



Palette: Image-to-Image Diffusion Models

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ABSTRACT

This paper develops a unified framework for image-to-image translation based on conditional diffusion models and evaluates this framework on four challenging image-to-image translation tasks, namely **colorization, inpainting, uncropping, and JPEG restoration**. Our simple implementation of image-to-image diffusion models outperforms strong GAN and regression baselines on all tasks, without task-specific hyper-parameter tuning, architecture customization, or any auxiliary loss or sophisticated new techniques needed. We uncover the impact of an L2 vs. L1 loss in the denoising diffusion objective on sample diversity, and demonstrate the importance of self-attention in the neural architecture through empirical studies. Importantly, we advocate a unified evaluation protocol based on ImageNet, with human evaluation and sample quality scores (FID, Inception Score, Classification Accuracy of a pre-trained ResNet-50, and Perceptual Distance against original images). We expect this standardized evaluation protocol to play a role in advancing image-to-image translation research. Finally, we show that a generalist, multi-task diffusion model performs as well or better than task-specific specialist counterparts. Check out <https://diffusion-palette.github.io/> for an overview of the results and code.

CCS CONCEPTS

• Computing methodologies → Neural networks.

KEYWORDS

Deep learning, Generative models, Diffusion models.

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Figure 1: Image-to-image diffusion models are able to generate high-fidelity output across tasks without task-specific customization or auxiliary loss.

1 INTRODUCTION

Many problems in vision and image processing can be formulated as image-to-image translation. Examples include restoration tasks, like super-resolution, colorization, and inpainting, as well as pixel-level image understanding tasks, such as instance segmentation and depth estimation. Many such tasks, like those in Fig. 1, **are complex inverse problems, where multiple output images are consistent with a single input**. A natural approach to image-to-image translation is to learn the conditional distribution of output images given the input, using deep generative models that can capture multi-modal distributions in the high-dimensional space of images.

Generative Adversarial Networks (GANs) [Goodfellow et al. 2014; Radford et al. 2015] have emerged as the model family of choice for many image-to-image tasks [Isola et al. 2017a]; they are capable of generating high fidelity outputs, are broadly applicable, and support efficient sampling. Nevertheless, **GANs can be challenging to train [Arjovsky et al. 2017; Gulrajani et al. 2017], and often drop modes in the output distribution** [Metz et al. 2016; Ravuri and Vinyals 2019]. Autoregressive Models [Parmar et al. 2018; van den Oord et al. 2016], VAEs [Kingma and Welling 2013; Vahdat and Kautz 2020], and Normalizing Flows [Dinh et al. 2016; Kingma and Dhariwal 2018] have seen success in specific applications, but arguably, **have not established the same level of quality and generality as GANs**.

Diffusion and score-based models [Ho et al. 2020; Sohl-Dickstein et al. 2015; Song and Ermon 2020] have received a surge of recent interest [Austin et al. 2021; Cai et al. 2020; Hoogeboom et al. 2021; Kingma et al. 2021; Song et al. 2021; Vahdat et al. 2021], resulting in several key advances in modeling continuous data. On speech synthesis, diffusion models have achieved human evaluation scores on par with SoTA autoregressive models [Chen et al. 2021a,b; Kong et al. 2021]. On the class-conditional ImageNet generation challenge they have outperformed strong GAN baselines in terms of FID scores [Dhariwal and Nichol 2021; Ho et al. 2021]. On image super-resolution, they have delivered impressive face enhancement results, outperforming GANs [Saharia et al. 2021]. Despite these results, it is not clear whether diffusion models rival GANs in offering a versatile and general framework for image manipulation.

This paper investigates the general applicability of *Palette*, our implementation of image-to-image diffusion models, to a suite of distinct and challenging tasks, namely colorization, inpainting, uncropping, and JPEG restoration (see Figs. 1, 2). We show that ***Palette*, with no task-specific architecture customization, nor changes to hyper-parameters or the loss, delivers high-fidelity outputs across all four tasks**. It outperforms task-specific baselines and a strong regression baseline with an identical neural architecture. Importantly, we show that a single *generalist* *Palette* model, trained on colorization, inpainting and JPEG restoration, outperforms a task-specific JPEG model and achieves competitive performance on the other tasks.

We study key components of *Palette*, including the denoising loss function and the neural net architecture. We find that while L_2 [Ho et al. 2020] and L_1 [Chen et al. 2021a] losses in the denoising objective yield similar sample-quality scores, L_2 leads to a higher degree of diversity in model samples, whereas L_1 [Chen et al. 2021a] produces more conservative outputs. We also find that removing

self-attention layers from the U-Net architecture of *Palette*, to build a fully convolutional model, hurts performance. Finally, we advocate a standardized evaluation protocol for inpainting, uncropping, and JPEG restoration based on ImageNet [Deng et al. 2009], and we report sample quality scores for several baselines. We hope this benchmark will help advance image-to-image translation research.

2 RELATED WORK

Our work is inspired by Pix2Pix [Isola et al. 2017a], which explored myriad image-to-image translation tasks with GANs. GAN-based techniques have also been proposed for image-to-image problems like unpaired translation [Zhu et al. 2017a], unsupervised cross-domain generation [Taigman et al. 2016], multi-domain translation [Choi et al. 2018], and few shot translation [Liu et al. 2019]. Nevertheless, existing GAN models are sometimes unsuccessful in holistically translating images with consistent structural and textural regularity.

Diffusion models [Sohl-Dickstein et al. 2015] recently emerged with impressive results on image generation [Dhariwal and Nichol 2021; Ho et al. 2020, 2021], audio synthesis [Chen et al. 2021a; Kong et al. 2020], and image super-resolution [Kadkhodae and Simoncelli 2021; Saharia et al. 2021], as well as unpaired image-to-image translation [Sasaki et al. 2021] and image editing [Meng et al. 2021; Sinha et al. 2021]. Our conditional diffusion models build on these recent advances, showing versatility on a suite of image-to-image translation tasks.

Most diffusion models for inpainting and other linear inverse problems have adapted unconditional models for use in conditional tasks [Meng et al. 2021; Sohl-Dickstein et al. 2015; Song et al. 2021]. This has the advantage that only one model need be trained. However, unconditional tasks are often more difficult than conditional tasks. We cast *Palette* as a conditional model, opting for multitask training should one want a single model for multiple tasks.

Early inpainting approaches [Barnes et al. 2009; Bertalmio et al. 2000; Hays and Efros 2007; He and Sun 2012] work well on textured regions but often fall short in generating semantically consistent structure. GANs are widely used but often require auxiliary objectives on structures, context, edges, contours and hand-engineered features [Iizuka et al. 2017; Kim et al. 2021; Liu et al. 2020; Nazari et al. 2019; Yi et al. 2020; Yu et al. 2018b, 2019], and they lack diversity in their outputs [Zhao et al. 2021; Zheng et al. 2019].

Image uncropping (a.k.a. outpainting) is considered more challenging than inpainting as it entails generating open-ended content with less context. Early methods relied on retrieval [Kopf et al. 2012; Shan et al. 2014; Wang et al. 2014]. GAN-based methods are now predominant [Teterwak et al. 2019], but are often domain-specific [Bowen et al. 2021; Cheng et al. 2021; Lin et al. 2021; Wang et al. 2019a; Yang et al. 2019a]. We show that conditional diffusion models trained on large datasets reliably address both inpainting and uncropping across image domains.

Colorization is a well-studied task [Ardizzone et al. 2019; Guadarrama et al. 2017; Kumar et al. 2021; Royer et al. 2017], requiring a degree of scene understanding, which makes it a natural choice for self-supervised learning [Larsson et al. 2016]. Challenges include diverse colorization [Deshpande et al. 2017], respecting semantic categories [Zhang et al. 2016], and producing high-fidelity



Figure 2: Given the central 256×256 pixels, we extrapolate to the left and right in steps of 128 pixels (2×8 applications of 50% Palette uncropping), to generate the final 256×2304 panorama. Figure D.2 in the Supplementary Material shows more samples.

color [Guadarrama et al. 2017]. While some prior work makes use of specialized auxiliary classification losses, we find that generic image-to-image diffusion models work well without task-specific specialization.

JPEG restoration (aka. JPEG artifact removal) is the nonlinear inverse problem of removing compression artifacts. [Dong et al. 2015] applied deep CNN architectures for JPEG restoration, and [Galteri et al. 2017, 2019] successfully applied GANs for artifact removal, but they have been restricted to quality factors above 10. We show the effectiveness of Palette in removing compression artifacts for quality factors as low as 5.

Multi-task training is a relatively under-explored area in image-to-image translation. [Qian et al. 2019; Yu et al. 2018a] train simultaneously on multiple tasks, but they focus primarily on enhancement tasks like deblurring, denoising, and super-resolution, and they use smaller modular networks. Several works have also dealt with simultaneous training over multiple degradations on a single task e.g., multi-scale super-resolution [Kim et al. 2016], and JPEG restoration on multiple quality factors [Galteri et al. 2019; Liu et al. 2018b]. **With Palette we take a first step toward building multi-task image-to-image diffusion models for a wide variety of tasks.**

3 PALETTE

Diffusion models [Ho et al. 2020; Sohl-Dickstein et al. 2015] convert samples from a standard Gaussian distribution into samples from an empirical data distribution through an iterative denoising process. Conditional diffusion models [Chen et al. 2021a; Saharia et al. 2021] make the denoising process conditional on an input signal. Image-to-image diffusion models are conditional diffusion models of the form $p(\mathbf{y} \mid \mathbf{x})$, where both \mathbf{x} and \mathbf{y} are images, e.g., \mathbf{x} is a grayscale image and \mathbf{y} is a color image. These models have been applied to image super-resolution [Nichol and Dhariwal 2021; Saharia et al. 2021]. We study the general applicability of image-to-image diffusion models on a broad set of tasks.

For a detailed treatment of diffusion models, please see Appendix A. Here, we briefly discuss the denoising loss function. Given a training output image \mathbf{y} , we generate a noisy version $\tilde{\mathbf{y}}$, and train a neural network f_θ to denoise $\tilde{\mathbf{y}}$ given \mathbf{x} and a noise level indicator

γ , for which the loss is

$$\mathbb{E}_{\mathbf{x}, \mathbf{y}} \mathbb{E}_{\epsilon \sim \mathcal{N}(0, I)} \mathbb{E}_{\gamma} \left\| \underbrace{f_\theta(\mathbf{x}, \sqrt{\gamma} \mathbf{y} + \sqrt{1-\gamma} \epsilon, \gamma)}_{\tilde{\mathbf{y}}} - \epsilon \right\|_p^p, \quad (1)$$

损失函数

[Chen et al. 2021a] and [Saharia et al. 2021] suggest using the L_1 norm, i.e., $p = 1$, whereas the standard formulation is based on the usual L_2 norm [Ho et al. 2020]. We perform careful ablations below, and analyze the impact of the choice of norm. We find that L_1 yields significantly lower sample diversity compared to L_2 . While L_1 may be useful, to reduce potential hallucinations in some applications, here we adopt L_2 to capture the output distribution more faithfully.

Architecture. Palette uses a U-Net architecture [Ho et al. 2020] with several modifications inspired by recent work [Dhariwal and Nichol 2021; Saharia et al. 2021; Song et al. 2021]. The network architecture is based on the 256×256 class-conditional U-Net model of [Dhariwal and Nichol 2021]. The two main differences between our architecture and theirs are (i) absence of class-conditioning, and (ii) additional conditioning of the source image via concatenation, following [Saharia et al. 2021].

4 EVALUATION PROTOCOL

Evaluating image-to-image translation models is challenging. Prior work on colorization [Guadarrama et al. 2017; Kumar et al. 2021; Zhang et al. 2016] relied on FID scores and human evaluation for model comparison. Tasks like inpainting [Yu et al. 2018b, 2019] and uncropping [Teterwak et al. 2019; Wang et al. 2019b] have often heavily relied on qualitative evaluation. For other tasks, like JPEG restoration [Dong et al. 2015; Galteri et al. 2019; Liu et al. 2018b], it has been common to use reference-based pixel-level similarity scores such as PSNR and SSIM. It is also notable that many tasks lack a standardized dataset for evaluation, e.g., different test sets with method-specific splits are used for evaluation.

We propose a unified evaluation protocol for inpainting, uncropping, and JPEG restoration on ImageNet [Deng et al. 2009], due to its scale, diversity, and public availability. For inpainting and uncropping, existing work has relied on Places2 dataset [Zhou et al. 2017] for evaluation. Hence, we also use a standard evaluation setup on Places2 for these tasks. Specifically, we advocate the use of ImageNet ctest10k split proposed by [Larsson et al. 2016] as a



Figure 3: Colorization results on ImageNet validation images. Baselines: [†][Guadarrama et al. 2017], [‡][Kumar et al. 2021], and our own strong regression baseline. Figure ?? shows more samples.

standard subset for benchmarking of all image-to-image translation tasks on ImageNet. We also introduce a similar category-balanced 10,950 image subset of Places2 validation set called *places10k*. We further advocate the use of automated metrics that capture both image quality and diversity, in addition to controlled human evaluation. We avoid pixel-level metrics like PSNR and SSIM as they are not reliable measures of sample quality for difficult tasks that require hallucination, like recent super-resolution work, where [Dahl et al. 2017; Ledig et al. 2017; Menon et al. 2020] observe that PSNR and SSIM tend to prefer blurry regression outputs, unlike human perception.

评价指标

We use four automated quantitative measures of sample quality for image-to-image translation: **Inception Score (IS)** [Salimans et al. 2017]; **Fréchet Inception Distance (FID)**; **Classification Accuracy (CA)** (top-1) of a pre-trained ResNet-50 classifier; and a simple measure of **Perceptual Distance (PD)**, i.e., Euclidean distance in Inception-v1 feature space (c.f., [Dosovitskiy and Brox 2016]). To facilitate benchmarking on our proposed subsets, we release our model outputs together with other data such as the inpainting masks (see <https://bit.ly/eval-pix2pix>). See Appendix C.5 for more details about our evaluation. For some tasks, we also assess **sample diversity** through pairwise SSIM and LPIPS scores between multiple model outputs. Sample diversity is challenging and has been a key limitation of many existing GAN-based methods [Yang et al. 2019b; Zhu et al. 2017b].

The ultimate evaluation of image-to-image translation models is **human evaluation**, i.e., whether or not humans can discriminate model outputs from natural images. To this end we use 2-alternative forced choice (2AFC) trials to evaluate the perceptual quality of model outputs against natural images from which we obtained test inputs (c.f., the Colorization Turing Test [Zhang et al. 2016]). We summarize the results in terms of the **fool rate**, the percentage of human raters who select model outputs over natural images when they were asked “Which image would you guess is from a camera?”. (See Supplementary Material for details.)

四个任务

5 EXPERIMENTS

We apply Palette to a suite of challenging image-to-image tasks:

- (1) **Colorization** transforms an input grayscale image to a plausible color image.
- (2) **Inpainting** fills in user-specified masked regions of an image with realistic content.
- (3) **Uncropping** extends an input image along one or more directions to enlarge the image.
- (4) **JPEG restoration** corrects for JPEG compression artifacts, restoring plausible image detail.

We do so without task-specific hyper-parameter tuning, architecture customization, or any auxiliary loss function. Inputs and outputs for all tasks are represented as 256×256 RGB images. Each task presents its own unique challenges. Colorization entails a representation of objects, segmentation and layout, with long-range image dependencies. Inpainting is challenging with large masks, image diversity and cluttered scenes. Uncropping is widely considered even more challenging than inpainting as there is less surrounding context to constrain semantically meaningful generation. While the other tasks are linear in nature, JPEG restoration is a non-linear inverse problem; it requires a good local model of natural image statistics to detect and correct compression artifacts. While previous work has studied these problems extensively, it is rare that a model with no task-specific engineering achieves strong performance in all tasks, beating strong task-specific GAN and regression baselines. Palette uses an L_2 loss for the denoising objective, unless otherwise specified. (Implementation details can be found in the Supplementary Material.)

5.1 Colorization

While prior works [Kumar et al. 2021; Zhang et al. 2016] have adopted LAB or YCbCr color spaces to represent output images for colorization, we use the RGB color space to maintain generality across tasks. Preliminary experiments indicated that Palette is equally effective in YCbCr and RGB spaces. We compare Palette with Pix2Pix [Isola et al. 2017b], PixColor [Guadarrama et al. 2017], and ColTran [Kumar et al. 2021]. Qualitative results are shown in

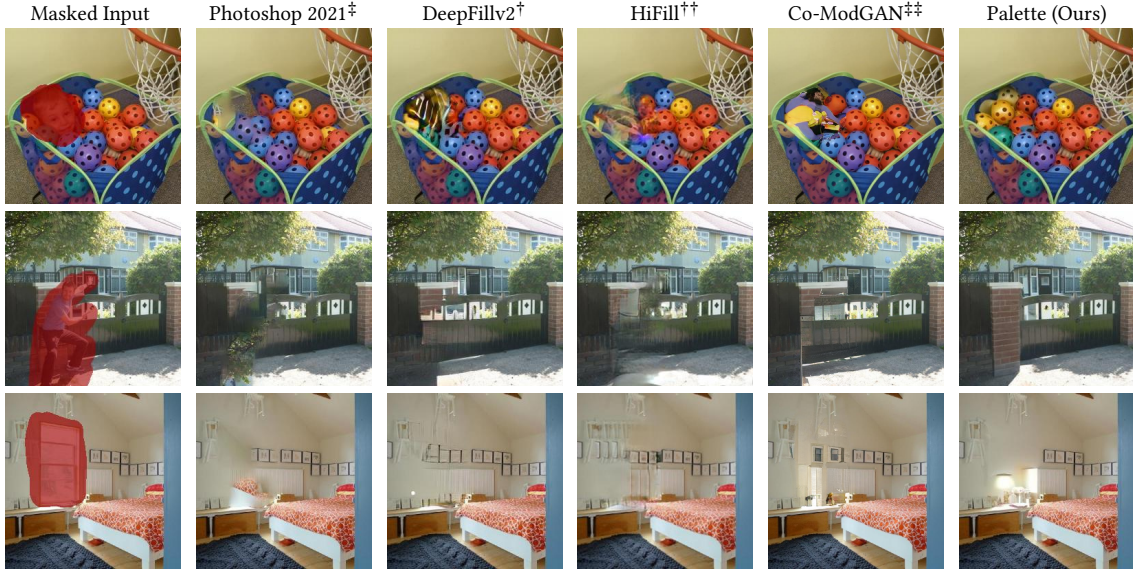


Figure 4: Comparison of inpainting methods on object removal. Baselines: ‡Photoshop’s *Content-aware Fill* built on Patch-Match [Barnes et al. 2009], †[Yu et al. 2019], ††[Yi et al. 2020] and ‡‡[Zhao et al. 2021]. See Figure C.5 for more samples.

Table 1: Colorization quantitative scores and fool rates on ImageNet val set indicate that Palette outputs are almost as realistic as the original images from which the greyscale inputs were created. Baselines: †[Isola et al. 2017b], ‡[Guadarrama et al. 2017] and ††[Kumar et al. 2021]. More results are provided in the Supplementary Material.

Model	FID-5K ↓	IS ↑	CA ↑	PD ↓	Fool rate ↑
<i>Prior Work</i>					
pix2pix †	24.41	-	-	-	-
PixColor ‡	24.32	-	-	-	29.90%
Coltran ††	19.37	-	-	-	36.55%
<i>This paper</i>					
Regression	17.89	169.8	68.2%	60.0	39.45%
Palette	15.78	200.8	72.5%	46.2	47.80%
Original images	14.68	229.6	75.6%	0.0	-

Fig. 3, with quantitative scores in Table 1. Palette establishes a new SoTA, outperforming existing works by a large margin. Further, the performance measures (FID, IS, and CA) indicate that Palette outputs are close to being indistinguishable from the original images that were used to create the test greyscale inputs. Surprisingly, our L_2 Regression baseline also outperforms prior task-specific techniques, highlighting the importance of modern architectures and large-scale training, even for a basic Regression model. On human evaluation, Palette improves upon human raters’ fool rate of ColTran by more than 10%, approaching an ideal fool rate of 50%.

5.2 Inpainting

We follow [Yu et al. 2019] and train inpainting models on free-form generated masks, augmented with simple rectangular masks. To

maintain generality of Palette across tasks, in contrast to prior work, we do not pass a binary inpainting mask to the models. Instead, we fill the masked region with standard Gaussian noise, which is compatible with denoising diffusion models. The training loss only considers the masked out pixels, rather than the entire image, to speed up training. We compare Palette with DeepFillv2 [Yu et al. 2019], HiFill [Yi et al. 2020], Photoshop’s *Content-aware Fill*, and Co-ModGAN [Zhao et al. 2021]. While there are other important prior works on image inpainting, such as [Liu et al. 2018a, 2020; Zheng et al. 2019], we were not able to compare with all of them.

Qualitative and quantitative results are given in Fig. 4 and Table 2. Palette exhibits strong performance across inpainting datasets and mask configurations, outperforming DeepFillv2, HiFill and Co-ModGAN by a large margin. Importantly, like the colorization task above, the FID scores for Palette outputs in the case of 20-30% free-form masks, are extremely close to FID scores on the original images from which we created the masked test inputs.

5.3 Uncropping

Recent works [Lin et al. 2021; Teterwak et al. 2019] have shown impressive visual effects by extending (extrapolating) input images along the right border. We train Palette on uncropping in any one of the four directions, or around the entire image border on all four sides. In all cases, we keep the area of the masked region at 50% of the image. Like inpainting, we fill the masked region with Gaussian noise, and keep the unmasked region fixed during inference. We compare Palette with Boundless [Teterwak et al. 2019] and InfinityGAN [Lin et al. 2021]. While other uncropping methods exist (e.g., [Guo et al. 2020; Wang et al. 2019b]), we only compare with two representative methods. From the results in Fig. 5 and Table 3, one can see that Palette outperforms baselines on ImageNet and Places2 by a large margin. On human evaluation,

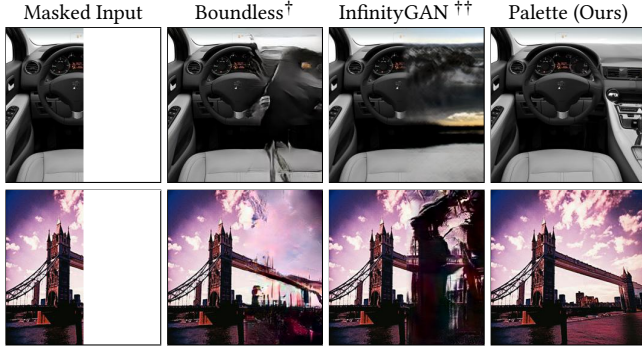


Figure 5: Image uncropping results on Places2 validation images. Baselines: Boundless[†] [Teterwak et al. 2019] and InfinityGAN^{††} [Lin et al. 2021] trained on a scenery subset of Places2. Figure C.8 in the Appendix shows more samples.



Figure 6: Example of JPEG restoration results. Figure D.1 in the Appendix shows more samples.

Table 2: Quantitative evaluation for free-form and center inpainting on ImageNet and Places2 validation images.

Model	ImageNet				Places2	
	FID ↓	IS ↑	CA ↑	PD ↓	FID ↓	PD ↓
<i>20-30% free form</i>						
DeepFillv2 [Yu et al. 2019]	9.4	174.6	68.8%	64.7	13.5	63.0
HiFill [Yi et al. 2020]	12.4	157.0	65.7%	86.2	15.7	92.8
Co-ModGAN [Zhao et al. 2021]	-	-	-	-	12.4	51.6
Palette (Ours)	5.2	205.5	72.3%	27.6	11.7	35.0
<i>128×128 center</i>						
DeepFillv2 [Yu et al. 2019]	18.0	135.3	64.3%	117.2	15.3	96.3
HiFill [Yi et al. 2020]	20.1	126.8	62.3%	129.7	16.9	115.4
Co-ModGAN [Zhao et al. 2021]	-	-	-	-	13.7	86.2
Palette (Ours)	6.6	173.9	69.3%	59.5	11.9	57.3
Original images	5.1	231.6	74.6%	0.0	11.4	0.0

Palette has a 40% fool rate, compared to 25% and 15% for Boundless and InfinityGAN (see Fig. C.2 for details).

We further assess the robustness of Palette by generating panoramas through repeated application of left and right uncropping (see Fig. 2). We observe that Palette is surprisingly robust, generating realistic and coherent outputs even after 8 repeated applications of

Table 3: Quantitative scores and human raters’ fool rates on uncropping. Table C.3 provides more results.

Model	ImageNet				Places2	
	FID ↓	IS ↑	CA ↑	PD ↓	FID ↓	PD ↓
Boundless [Teterwak et al. 2019]	18.7	104.1	58.8%	127.9	11.8	129.3
Palette (Ours)	5.8	138.1	63.4%	85.9	3.53	103.3
Original images	2.7	250.1	76.0%	0.0	2.1	0.0

Table 4: Quantitative evaluation for JPEG restoration for various Quality Factors (QF).

QF	Model	FID-5K ↓	IS ↑	CA ↑	PD ↓
5	Regression	29.0	73.9	52.8%	155.4
	Palette (Ours)	8.3	133.6	64.2%	95.5
10	Regression	18.0	117.2	63.5%	102.2
	Palette (Ours)	5.4	180.5	70.7%	58.3
20	Regression	11.5	158.7	69.7%	65.4
	Palette (Ours)	4.3	208.7	73.5%	37.1
	Original images	2.7	250.1	76.0%	0.0

uncrop. We also generate zoom-out sequences by repeated uncropping around the entire border of the image with similarly appealing results (<https://diffusion-palette.github.io/>).

5.4 JPEG restoration

Finally, we evaluate Palette on the task of removing JPEG compression artifacts, a long standing image restoration problem [Dong et al. 2015; Galteri et al. 2019; Liu et al. 2018b]. Like prior work [Ehrlich et al. 2020; Liu et al. 2018b], we train Palette on inputs compressed with various quality factors (QF). While prior work has typically limited itself to a Quality Factor ≥ 10 , we increase the difficulty of the task and train on Quality Factors as low as 5, producing severe compression artifacts. Table 4 summarizes the ImageNet results, with Palette exhibiting strong performance across all quality factors, outperforming the regression baseline. As expected, the performance gap between Palette and the regression baseline widens with decreasing quality factor. Figure 6 shows the qualitative comparison between Palette and our Regression baseline at a quality factor of 5. It is easy to see that the regression model produces blurry outputs, while Palette produces sharper images.

5.5 Self-attention in model architectures

Self-attention layers [Vaswani et al. 2017] have been an important component in recent U-Net architectures for diffusion models [Dhariwal and Nichol 2021; Ho et al. 2020]. While self-attention layers provide a direct form of global dependency, they prevent generalization to unseen image resolutions. Generalization to new resolutions at test time is convenient for many image-to-image tasks, and therefore previous works have relied primarily on fully convolutional architectures [Galteri et al. 2019; Yu et al. 2019].

We analyze the impact of these self-attention layers on sample quality for inpainting, one of the more difficult image-to-image



Figure 7: Palette diversity for colorization, inpainting, and uncropping. Figures C.4, C.6, C.9 and C.10 show more samples.

translation tasks. In order to enable input resolution generalization for Palette, we explore replacing global self-attention layers with different alternatives each of which represents a trade-off between large context dependency, and resolution robustness. In particular, we experiment with the following four configurations:

- (1) **Global Self-Attention:** Baseline configuration with global self-attention layers at 32×32 , 16×16 and 8×8 resolutions.
- (2) **Local Self-Attention:** Local self-attention layers [Vaswani et al. 2021] at 32×32 , 16×16 and 8×8 resolutions, at which feature maps are divided into 4 non-overlapping query blocks.
- (3) **More ResNet Blocks w/o Self-Attention:** $2 \times$ residual blocks at 32×32 , 16×16 and 8×8 resolutions allowing deeper convolutions to increase receptive field sizes.
- (4) **Dilated Convolutions w/o Self-Attention:** Similar to 3. ResNet blocks at 32×32 , 16×16 and 8×8 resolutions with increasing dilation rates [Chen et al. 2017] allowing exponentially increasing receptive fields.

We train models for 500K steps, with a batch size of 512. Table 5 reports the performance of different configurations for inpainting. Global self-attention offers better performance than fully-convolutional alternatives (even with 15% more parameters), reaffirming the importance of self-attention layers for such tasks. Surprisingly, local self-attention performs worse than fully-convolutional alternatives. Sampling speed is slower than GAN models. There is a large overhead for loading models and the initial jit compilation, but for 1000 test images, Palette requires 0.8 sec./image on a TPUv4.

5.6 Sample diversity

We next analyze sample diversity of Palette on two tasks, colorization and inpainting. Specifically, we analyze the impact of the changing the diffusion loss function L_{simple} [Ho et al. 2020],

Table 5: Architecture ablation for inpainting.

Model	# Params	FID ↓	IS ↑	PD ↓
<i>Fully Convolutional</i>				
Dilated Convolutions	624M	8.0	157.5	70.6
More ResNet Blocks	603M	8.1	157.1	71.9
<i>Self-Attention</i>				
Local Self-Attention	552M	9.4	149.8	78.2
Global Self-Attention	552M	7.4	164.8	67.1

Table 6: Comparison of L_p norm in denoising objective.

Model	Inpainting			Colorization		
	FID ↓	PD ↓	LPIPS ↑	FID ↓	PD ↓	LPIPS ↑
Diffusion L_1	3.6	41.9	0.11	3.4	45.8	0.09
Diffusion L_2	3.6	43.8	0.13	3.4	48.0	0.15

and compare L_1 vs. L_2 on sample diversity. While existing conditional diffusion models, SR3 [Saharia et al. 2021] and WaveGrad [Chen et al. 2021a], have found L_1 norm to perform better than the conventional L_2 loss, there has not been a detailed comparison of the two. To quantitatively compare sample diversity, we use multi-scale SSIM [Guadarrama et al. 2017] and the LPIPS diversity score [Zhu et al. 2017b]. Given multiple generated outputs for each input image, we compute pairwise multi-scale SSIM between the first output sample and the remaining samples. We do this for multiple input images, and then plot the histogram of SSIM values (see Fig. 8). Following [Zhu et al. 2017b], we also compute LPIPS scores between consecutive pairs of model outputs for a given input image,

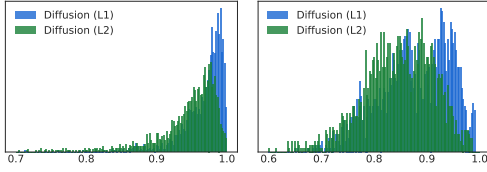


Figure 8: Pairwise multi-scale SSIM for colorization (left) and inpainting (right).

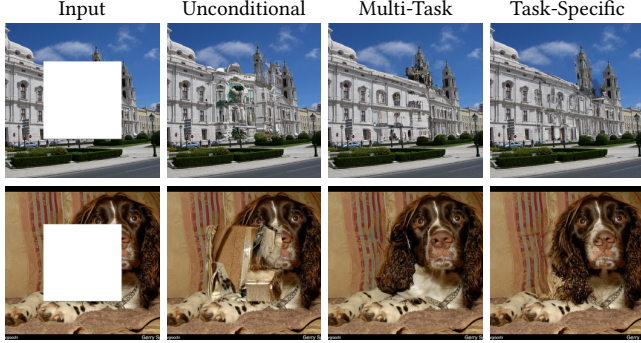


Figure 9: Comparison of conditional and unconditional diffusion models for inpainting. Fig. C.7 shows more results.

and then average across all outputs and input images. Lower SSIM and higher LPIPS scores imply more sample diversity. The results in Table 6 thus clearly show that models trained with the L_2 loss have greater sample diversity than those trained with the L_1 loss.

Interestingly, Table 6 also indicates that L_1 and L_2 models yield similar FID scores (i.e., comparable perceptual quality), but that L_1 has somewhat lower Perceptual Distance scores than L_2 . One can speculate that L_1 models may drop more modes than L_2 models, thereby increasing the likelihood that a single sample from an L_1 model is from the mode containing the corresponding original image, and hence a smaller Perceptual Distance.

Some existing GAN-based models explicitly encourage diversity; [Yang et al. 2019b; Zhu et al. 2017b] propose methods for improving diversity of conditional GANs, and [Han et al. 2019; Zhao et al. 2020] explore diverse sample generation for image inpainting. We leave comparison of sample diversity between Palette and other such GAN based techniques to future work.

5.7 Multi-task learning

Multi-task training is a natural approach to learning a single model for multiple image-to-image tasks, i.e., blind image enhancement. Another is to adapt an unconditional model to conditional tasks with imputation. For example, [Song et al. 2021] do this for inpainting; in each step of iterative refinement, they denoise the noisy image from the previous step, and then simply replace any pixels in the estimated image \mathbf{y} with pixels from the observed image regions, then adding noise and proceeding to the next denoising iteration. Figure 9 compares this method with a multi-task Palette model trained on all four tasks, and a Palette model trained solely

Table 7: Performance of multi-task Palette on various tasks.

Model	FID ↓	IS ↑	CA ↑	PD ↓
<i>Inpainting (128×128 center mask)</i>				
Palette (<i>Task-specific</i>)	6.6	173.9	69.3%	59.5
Palette (<i>Multi-task</i>)	6.8	165.7	68.9%	65.2
<i>Colorization</i>				
Regression (<i>Task-specific</i>)	5.5	176.9	68.0%	61.1
Palette (<i>Task-specific</i>)	3.4	212.9	72.0%	48.0
Palette (<i>Multi-task</i>)	3.7	187.4	69.4%	57.1
<i>JPEG Restoration (QF = 5)</i>				
Regression (<i>Task-specific</i>)	29.0	73.9	52.8%	155.4
Palette (<i>Task-specific</i>)	8.3	133.6	64.2%	95.5
Palette (<i>Multi-task</i>)	7.0	137.8	64.7%	92.4

on inpainting. All models use the same architecture, training data and number of training steps. The results in Fig. 9 are typical; the re-purposed unconditional model does not perform well, in part because it is hard to learn a good unconditional model on diverse datasets like ImageNet, and also because, during iterative refinement, noise is added to all pixels, including the observed pixels. By contrast, Palette is condition directly on noiseless observations for all steps.

To explore the potential for multi-task models in greater depth, Table 7 provides a quantitative comparison between a single generalist Palette model trained simultaneously on JPEG restoration, inpainting, and colorization. It indicates that multi-task generalist Palette outperforms the task-specific JPEG restoration specialist model, but slightly lags behind task-specific Palette models on inpainting and colorization. The multi-task and task-specific Palette models had the same number of training steps; we expect multi-task performance to improve with more training.

6 CONCLUSION

We present Palette, a simple, general framework for image-to-image translation. Palette achieves strong results on four challenging image-to-image translation tasks (colorization, inpainting, uncropping, and JPEG restoration), outperforming strong GAN and regression baselines. Unlike many GAN models, Palette produces diverse and high fidelity outputs. This is accomplished without task-specific customization nor optimization instability. We also present a multi-task Palette model, that performs just as well or better over their task-specific counterparts. Further exploration and investigation of multi-task diffusion models is an exciting avenue for future work. This paper shows some of the potential of image-to-image diffusion models, but we look forward to seeing new applications.

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