications, where one would like to reconstruct an unknown clean image $\mathbf{x} \in \mathbb{R}^n$ from its degraded version $\mathbf{y} \in \mathbb{R}^m$, which can be noisy, blurry, low-resolution, etc. The acquisition (forward) model of $\mathbf{y}$ in many important degradation settings can be formulated using the following linear model

$$\mathbf{y} = \mathbf{A}\mathbf{x} + \mathbf{e}, \tag{1}$$

where $\mathbf{A} \in \mathbb{R}^{m \times n}$ is the measurement operator (blurring, masking, sub-sampling, etc.) and $\mathbf{e} \in \mathbb{R}^m \sim \mathcal{N}(0, \sigma^2 \mathbf{I}_m)$ is the measurement noise. Typically, just fitting the observation model is not sufficient for recovering $\mathbf{x}$ successfully. Thus, prior knowledge of the characteristics of $\mathbf{x}$ is needed.

Over the past decade, many works suggested solving the inverse problem in Eq. equation 1 using a single execution of a deep neural network, which has been trained on pairs of clean $\{\mathbf{x}_i\}$ images and their degraded versions $\{\mathbf{y}_i\}$ obtained by applying the forward model equation 1 on $\{\mathbf{x}_i\}$ Dong et al. (2015); Sun et al. (2015); Lim et al. (2017); Zhang et al. (2017a); Lugmayr et al. (2020); Liang et al. (2021). Yet, these approaches tend to overfit the observation model and perform poorly on setups that have not been considered in training and several methods have been proposed to overcome that Shocher et al. (2018); Tirer & Giryes (2019); Hussein et al. (2020b); Ji et al. (2020); Wei et al. (2020); Wang et al. (2021); Zhang et al. (2021b; 2022). Tackling this limitation with dedicated training for each application is not only computationally inefficient but also often impractical. This is because the exact observation model may not be known before inference time.

Several approaches such as Deep Image Prior Ulyanov et al. (2018), zero-shot-super-resolution Shocher et al. (2018) or GSURE-based test-time optimization Abu-Hussein et al. (2022) rely solely on the observation image $\mathbf{y}$. They utilize the implicit bias of deep neural networks and gradient-based optimizers, as well as the self-recurrence of patterns in natural images when training a neural model directly on the observation and in this way reconstruct the original image. Although these methods are not limited to a family of observation models, they usually perform worse than data-driven methods, since they do not exploit the robust prior information that the unknown image $\mathbf{x}$ share with external data that may contain images of the same kind. The alternative popular approach that exploits external data while remaining flexible to the observation model, uses deep models for imposing only the prior. It typically uses pretrained deep denoisers Zhang et al. (2017b); Arjomand Bigdeli et al. (2017); Tirer & Giryes (2018); Zhang et al. (2021a) or generative models Bora et al. (2017); Dhar et al. (2018); Hussein et al. (2020a) within the optimization scheme, where consistency of the reconstruction with the observation $\mathbf{y}$ is maintained by minimizing a data-fidelity term.

Recently, diffusion models Dhariwal & Nichol (2021); Nichol & Dhariwal (2021); Sohl-Dickstein et al. (2015); Ho et al. (2020) have shown remarkable capabilities in generating high-fidelity images. These models are based on a Markov chain diffusion process performed on each training sample. They learn the reverse process, namely, the denoising operation between each two points in the chain. Sampling images via pretrained diffusion models is performed by starting with a pure white Gaussian noise image, which is followed by progressively sampling a less noisy image, given the previous one, until reaching a clean image after T iterations. Since diffusion models capture prior knowledge of the data, one may utilize them as deep priors/regularization for inverse problems of the form equation 1 Song et al. (2021); Lugmayr et al. (2022); Avrahami et al. (2022b); Kawar et al. (2022a); Choi et al. (2021); Rombach et al. (2022).

In this work, we propose an Adaptive Diffusion framework for Image Reconstruction (ADIR). First, we devise a diffusion guidance sampling scheme that solves equation 1 while restricting the reconstruction of $\mathbf{x}$ to the range of a pretrained diffusion model. Our scheme is based on novel modifications to the guidance used in Dhariwal & Nichol (2021) (see Figure 2 and Section 3.2 for details). Then, we propose two techniques that use the observations $\mathbf{y}$ to adapt the diffusion network to patterns beneficial for recovering the unknown $\mathbf{x}$. Adapting the model's parameters is based either directly on $\mathbf{y}$ or on K external images similar to $\mathbf{y}$ in some neural embedding space that is not sensitive to the degradation of $\mathbf{y}$. These images may be retrieved from a diverse dataset and the embedding can be calculated using an off-the-shelf encoder model for images such as CLIP Radford et al. (2021).

In this work, ADIR is mainly developed for image reconstruction tasks. Yet, we also showcase that the ADIR adaptation strategy can be employed for text-guided image editing. Note that for the latter, we just show the potential of our strategy and that can be combined with existing edting techniques. We leave further exploration of the use of ADIR to editing to a future work.

The contribution of the ADIR framework is the proposal of an *adaptive* diffusion approach to inverse problems. We evaluate it with two state-of-the-art diffusion models: Stable Diffusion Rombach et al. (2022) and Guided Diffusion Dhariwal & Nichol (2021), and show that it outperforms existing methods in the super-resolution and deblurring tasks.

2 Related Work

Diffusion models In recent years, many works utilized diffusion models for image manipulation and reconstruction tasks Rombach et al. (2022); Kawar et al. (2022b;a); Whang et al. (2022); Saharia et al. (2022b), where a denoising network is trained to learn the prior distribution of the data. At test time, some conditioning mechanism is combined

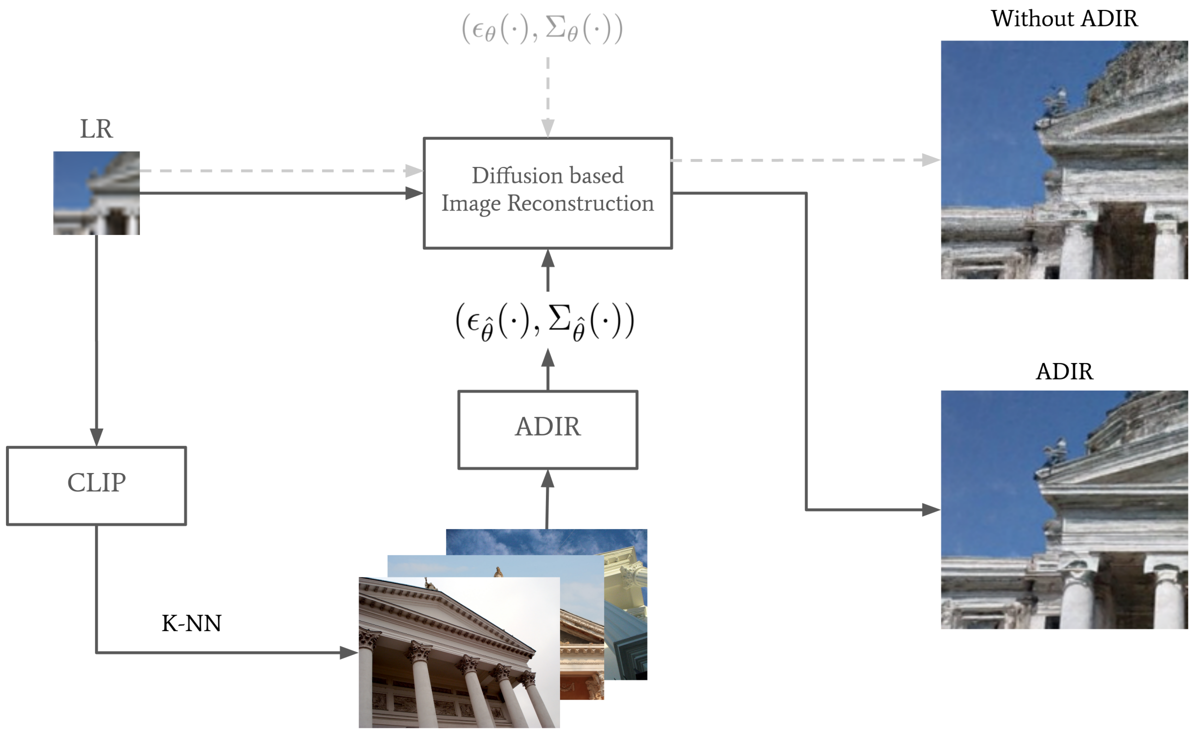


Figure 2: Diagram of our proposed method ADIR (Adaptive Diffusion for Image Reconstruction) applied to the super resolution task. Given a pretrained diffusion model $(\boldsymbol{\epsilon}_\theta(\cdot), \boldsymbol{\Sigma}_\theta(\cdot))$ and a Low Resolution (LR) image, we look for the K nearest neighbor images to the LR image, then using ADIR we adapt the diffusion model and use it for reconstruction.

with the learned prior to solve very challenging imaging tasks Avrahami et al. (2022b;a); Chung et al. (2022a). Note that our novel adaptive diffusion ingredient can be incorporated with any conditional sampling scheme that is based on diffusion models.

In Whang et al. (2022); Saharia et al. (2022b) the problems of deblurring and super-resolution were considered. Then, a diffusion model has been trained to perform this task where instead of adding noise at each of its steps, a blur or downsampling is performed. In this way, the model learns to carry out the deblurring or super-resolution task directly. Notice that these models are trained for one specific task and cannot be used for the other as is.

The closest works to us are Giannone et al. (2022); Sheynin et al. (2022); Kawar et al. (2022b). These very recent concurrent works consider the task of image editing and perform an adaptation of the used diffusion model using the provided input and external data. Yet, notice that neither of these works consider the task of image reconstruction as we do here or apply our proposed sampling scheme for this task.

Image-Adaptive Reconstruction Adaptation of pretrained deep models, which serve as priors in inverse problems, to the unknown true $\mathbf{x}$ through its observations at hand was proposed in Hussein et al. (2020a); Tirer & Giryes (2019). These works improve the reconstruction performance by fine-tuning the parameters of pretrained deep denoisers Tirer & Giryes (2019) and GANs Hussein et al. (2020a) via the observed image $\mathbf{y}$ instead of keeping them fixed during inference time. The image-adaptive GAN (IAGAN) approach Hussein et al. (2020a) has led to many follow up works with different applications, e.g., Bhadra et al. (2020); Pan et al. (2021); Roich et al. (2022); Nitzan et al. (2022). Recently, it has been shown that one may even fine-tune a masked-autoencoder to the input data at test-time for improving the adaptivity of classification neural networks to new domains Gandelsman et al. (2022).

In this paper we consider test-time adaptation of diffusion models for inverse problems. As far as we know, adaptation of diffusion models has not been proposed. Furthermore, while existing works fine-tune the deep priors directly using $\mathbf{y}$, we propose an improved strategy where the tuning is based on K external images similar to $\mathbf{y}$ that are automatically retrieved from an external dataset.

3 Method

We now turn to present our proposed approach. We start with a brief introduction to regular denoising diffusion models. After that we describe our proposed strategy for modifying the sampling scheme of diffusion models for the task of image reconstruction. Finally, we present our suggested adaptation scheme.

3.1 Denoising Diffusion Models

Denoising diffusion models Sohl-Dickstein et al. (2015); Ho et al. (2020) are latent variable generative models, with latent variables $\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_T \in \mathbb{R}^n$ (the same dimensionality as the data $\mathbf{x} \sim q_{\mathbf{x}}$). Given a training sample $\mathbf{x}_0 \sim q_{\mathbf{x}}$, these models are based on constructing a diffusion process (forward process) of the variables $\mathbf{x}_{1:T} := \mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_T$ as a Markov chain from $\mathbf{x}_0$ to $\mathbf{x}_T$ of the form

$$q(\mathbf{x}_{1:T}|\mathbf{x}_0) := \prod_{t=1}^{T} q(\mathbf{x}_t|\mathbf{x}_{t-1}), \tag{2}$$

where $q(\mathbf{x}_t|\mathbf{x}_{t-1}) := \mathcal{N}(\sqrt{1-\beta_t}\mathbf{x}_{t-1}, \beta_t \mathbf{I}_n)$, and $0 < \beta_1 < ... < \beta_T = 1$ is the diffusion variance schedule (hyperparameters of the model). Note that sampling $\mathbf{x}_t|\mathbf{x}_0$ can be done via a simplified way using the parametrization Ho et al. (2020):

$$\mathbf{x}_t = \sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}, \ \boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_n), \tag{3}$$

where $\alpha_t := 1 - \beta_t$ and $\bar{\alpha}_t := \prod_{s=1}^{t} \alpha_s$. The goal of these models is to learn the distribution of the reverse chain from $\mathbf{x}_T$ to $\mathbf{x}_0$, which is parameterized as the Markov chain

$$p_\theta(\mathbf{x}_{0:T}) := p(\mathbf{x}_T) \prod_{t=1}^{T} p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t), \tag{4}$$

where $p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) := \mathcal{N}(\boldsymbol{\mu}_\theta(\mathbf{x}_t, t)), \boldsymbol{\Sigma}_\theta(\mathbf{x}_t, t),$

$$\boldsymbol{\mu}_\theta(\mathbf{x}_t, t) := \frac{1}{\sqrt{\alpha_t}}(\mathbf{x}_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}}\boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t)), \tag{5}$$

and θ denotes all the learnable parameters. Essentially, $\boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t)$ is an estimator for the noise in $\mathbf{x}_t$ (up to scaling).

The parameters θ of the diffusion model $(\boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t), \boldsymbol{\Sigma}_\theta(\mathbf{x}_t, t))$ are optimized by minimizing evidence lower bound Sohl-Dickstein et al. (2015), a simplified score-matching loss Ho et al. (2020); Song & Ermon (2019), or a combination of both Dhariwal & Nichol (2021); Nichol & Dhariwal (2021). For example, the simplified loss involves the minimization of

$$\ell_{\text{simple}}(\mathbf{x}_0, \boldsymbol{\epsilon}_\theta, t) = \|\boldsymbol{\epsilon} - \boldsymbol{\epsilon}_\theta(\sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}, t)\|_2^2 \tag{6}$$

w.r.t. θ in each training iteration, where $\mathbf{x}_0$ is drawn from the training data, t uniformly drawn from $\{1, ..., T\}$ and the noise $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_n)$.

Given a trained diffusion model $(\boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t), \boldsymbol{\Sigma}_\theta(\mathbf{x}_t, t))$, one may generate a sample $\mathbf{x}_0$ from the learned data distribution p_θ by initializing $\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_n)$ and running the reverse diffusion process by sampling

$$\mathbf{x}_{t-1} \sim \mathcal{N}(\boldsymbol{\mu}_\theta(\mathbf{x}_t, t), \boldsymbol{\Sigma}_\theta(\mathbf{x}_t, t)), \tag{7}$$

where $0 < t \leq T$ and $\boldsymbol{\mu}_\theta(\mathbf{x}_t, t)$ is defined in equation 5.

The class-guided sampling method that has been proposed in Dhariwal & Nichol (2021) modifies the sampling procedure in equation 7 by adding to the mean of the Gaussian a term that depends on the gradient of an offline-trained classifier, which has been trained using noisy images $\{\mathbf{x}_t\}$ for each t, and approximates the likelihood $p_{c|\mathbf{x}_t}$, where c is the desired class. This procedure has been shown to improve the quality of the samples generated for the learned classes.

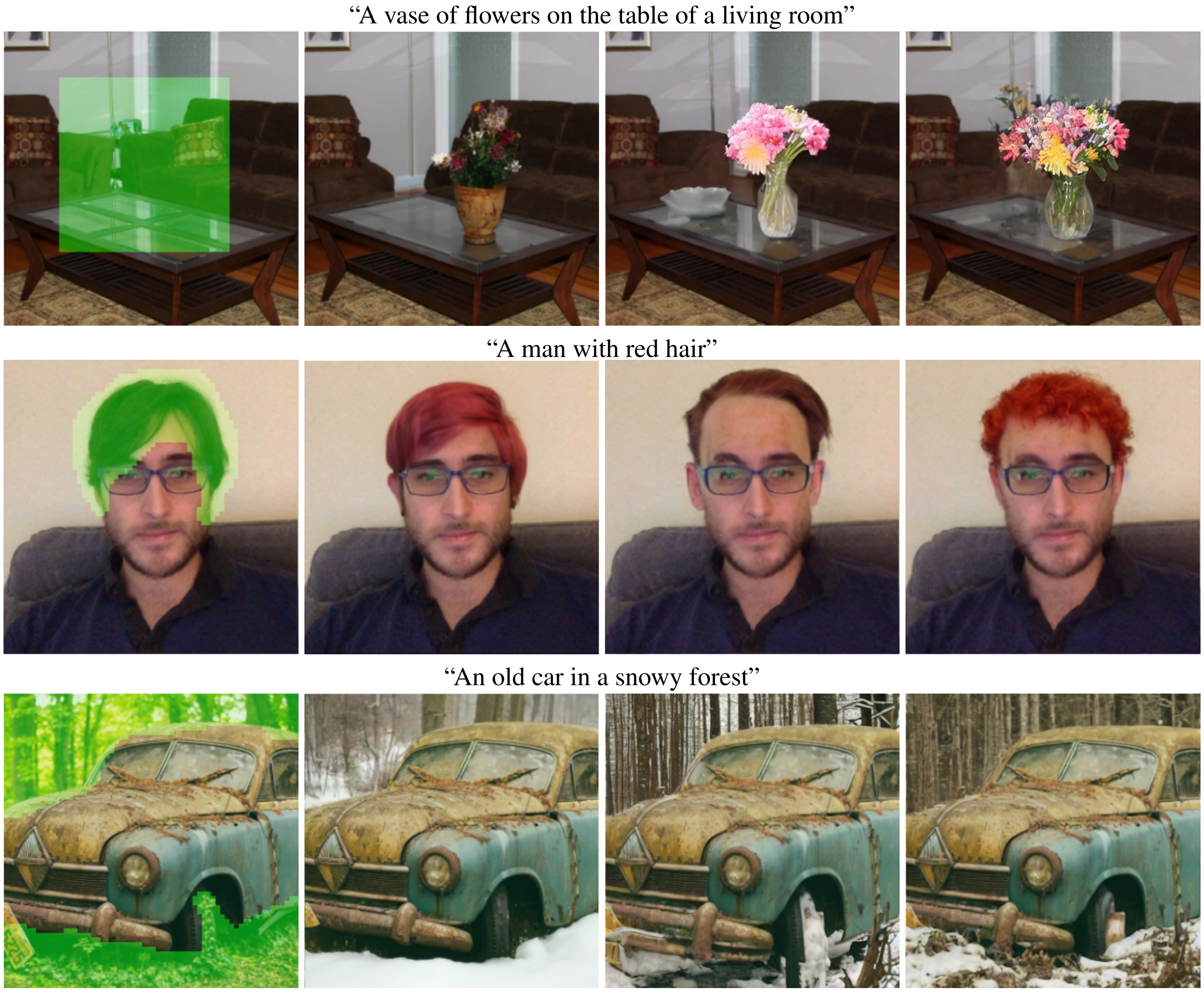


Figure 3: Text-based image editing comparison between GLIDE (full) Nichol et al. (2021), Stable Diffusion Rombach et al. (2022) and ADIR applied to the Stable Diffusion model. The images are taken from Nichol et al. (2021), since their official high-res model was not publicly released. As can be seen, our method produces more realistic images in cases where Stable Diffusion either was not accurate (brown hair instead of red) or in terms of artifacts.

3.2 Diffusion based Image Reconstruction

We turn to extend the guidance method of Dhariwal & Nichol (2021) to image reconstruction. First, we generalize their framework to inverse problems in the form of equation 1. Namely, given the observed image $\mathbf{y}$, we modify the guided reverse diffusion process to generate possible reconstructions of $\mathbf{x}$ that are associated with $\mathbf{y}$ rather than arbitrary samples of a certain class. Similar to Dhariwal & Nichol (2021), ideally, the guiding direction at iteration t should follow (the gradient of) the likelihood function $p_{\mathbf{y}|\mathbf{x}_t}$.

The key difference between our framework and Dhariwal & Nichol (2021) is that we need to base our method on the specific degraded image $\mathbf{y}$ rather than on a classifier that has been trained for each level of noise of $\{\mathbf{x}_t\}$. However, only the likelihood function $p_{\mathbf{y}|\mathbf{x}_0}$ is known, i.e., of the clean image $\mathbf{x}_0$ that is available only at the end of the procedure, and not for every $1 \leq t \leq T$. To overcome this issue, we propose a surrogate for the intermediate likelihood functions $p_{\mathbf{y}|\mathbf{x}_t}$. Our relaxation resembles the one in a recent concurrent work Chung et al. (2022b). Yet, their sampling scheme is significantly different and has no adaptation ingredient.

Similar to Dhariwal & Nichol (2021), we guide the diffusion progression using the log-likelihood gradient. Formally, we are interested in sampling from the posterior

$$p_\theta(\mathbf{x}_t|\mathbf{x}_{t+1}, \mathbf{y}) \propto p_\theta(\mathbf{x}_t|\mathbf{x}_{t+1}) p_{\mathbf{y}|\mathbf{x}_t}(\mathbf{y}|\mathbf{x}_t), \tag{8}$$

where $p_{\mathbf{y}|\mathbf{x}_t}(\cdot|\mathbf{x}_t)$ is the distribution of $\mathbf{y}$ conditioned on $\mathbf{x}_t$, and $p_\theta(\mathbf{x}_t|\mathbf{x}_{t+1}) = \mathcal{N}(\boldsymbol{\mu}_\theta(\mathbf{x}_{t+1}, t+1)), \boldsymbol{\Sigma}_\theta(\mathbf{x}_{t+1}, t+1))$ is the learned diffusion prior. For brevity, we omit the arguments of $\boldsymbol{\mu}_\theta$ and $\boldsymbol{\Sigma}_\theta$ in the rest of this subsection.

Under the assumption that the likelihood $\log p_{\mathbf{y}|\mathbf{x}_t}(\mathbf{y}|\cdot)$ has low curvature compared to $\boldsymbol{\Sigma}_\theta^{-1}$ Dhariwal & Nichol (2021), the following Taylor expansion around $\mathbf{x}_t = \boldsymbol{\mu}_\theta$ is valid

$$\log p_{\mathbf{y}|\mathbf{x}_t}(\mathbf{y}|\mathbf{x}_t) \approx \log p_{\mathbf{y}|\mathbf{x}_t}(\mathbf{y}|\mathbf{x}_t)|_{\mathbf{x}_t=\boldsymbol{\mu}_\theta} + (\mathbf{x}_t - \boldsymbol{\mu}_\theta)^\top \nabla_{\mathbf{x}_t} \log p_{\mathbf{y}|\mathbf{x}_t}(\mathbf{y}|\mathbf{x}_t)|_{\mathbf{x}_t=\boldsymbol{\mu}_\theta} = (\mathbf{x}_t - \boldsymbol{\mu}_\theta)^\top \mathbf{g} + C_1, \tag{9}$$

where $\mathbf{g} = \nabla_{\mathbf{x}_t} \log p_{\mathbf{y}|\mathbf{x}_t}(\mathbf{y}|\mathbf{x}_t)|_{\mathbf{x}_t=\boldsymbol{\mu}_\theta}$, and C_1 is a constant that does not depend on $\mathbf{x}_t$. Then, similar to the computation in Dhariwal & Nichol (2021), we can use equation 9 to express the posterior in equation 8, i.e.,

$$\log(p_\theta(\mathbf{x}_t|\mathbf{x}_{t+1}) p_{\mathbf{y}|\mathbf{x}_t}(\mathbf{y}|\mathbf{x}_t)) \approx C_2 + \log p(\mathbf{z}), \tag{10}$$

where $\mathbf{z} \sim \mathcal{N}(\boldsymbol{\mu}_\theta + \boldsymbol{\Sigma}_\theta \mathbf{g}, \boldsymbol{\Sigma}_\theta)$, and C_2 is some constant that does not depend on $\mathbf{x}_t$. Therefore, for conditioning the diffusion reverse process on $\mathbf{y}$, one needs to evaluate the derivative $\mathbf{g}$ from a (different) log-likelihood function $\log p_{\mathbf{y}|\mathbf{x}_t}(\mathbf{y}|\cdot)$ at each iteration t.

Observe that we know the exact log-likelihood function for $t = 0$. Since the noise $\mathbf{e}$ in equation 1 is white Gaussian with variance σ^2, we therefore have following distribution

$$p_{\mathbf{y}|\mathbf{x}}(\mathbf{y}|\mathbf{x}) = \mathcal{N}(\mathbf{A}\mathbf{x}, \sigma^2 \mathbf{I}_m) \propto e^{-\frac{1}{2\sigma^2}\|\mathbf{y}-\mathbf{A}\mathbf{x}\|_2^2}. \tag{11}$$

In the denoising diffusion setup, $\mathbf{y}$ is related to $\mathbf{x}_0$ using the observation model equation 1. Therefore,

$$\log p_{\mathbf{y}|\mathbf{x}_0}(\mathbf{y}|\mathbf{x}_0) \propto -\|\mathbf{A}\mathbf{x}_0 - \mathbf{y}\|_2^2. \tag{12}$$

However, we do not have tractable expressions for the likelihood functions $\{p_{\mathbf{y}|\mathbf{x}_t}(\mathbf{y}|\cdot)\}_{t=1}^T$. Therefore, motivated by the expression above, we propose the following approximation

$$\log p_{\mathbf{y}|\mathbf{x}_t}(\mathbf{y}|\mathbf{x}_t) \approx \log p_{\mathbf{y}|\mathbf{x}_0}(\mathbf{y}|\hat{\mathbf{x}}_0(\mathbf{x}_t)), \tag{13}$$

where

$$\hat{\mathbf{x}}_0(\mathbf{x}_t) := \left(\mathbf{x}_t - \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t)\right) / \sqrt{\bar{\alpha}_t} \tag{14}$$

is an estimation of $\mathbf{x}_0$ from $\mathbf{x}_t$, which is based on the (stochastic) relation of $\mathbf{x}_t$ and $\mathbf{x}_0$ in equation 3 and the random noise $\boldsymbol{\epsilon}$ is replaced by its estimation $\boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t)$.

From equation 11 and equation 13 it follows that $\mathbf{g}$ in equation 9 can be approximated at each iteration t by evaluating (e.g., via automatic-differentiation)

$$\mathbf{g} \approx -\nabla_{\mathbf{x}_t} \|\mathbf{A}\hat{\mathbf{x}}_0(\mathbf{x}_t) - \mathbf{y}\|_2^2|_{\mathbf{x}_t=\boldsymbol{\mu}_\theta}. \tag{15}$$

Note that existing methods Chung et al. (2022b); Kawar et al. (2022a); Song et al. (2021) either use a term that resembles equation 15 with the naive approximation $\hat{\mathbf{x}}_0(\mathbf{x}_t) = \mathbf{x}_t$ Kawar et al. (2022a); Song et al. (2021), or significantly modify equation 15 before computing it via the automatic derivation framework Chung et al. (2022b) (we observed that trying to compute the exact equation 15 is unstable due to numerical issues). For example, in the official implementation of Chung et al. (2022b), which uses automatic derivation, the squaring of the norm in equation 15 is dropped even though this is not stated in their paper (otherwise, the reconstruction suffers from significant artifacts). In our case, we use the following relaxation to overcome the stability issue of using equation 15 directly. For a pretrained denoiser predicting $\boldsymbol{\epsilon}_\theta$ from $\mathbf{x}_t$ and $0 < t \leq T$ we have

$$\begin{aligned}
\|\mathbf{A}\hat{\mathbf{x}}_0(\mathbf{x}_t) - \mathbf{y}\|_2^2 &= \|\mathbf{A}(\mathbf{x}_t - \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}_\theta)/\sqrt{\bar{\alpha}_t} - \mathbf{y}\|_2^2 \\
&\propto \|\mathbf{A}\mathbf{x}_t - \sqrt{1-\bar{\alpha}_t}\mathbf{A}\boldsymbol{\epsilon}_\theta - \sqrt{\bar{\alpha}_t}\mathbf{y}\|_2^2 \\
&= \|\mathbf{A}\mathbf{x}_t - \sqrt{\bar{\alpha}_t}\mathbf{y} - \sqrt{1-\bar{\alpha}_t}\mathbf{A}\epsilon_\theta\|_2^2 \\
&= \|\mathbf{A}\mathbf{x}_t - \mathbf{y}_t\|_2^2,
\end{aligned} \tag{16}$$

Algorithm 1 Proposed GD sampling for image reconstruction given a diffusion model $(\boldsymbol{\epsilon}_\theta(\cdot), \boldsymbol{\Sigma}_\theta(\cdot))$, and a guidance scale s

Require: $(\boldsymbol{\epsilon}_\theta(\cdot), \boldsymbol{\Sigma}_\theta(\cdot))$, $\mathbf{y}$, s
1: $\mathbf{x}_T \leftarrow$ sample from $\mathcal{N}(\mathbf{0}, \mathbf{I}_n)$
2: **for** t from T to 1 **do**
3: $\hat{\boldsymbol{\epsilon}}$, $\hat{\boldsymbol{\Sigma}} \leftarrow \boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t)$, $\boldsymbol{\Sigma}_\theta(\mathbf{x}_t, t)$
4: $\hat{\boldsymbol{\mu}} \leftarrow \frac{1}{\sqrt{\alpha_t}}(\mathbf{x}_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}}\hat{\boldsymbol{\epsilon}})$
5: $\mathbf{y}_t \leftarrow \sqrt{\bar{\alpha}_t}\mathbf{y} + \sqrt{1-\bar{\alpha}_t}\mathbf{A}\hat{\epsilon}$
6: $\mathbf{g} \leftarrow -2\mathbf{A}^T(\mathbf{A}\hat{\boldsymbol{\mu}} - \mathbf{y}_t)$
7: $\mathbf{x}_{t-1} \leftarrow$ sample from $\mathcal{N}(\hat{\boldsymbol{\mu}} + s\hat{\boldsymbol{\Sigma}}\mathbf{g}, \hat{\boldsymbol{\Sigma}})$
8: **end forreturn** $\mathbf{x}_0$

where $\mathbf{y}_t := \sqrt{\bar{\alpha}_t}\mathbf{y} + \sqrt{1-\bar{\alpha}_t}\mathbf{A}\boldsymbol{\epsilon}_\theta$. Consequently, we propose to replace the expression for $\mathbf{g}$ (the guiding likelihood direction at each iteration t) that is given in equation 15 with a surrogate obtained by evaluating the derivative of equation 16 w.r.t. $\mathbf{x}_t$, which is given by

$$\mathbf{g} \approx -2\mathbf{A}^T(\mathbf{A}\mathbf{x}_t - \mathbf{y}_t)|_{\mathbf{x}_t=\boldsymbol{\mu}_\theta} \tag{17}$$

that can be used for sampling the posterior distribution as detailed in Algorithm 1.

3.3 Adaptive Diffusion

Having defined the guided inverse diffusion flow for image reconstruction, we turn to discuss how one may adapt a given diffusion model to a given degraded image $\mathbf{y}$ as defined in equation 1. Assume we have a pretrained diffusion model $(\boldsymbol{\epsilon}_\theta(\cdot), \boldsymbol{\Sigma}_\theta(\cdot))$, then the adaptation scheme is defined by the following minimization problem

$$\hat{\theta} = \arg\min_\theta \sum_{t=1}^{T} \ell_{\text{simple}}(\mathbf{y}, \boldsymbol{\epsilon}_\theta, t) \tag{18}$$

with ℓ_{simple} defined in equation 6, which can be solved efficiently using stochastic gradient descent, where at each iteration the gradient step is performed on a single term of the sum above, for $0 < t \leq T$ chosen randomly.

Adapting the denoising network to the measurement image $\mathbf{y}$, allows it to learn cross-scale features recurring in the image. Such an approach has been proven to be very helpful in reconstruction-based algorithms Hussein et al. (2020a); Tirer & Giryes (2019).

However, in some cases where the image does not satisfy the assumption of recurring patterns across scales, this approach can lose some of the sharpness captured in training. Therefore, in this work we extend the approach to few-shot fine-tuning adaptation, where instead of solving equation 18 w.r.t. $\mathbf{y}$, we propose an algorithm for retrieving K images similar to $\mathbf{x}$ from a large dataset of diverse images, using off-the-shelf embedding distance.

Let $(\xi_v(\cdot), \xi_\ell(\cdot))$ be some off-the-shelf multi-modal encoder trained on visual-language modalities, e.g., CLIP Radford et al. (2021), BLIP Li et al. (2022), or CyCLIP Goel et al. (2022)). Let $\xi_v(\cdot)$ and $\xi_\ell(\cdot)$ be the visual and language encoders respectively. Then, given a large diverse dataset of natural images, we propose to retrieve K images, denoted by $\{\mathbf{z}_k\}_{k=1}^K$, with minimal embedding distance from $\mathbf{y}$. Formally, let $\mathcal{D}_{\text{IA}}$ be an arbitrary external dataset, then

$$\begin{aligned}\{\mathbf{z}_k\}_{k=1}^K = \{&\mathbf{z}_1, ..., \mathbf{z}_K | \phi_\xi(\mathbf{z}_1, \mathbf{y}) \leq ... \leq \phi_\xi(\mathbf{z}_K, \mathbf{y}) \\ &\leq \phi_\xi(\mathbf{z}, \mathbf{y}), \forall \mathbf{z} \in \mathcal{D}_{\text{IA}} \setminus \{\mathbf{z}_1, ..., \mathbf{z}_K\}\},\end{aligned} \tag{19}$$

where $\phi_\xi(\mathbf{a}, \mathbf{b}) = 2\arcsin(0.5\|\xi(\mathbf{a}) - \xi(\mathbf{b})\|_2)$ is the spherical distance and ξ can be either the visual or language encoder depending on the provided conditioning of the application.

After retrieving K-NN images $\{\mathbf{z}_k\}_{k=1}^K$ from $\mathcal{D}_{\text{IA}}$, we fine-tune the diffusion model on them, which adapts the denoising network to the context of $\mathbf{y}$. Specifically, we modify the denoiser parameters θ based on minimizing a loss similar to equation 18, but with $\{\mathbf{z}_k\}_{k=1}^K$ rather than $\mathbf{y}$. We refer to this K-NN based adaptation technique as ADIR (Adaptive Diffusion for Image Reconstruction), which is described schematically in Figure 2.

	IA Iter.	LR	NN imag.	s	diff. steps
ADIR-GD	400	10^{-4}	20	10	1000
ADIR-SD	400	10^{-4}	50	-	500

Table 1: Configurations used for ADIR.

	SRx4	SRx8
Real-ESRGAN	0.3171/5.0201/**69.4156**	-
DDRM	**0.2968**/3.4240/28.961	0.5717/3.1300/20.681
GD	0.3249/4.8756/64.630	0.3649/4.3559/53.987
ADIR	0.3347/**5.0595**/66.329	**0.3475/4.4060/55.889**

Table 2: x4 Super resolution results ($128^2 \rightarrow 512^2$) and 8 ($64^2 \rightarrow 512^2$) for the unconditional guided diffusion model Dhariwal & Nichol (2021). The results are averaged on the first 50 images of the DIV2K validation set Agustsson & Timofte (2017). We compare ADIR to the baseline approach presented in Section 3.2, Real-ESRGAN Wang et al. (2021), DDRM Kawar et al. (2022a). We use the traditional LPIPS Zhang et al. (2018) as well as the state-of-the-art no reference perceptual losses AVA-MUSIQ and KonIQ-MUSIQ Ke et al. (2021) for evaluation (LPIPS/MUSIQ-AVA/MUSIQ-KONIQ). The best results are in bold black, and the second best is highlighted in blue.

4 Experiments

We evaluate our method on two state-of-the-art diffusion models, Guided Diffusion (GD) Dhariwal & Nichol (2021) and Stable Diffusion (SD) Rombach et al. (2022), showing results for super-resolution and deblurring. In addition, we show how adaptive diffusion can be used for the task of text-based editing using stable diffusion.

Guided diffusion Dhariwal & Nichol (2021) provides several models with a conditioning mechanism built-in to the denoiser. However, in our case, we perform the conditioning using the $\log$-likelihood term. Therefore, we used the unconditional model that was trained on ImageNet Russakovsky et al. (2015) and produces images of size 256×256. In the original work, the conditioning for generating an image from an arbitrary class was performed using a classifier trained to classify the noisy sample $\mathbf{x}_t$ directly, where the log-likelihood derivative can be obtained by deriving the corresponding logits w.r.t. $\mathbf{x}_t$ directly. In our setup, the conditioning is performed using $\mathbf{g}$ in equation 17, where $\mathbf{A}$ is defined by the reconstruction task, which we specify in the sequel.

In addition to GD, we demonstrate the improvement that can be achieved using stable diffusion Rombach et al. (2022), where we use publicly available super-resolution and text-based editing models for it. Instead of training the denoiser on the natural images domain directly, they suggest using a Variational Auto Encoder (VAE) and train the denoiser using a latent representation of the data. Note that the lower dimensionality of the latent enables the network to be trained at higher resolutions.

In all cases, we adapt the diffusion models in the image adaptive scheme presented in section 3.3, using the Google Open Dataset Kuznetsova et al. (2020) as the external dataset $\mathcal{D}_{\text{IA}}$, from which we retrieve K images, where $K = 20$ for GD and $K = 50$ for SD (several examples of retrieved images are shown in the sup. mat.). In practice we found that regularizing the objective loss with LPIPS Zhang et al. (2018) term yields to better results, therefore we add it with weight 0.1. For optimizing the network parameters we use LoRA Hu et al. (2021) with rank $r = 16$ and scaling $\alpha = 8$ for all the convolution layers, which is then optimized using Adam Kingma & Ba (2014). The specific implementation configurations are detailed in Table 1. We run all of our experiments on a NVIDIA RTX A6000 48GB card, which allows us to fine-tune the models by randomly sampling a batch of 6 images from $\{\mathbf{z}_k\}_{k=1}^{K}$, where in each iteration we use the same $0 < t \leq T$ for images in the batch.

4.1 Super Resolution

In the Super-Resolution (SR) task one would like to reconstruct a high resolution image $\mathbf{x}$ from its low resolution image $\mathbf{y}$, where in this case $\mathbf{A}$ represents an anti-aliasing filter followed by sub-sampling with stride γ, which we refer to as the scaling factor. In our use-case we employ a bicubic anti-aliasing filter and assume $\mathbf{e} = 0$, similarly to most SR works.

Here we apply our approach on two different diffusion based SR methods, Stable Diffusion Rombach et al. (2022), and section 3.2 approach combined with the unconditional diffusion model from Dhariwal & Nichol (2021). In Stable

	Real-ESRGAN	Stable Diffusion	ADIR (SD)
SRx4	0.305 / 4.93 / 69.11	0.331/5.07/69.18	**0.213/5.51/72.56**

Table 3: x4 Super resolution ($256^2 \rightarrow 1024^2$) using Stable Diffusion SR Rombach et al. (2022). Similar to Table 2, the results are averaged on the first 50 images of the DIV2K validation set Agustsson & Timofte (2017). We compare our method to the baseline approach presented by Stable Diffusion, as well as Real-ESRGAN Wang et al. (2021) We use LPIPS Zhang et al. (2018) as well as AVA-MUSIQ and KonIQ-MUSIQ Ke et al. (2021) for evaluation (LPIPS/MUSIQ-AVA/MUSIQ-KONIQ). The best results are in bold black, and the second best is highlighted in blue.

	Guided Diffusion	ADIR (GD)
Uniform Deblur (256)	0.4227 / 4.196 /49.195	**0.3936 / 4.305 /55.782**
Uniform Deblur (512)	0.4112 / 4.812 /58.665	**0.3121 / 4.766 /60.132**
Gaussian deblur (256)	0.4241 / 4.013 /48.114	**0.4152 / 4.194 /51.804**

Table 4: Deblurring with 5×5 box filter and 10 noise levels results for the unconditional guided diffusion model Dhariwal & Nichol (2021). Similar to SR in Table 2, the results are averaged on the first 50 images of the DIV2K validation set Agustsson & Timofte (2017). We compare our method to the baseline presented in Section 3.2. We use LPIPS Zhang et al. (2018) as well as AVA-MUSIQ and KonIQ-MUSIQ Ke et al. (2021) for evaluation (LPIPS/MUSIQ-AVA/MUSIQ-KONIQ).

Diffusion, the low-resolution image $\mathbf{y}$ is upscaled from 256×256 to 1024×1024, while in Guided Diffusion we use the unconditional model trained on 256×256 images, to upscale $\mathbf{y}$ from 128×128 to 512×512 resolution. When adapting Stable diffusion, we downsample random crops of the K-NN images using $\mathbf{A}$, which we encode using the VAE and plug into the network conditioning mechanism. We fine-tune both models using random crops of the K-NN images, to which we then add noise using the scheduler provided by each model.

The perception preference of generative models-based image reconstruction has been seen in many works Hussein et al. (2020a); Bora et al. (2017); Blau & Michaeli (2018). Therefore, we chose a perception-based measure to evaluate the performance of our method. Specifically, we use the state-of-the-art AVA-MUSIQ and KonIQ-MUSIQ perceptual quality assessment measures Ke et al. (2021), which are state-of-the-art image quality assessment measures. We report our results using the two measures averaged on the first 50 validation images of the DIV2K Agustsson & Timofte (2017) dataset. As can be seen in Tables 2, 3, our method significantly outperforms both Stable Diffusion and GD-based reconstruction approaches. We compare our SR results to Stable Diffusion SR and Guided Diffusion without adaptation, as well as using Image Adaptation (IA) performed on $\mathbf{y}$ with no external data. The latter is done only for guided diffusion and show inferior performance compared to using external data. Therefore, in the other experiments we use only the external data for improving the optimization. A clear dominance of our method can be seen in the tables.

Figures 1 and 7 present qualitative results. Note that our method achieves superior restoration quality. In some cases it restores even fine details that were blurred in the acquisition of the GT image.

4.2 Deblurring

In deblurring, $\mathbf{y}$ is obtained by applying a blur filter (uniform blur of size 5×5 in our case) on $\mathbf{x}$, followed by adding measurement noise $\mathbf{e} \sim \mathcal{N}(0, \sigma^2 I_n)$, where in our setting $\sigma = 10$. We apply our proposed approach in Section 3.2 for the Guided Diffusion unconditional model Dhariwal & Nichol (2021) to solve the task. In this case, $\mathbf{A}$ can be implemented by applying the blur kernel on a given image.

As a baseline, we use the unconditional diffusion model provided by GD Dhariwal & Nichol (2021), which was trained on 256×256 size images. Yet, in our tests, we solve the deblurring task on images of size 256×256 as well as 512×512, which emphasizes the remarkable benefit of the adaptation, as it allows the model to generalize to resolutions not seen during training.

Similar to SR, in Table 4 we report the KonIQ-MUSIQ and AVA-MUSIQ Ke et al. (2021) measures, averaged on the first 50 DIV2K validation images Agustsson & Timofte (2017), where we compare our approach to the guided

DDRM	Guided Diffusion (GD)	ADIR (GD)
4.012/53.458	4.195/56.044	**4.214/58.679**

Table 5: Image colorization for the unconditional guided diffusion model Dhariwal & Nichol (2021). The results are averaged on the first 50 images of the DIV2K validation set Agustsson & Timofte (2017). We compare ADIR to the baseline presented in Section 3.2 and DDRM Kawar et al. (2022a). We use AVA-MUSIQ and KonIQ-MUSIQ Ke et al. (2021) for evaluation (MUSIQ-AVA/MUSIQ-KONIQ). The best results are in bold black, and the second best is highlighted in blue.

diffusion reconstruction without image adaptation. A visual comparisons are also available in Figure 4, where a very significant improvement can be seen in both robustness to noise and reconstructing details.

4.3 Colorization

In colorization, $\mathbf{y}$ is obtained by averaging the colors of $\mathbf{x}$ using RGB2Gray transform. Similar to deblurring, we apply our proposed approach in Section 3.2 to solve the task. In this case, $\mathbf{A}$ can be implemented by averaging the color dimension of $\mathbf{x}$, while $\mathbf{A}^T$ can simply be viewed as a replication of the color dimension. We use the unconditional diffusion model provided by GD Dhariwal & Nichol (2021) as a baseline for coloring 256×256 images. Visual comparison of the results can be seen in Figure 6. We report the average MUSIQ Ke et al. (2021) perceptual measure for this case, as shown in Table 5. Note that we do not report LPIPS as there are many colorization solutions and therefore the reconstructed image may differ a lot from the ground truth. Thus, we focus on the non-reference perceptual measures for the colorization task.

4.4 Text-Guided Editing

Text-guided image editing is the task of completing a masked region of $\mathbf{x}$ according to a prompt provided by the user. In this case, the diffusion model needs to predict objects and textures correspondent to the provided prompt, therefore we chose to adapt the network on $\{\mathbf{z}_k\}_{k=1}^K$ retrieved using the text encoder, i.e. by solving equation 19 using ξ_ℓ. For evaluating our method for this application, we use the state-of-the-art inpainting model of Stable Diffusion Rombach et al. (2022). Where $\mathbf{y}$ encoded and concatenated with the mask resized to latent dimension, which are then plugged to the denoising network. When adapting the network, we follow the training scheme of Stable Diffusion, where we use random masks and the classifier-free conditioning approach Ho & Salimans (2022) used for training Stable Diffusion, where the text embedding is randomly chosen to either be the encoded prompt or the embedding of an empty prompt. Notice that we cannot compare to Giannone et al. (2022); Sheynin et al. (2022); Kawar et al. (2022b) as there is no code available for them. For some of them, we do not even have access to the diffusion model that they adapt Saharia et al. (2022a). Note though that our goal is not to show state-of-the-art editing results but rather to show here the potential contribution of ADIR to text-guided editing. As it is a general framework, it may be used also with other existing editing techniques in order to improve them.

Figure 3 presents the editing results and compares them to both stable diffusion and GLIDE. GLIDE is the basis of the popular DALL-E-2 model. The images of GLIDE are taken from the paper. We use ADIR with stable diffusion and optimize them using the same seed.

Since Stable Diffusion was trained using a lossy latent representation with smaller dimensionality than the data, it is clear that GLIDE can achieve better results. However, because our method adapts the network to a specific scenario, it enables the model to produce cleaner and more accurate generations, as can be seen in Figure 3. In the first image we see that Stable Diffusion adds an object that does not blend well and has artifacts, while when combined with our approach the quality improves significantly. Similarly, in the second image we see that Stable Diffusion produces an inaccurate edit, where it adds a brown hair instead of red hair. This is again improved by our adaptation method.

Limitation. One limitation of our approach is that as is the case with all diffusion models, there is randomness in the generation process of the results. Therefore, the quality of the output may depend on the random seed being used. For a fair comparison, we used the same seed both for ADIR and the baseline. In the appendix, we provide more examples with different random seeds. We still find that when we compare our approach and the baseline with the same seed, we consistently get an improvement.

Figure 4: Image deblurring using Guided Diffusion approach from section 3.2 and ADIR, using the unconditional model from Dhariwal & Nichol (2021). The degradation is performed using 5×5 uniform blur filter with 10 levels of additive Gaussian noise. Note the better quality of our method.

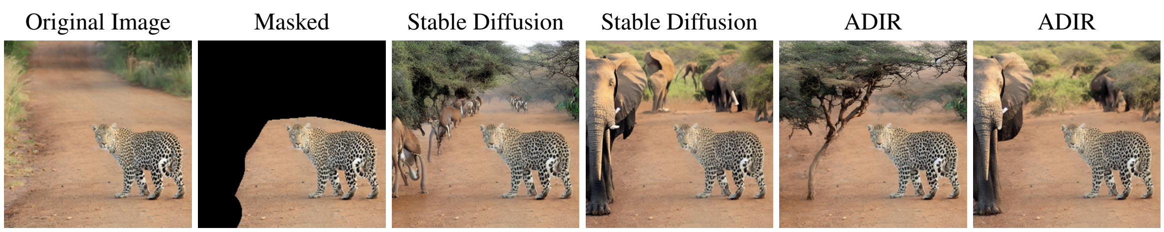
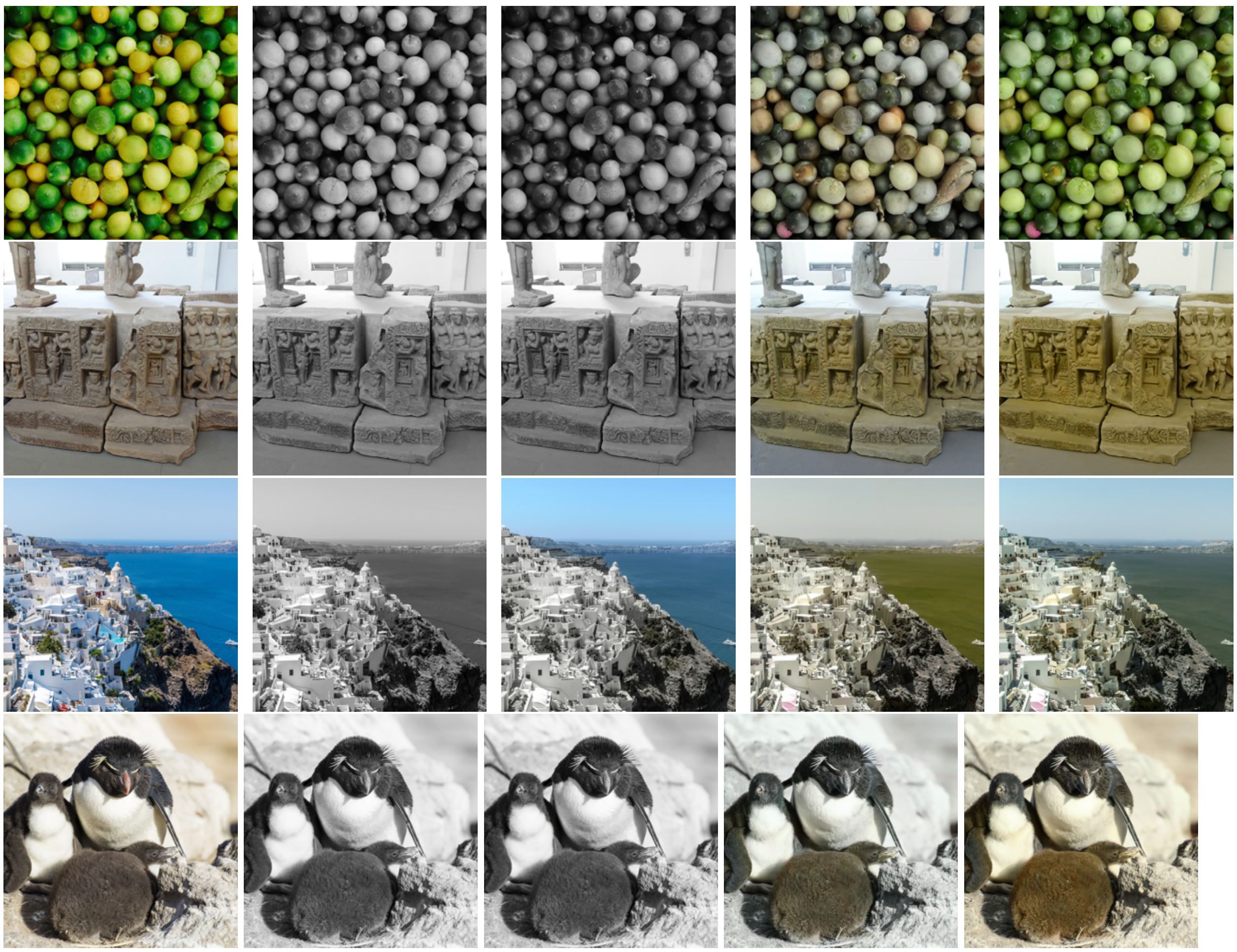


Figure 5: Text-based editing comparison between Stable Diffusion and ADIR, using the prompt "Africa" for two different seeds. Note that Stable diffusion adds partial animals while ADIR completes the scene more naturally.

5 Conclusion

We have presented the Adaptive Diffusion Image Reconstruction (ADIR) method, in which we improve the reconstruction results in several imaging tasks using off-the-shelf diffusion models. We have demonstrated how our adaptation can significantly improve existing state-of-the-art methods, e.g. Stable Diffusion for super resolution, where the exploitation of external data with the same context as $\mathbf{y}$, combined with our adaptation scheme leads to a significant improvement. Specifically, the produced images are sharper and have more details than the original ground truth image. Importantly, note that our novel adaptive diffusion ingredient can be incorporated into any conditional sampling scheme that is based on diffusion models, beyond those that are examined in this paper. One such possible direction is integrating our method with advanced diffusion models-based editing techniques Meng et al. (2022); Kim et al. (2022); Mokady et al. (2023); Bar-Tal et al. (2023); Molad et al. (2023); Wei et al. (2023); Huang et al. (2023); Qi et al. (2023); Liu et al. (2023). We believe that our proposed novel concept can be a useful tool for improving diffusion-based reconstruction and editing.



Original Image Grayscale DDRM Guided Diffusion ADIR

Figure 6: Image colorization results comparison between DDRM Kawar et al. (2022a), Guided diffusion proposed in section 3.2, and our adaptive approach ADIR. As can be seen, adapting the denoiser network to the given image can improve the results significantly.

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A Additional Results

In the following we

- Show results for super resolution with scaling factor of 8.
- Show more results of deblurring task.
- Show more results of colorization use-case.
- Compare our method to Stable Diffusion for editing task in multiple scenarios.
- Examples of retrieved nearest neighbours images

Figure 7: Comparison of super resolution ($256^2 \rightarrow 1024^2$) results of Stable Diffusion modelRombach et al. (2022) and our method (ADIR). As can be seen from the images, our method outperforms Stable Diffusion in both sharpness and reconstructing details.

Figure 8: Comparison of super resolution ($64^2 \rightarrow 512^2$) results of Guided Diffusion from section 3.2 and our method (ADIR), using the unconditional model from Rombach et al. (2022). As can be seen from the images, our method outperforms guided diffusion in both sharpness and reconstruction details.

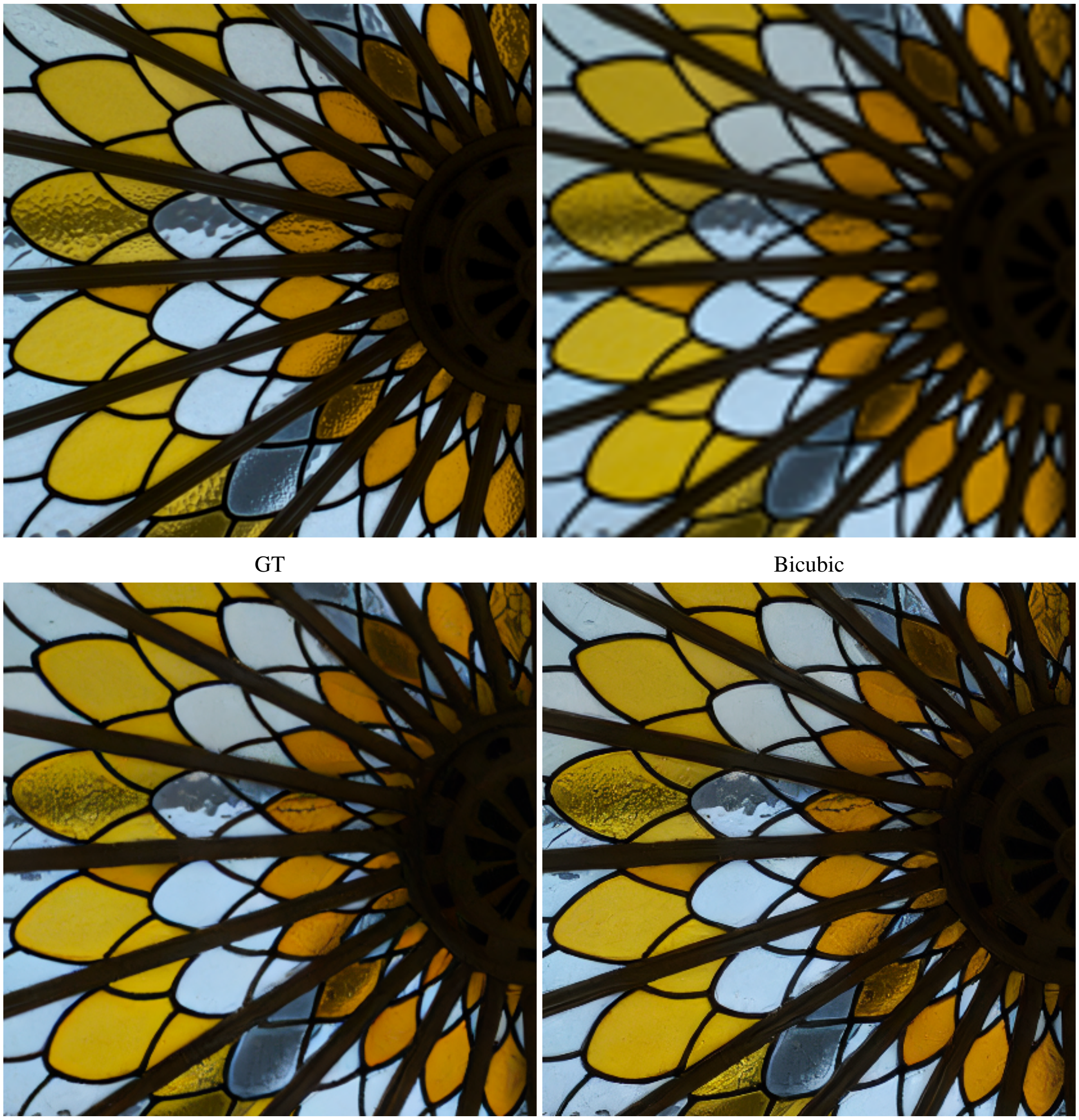


Figure 9: Comparison of super resolution ($256^2 \rightarrow 1024^2$) results of Stable Diffusion Rombach et al. (2022) and our method (ADIR), using the unconditional model from Rombach et al. (2022). As can be seen from the images, our method outperforms guided diffusion in both sharpness and reconstruction details.

GT Bicubic

Stable Diffusion ADIR

Figure 10: Comparison of super resolution ($256^2 \rightarrow 1024^2$) results of Stable Diffusion Rombach et al. (2022) and our method (ADIR), using the unconditional model from Rombach et al. (2022). As can be seen from the images, our method outperforms guided diffusion in both sharpness and reconstruction details.

Figure 11: Comparison of super resolution ($256^2 \rightarrow 1024^2$) results of Stable Diffusion Rombach et al. (2022) and our method (ADIR), using the unconditional model from Rombach et al. (2022). As can be seen from the images, our method outperforms guided diffusion in both sharpness and reconstruction details.

Figure 12: Comparison of super resolution ($64^2 \rightarrow 512^2$) results of Guided Diffusion from section 3.2 and our method (ADIR), using the unconditional model from Rombach et al. (2022). As can be seen from the images, our method outperforms guided diffusion in both sharpness and reconstruction details.

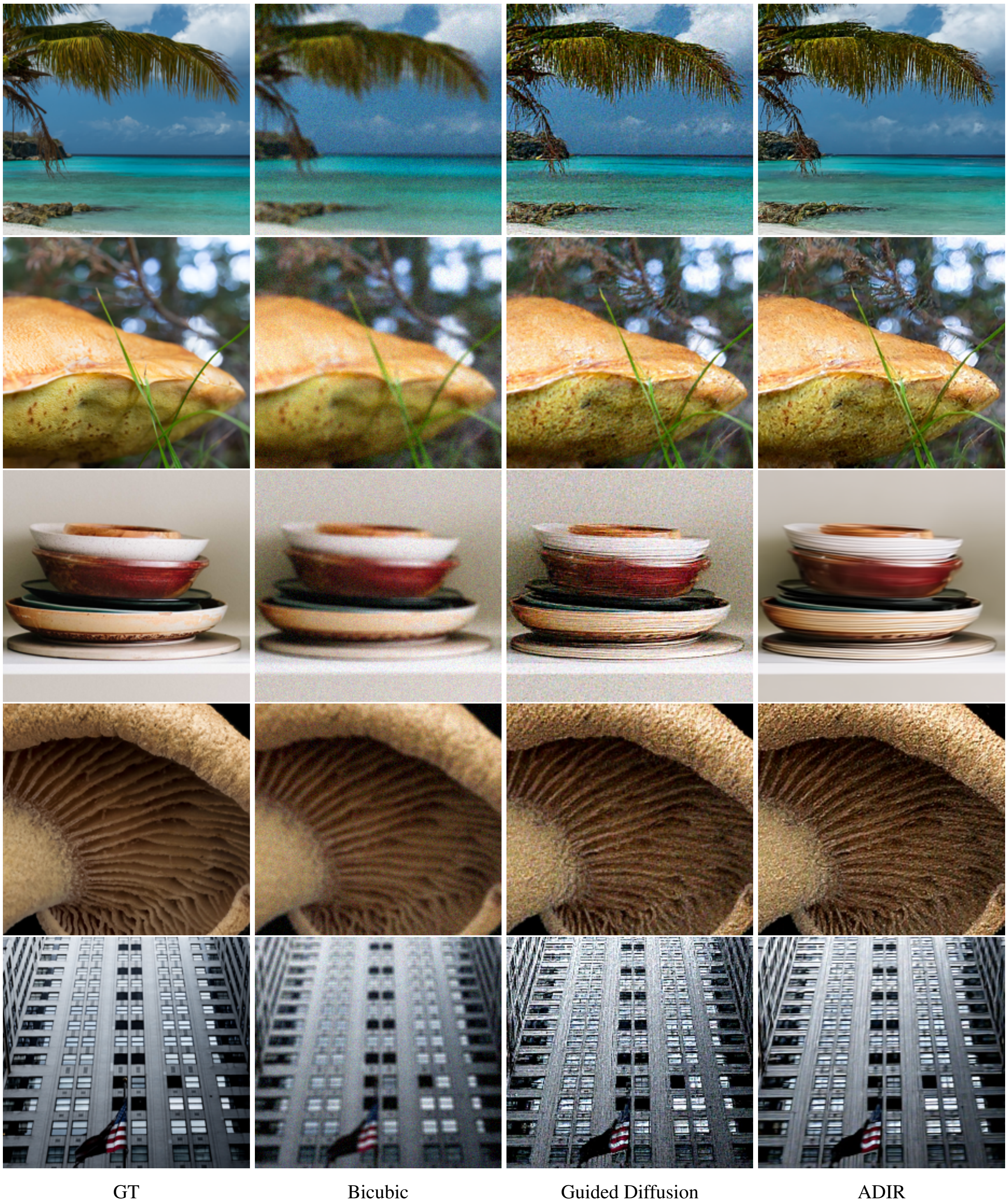


Figure 13: Deblurring (5×5 box filter, $\sigma = 10$) results of Guided Diffusion from section 3.2 and our method (ADIR), using the unconditional model from Rombach et al. (2022). As can be seen from the images, our method outperforms guided diffusion in both sharpness and reconstruction details.

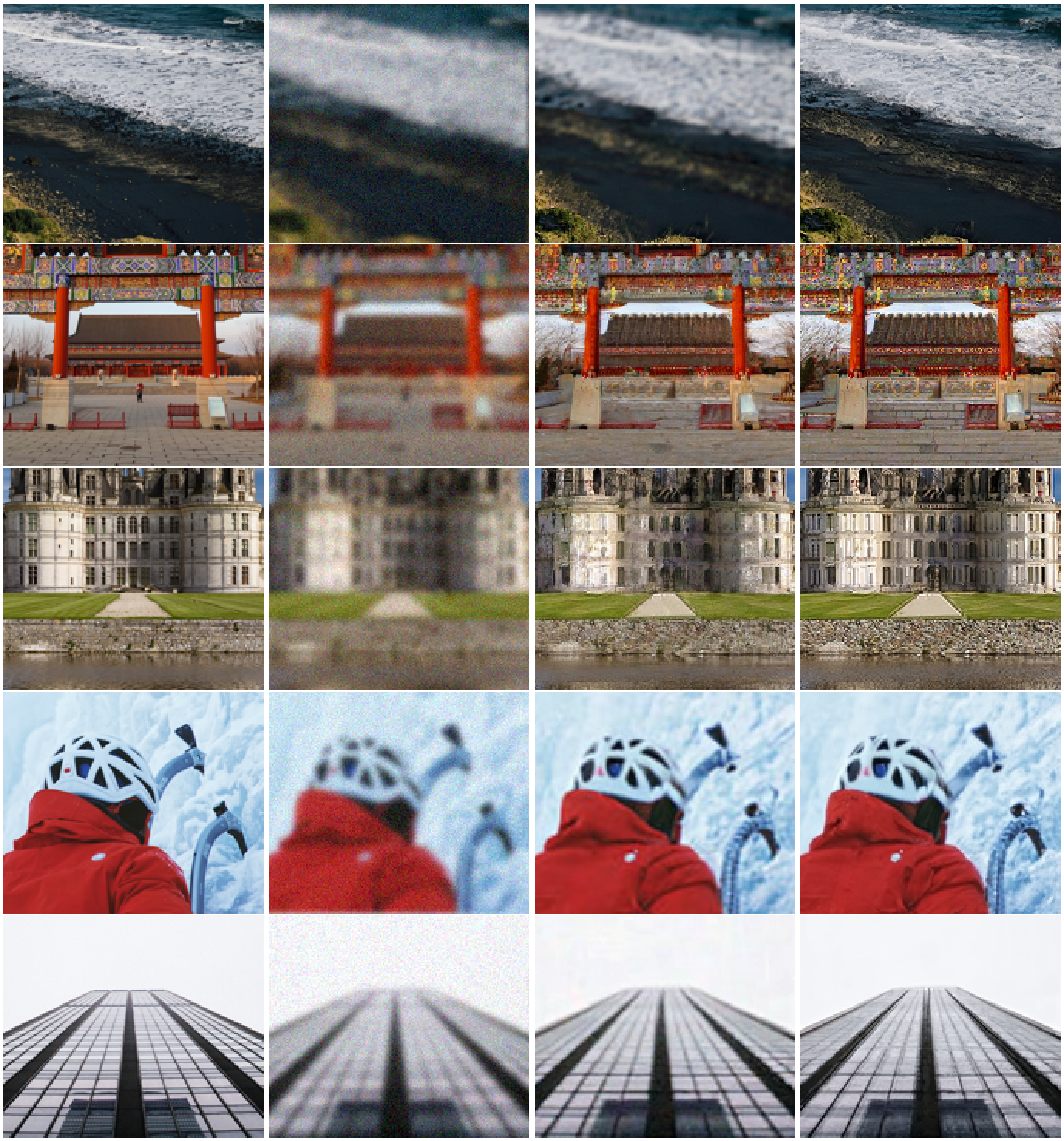


Figure 14: Gaussian deblurring ($\sigma_{\text{blur}} = 2$ and $\sigma_{\text{noise}} = 10$) results of Guided Diffusion from section 3.2 and our method (ADIR), using the unconditional model from Rombach et al. (2022). As can be seen from the images, our method outperforms guided diffusion in both sharpness and reconstruction details.

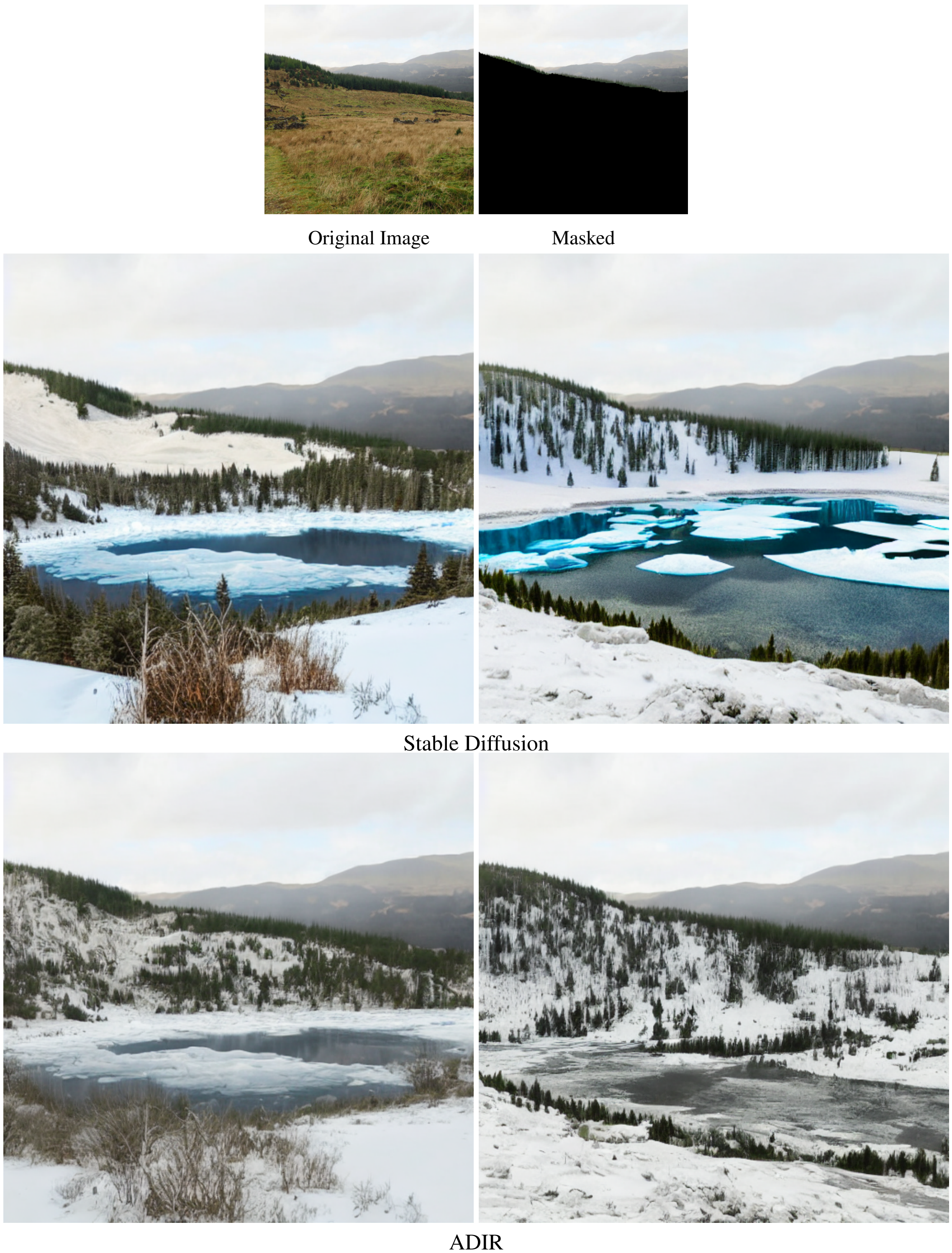


Figure 15: Text-based image editing comparison between Stable Diffusion Rombach et al. (2022) and ADIR, using the prompt “A beautiful frozen lake between mountains in the snow” for two different seeds.

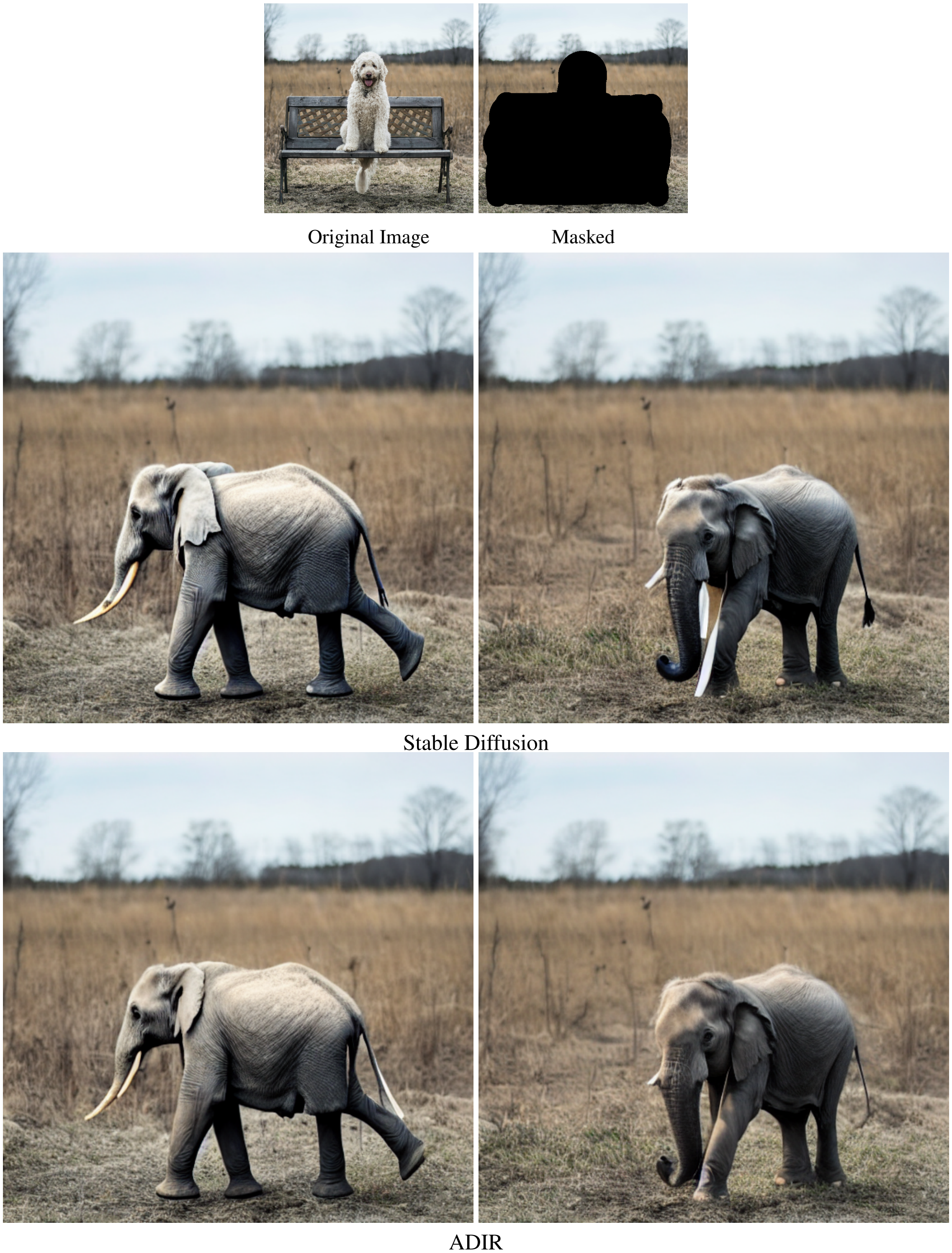
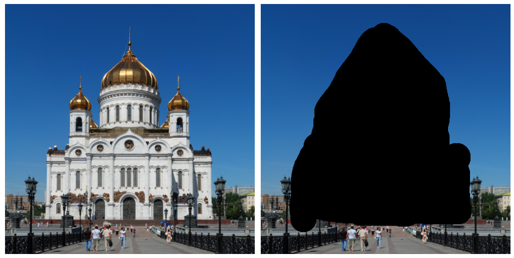


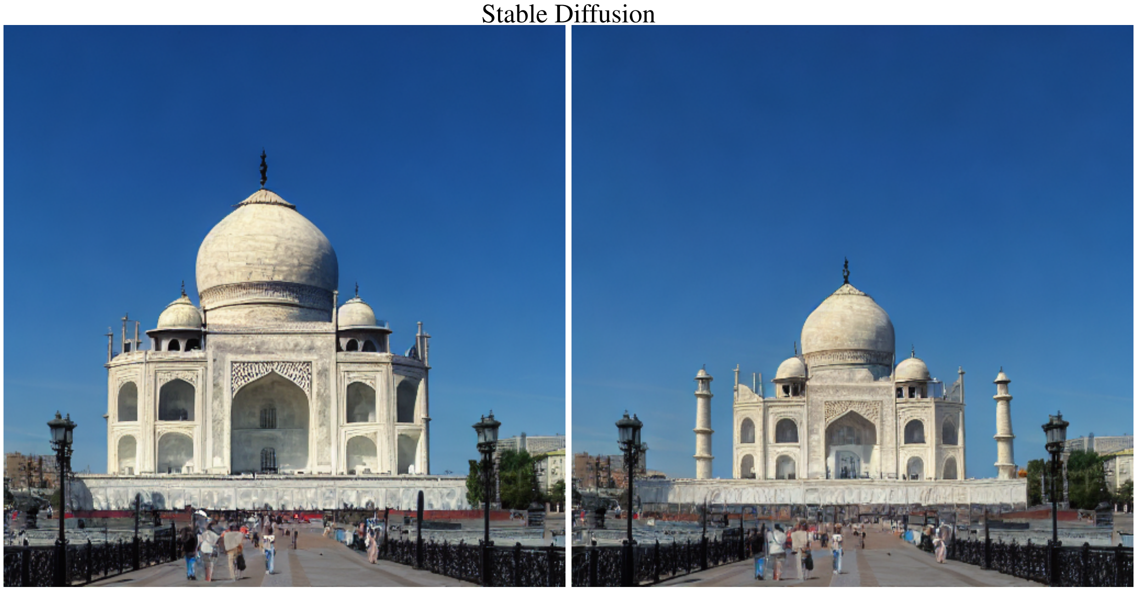
Figure 16: Text-based image editing comparison between Stable Diffusion Rombach et al. (2022) and ADIR, using the prompt "An elephant walking" for two different seeds.

Figure 17: Text-based image editing comparison between Stable Diffusion Rombach et al. (2022) and ADIR applied to the Stable Diffusion model, for the prompt “A fox sitting in the middle of the desert”



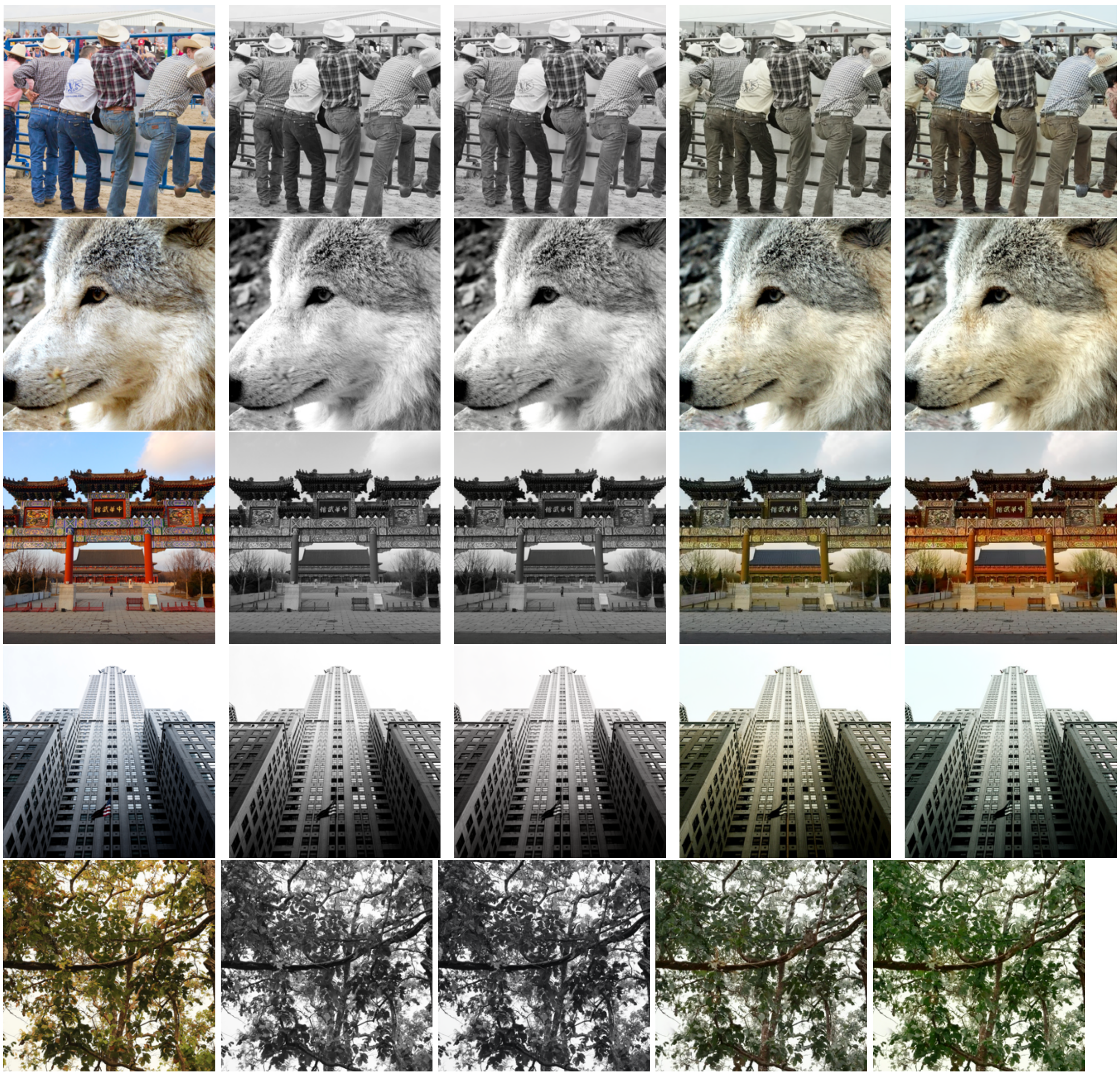
Original Image Masked

Stable Diffusion



ADIR

Figure 18: Text-based image editing comparison between Stable Diffusion Rombach et al. (2022) and ADIR applied to the Stable Diffusion model, for the prompt "Taj Mahal"



Original Image Grayscale DDRM Guided Diffusion ADIR

Figure 19: Image colorization results comparison between DDRM Kawar et al. (2022a), Guided diffusion proposed in section 3.2, and our adaptive approach ADIR. As can be seen, adapting the denoiser network to the given image can improve the results significantly.

Ground Truth NN-1 NN-2 NN-3

Figure 20: Examples of images retrieved from Google Open Dataset Kuznetsova et al. (2020) using CLIP Radford et al. (2021) for super resolution with scale factor of 8 ($64^2 \rightarrow 512^2$).