SHAPING INDUCTIVE BIAS IN DIFFUSION MODELS THROUGH FREQUENCY-BASED NOISE CONTROL

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ABSTRACT

Diffusion Probabilistic Models (DPMs) are powerful generative models that have achieved unparalleled success in a number of generative tasks. In this work, we aim to build inductive biases into the training and sampling of diffusion models to better accommodate the target distribution of the data to model. For topologically structured data, we devise a frequency-based noising operator to purposefully manipulate, and set, these inductive biases. We first show that appropriate manipulations of the noising forward process can lead DPMs to focus on particular aspects of the distribution to learn. We show that different datasets necessitate different inductive biases, and that appropriate frequency-based noise control induces increased generative performance compared to standard diffusion. Finally, we demonstrate the possibility of ignoring information at particular frequencies while learning. We show this in an image corruption and recovery task, where we train a DPM to recover the original target distribution after severe noise corruption.

1 INTRODUCTION

Diffusion Probabilistic Models (DPMs) have recently emerged as powerful tools for approximating complex data distributions, finding applications across a variety of domains, from image synthesis to probabilistic modeling (Yang et al., 2024; Ho et al., 2020b; Sohl-Dickstein et al., 2015; Venkatraman et al., 2024; Sendera et al., 2024). These models operate by gradually transforming data into noise through a defined diffusion process and training a denoising model (Vincent et al., 2008; Alain & Bengio, 2014) to learn to reverse this process, enabling the generation of samples from the desired distribution via appropriate scheduling. Despite their success, the inductive biases inherent in diffusion models remain largely unexplored, particularly in how these biases influence model performance and the types of distributions that can be effectively modeled.

Inductive biases are known to play a crucial role in deep learning models, guiding the learning process by favoring certain types of data representations over others (Geirhos et al., 2019; Bietti & Mairal, 2019; Tishby & Zaslavsky, 2015). A well-studied example is the Frequency Principle (F-principle) or spectral bias, which suggests that neural networks tend to learn low-frequency components of data before high-frequency ones (Xu et al., 2019; Rahaman et al., 2019). Another related phenomenon is what is also known as the simplicity bias, or shortcut learning (Geirhos et al., 2020; Scimeca et al., 2021; 2023b), in which models are observed to preferentially pick up on simple, easy-to-learn, and often spuriously correlated features in the data for prediction. If left implicit, it is often unclear whether these biases will improve or hurt the performance of generative model on downstream

task, and they could lead to flawed approximations(Scimeca et al., 2023a). In this work, we aim to explicitly tailor the inductive biases of DPMs to better learn the target distribution of interest.

Recent studies have begun to explore the inductive biases inherent in diffusion models. For instance, Kadkhodaie et al. (2023) analyze how the inductive biases of deep neural networks trained for image denoising contribute to the generalization capabilities of diffusion models. They demonstrate that these biases lead to geometry-adaptive harmonic representations, which play a crucial role in the models' ability to generalize beyond the training data (Kadkhodaie et al., 2023). Similarly, Zhang et al. (2024) investigate the role of inductive and primacy biases in diffusion models, particularly in the context of reward optimization. They propose methods to mitigate overoptimization by aligning the models' inductive biases with desired outcomes (Zhang et al., 2024). Other methods, such as noise schedule adaptations (Sahoo et al., 2024) and the introduction of non-Gaussian noise (Bansal et al., 2022) have shown promise in improving the performance of diffusion models on various tasks. However, the exploration of frequency domain techniques within diffusion models is a relatively new area of interest. One of the pioneering studies in this domain investigates the application of diffusion models to time series data, where frequency domain methods have shown potential for capturing temporal dependencies more effectively (Crabbé et al., 2024). Similarly, the integration of spatial frequency components into the denoising process has been explored for enhancing image generation tasks (Qian et al., 2024; Yuan et al., 2023), showcasing the importance of considering frequency-based techniques as a means of refining the inductive biases of diffusion models.

In this work, we explore a new avenue, to build inductive biases in DPMs by frequency-based noise control. The main hypothesis in this paper is that the noising operator in a diffusion model has a direct influence on the model's representation of the data. Intuitively, the information erased by the noising process is the very information that the denoising model has pressure to learn, so that reconstruction is possible. Accordingly, we propose that by strategically manipulating the noising operation, we can effectively steer the model to learn particular aspects of the data distribution. We focus our attention to the generative learning of topologically structured data, and propose an approach that involves designing a frequency-based noise schedule that selectively emphasizes or de-emphasizes certain frequency components during the noising process. In this paper, we refer to our approach as *frequency diffusion*. Because the Fourier transform of a Gaussian is just another Gaussian in the frequency domain, this approach allows us to maintain the Gaussian assumptions of the diffusion process while reorienting the noising operator within the frequency domain, enabling the generation of Gaussian noise at different frequencies and thereby influencing the model's learning trajectory.

We report several findings. First, we show that when the information content in the data lies more heavily in particular frequencies, frequency diffusion yields better samplers. Furthermore, we test this in several natural datasets, and show that depending on the dataset characteristic, different settings of our frequency diffusion approach yield optimal results, often with comparable or superior performance to standard diffusion. Finally, we show that through frequency-denoising we can recover complex distributions after severe noise corruption at particular frequencies, opening interesting venues for applications within the generative landscape.

We summarize our contributions as follows:

1. We introduce a frequency-informed noising operator that can shape the inductive biases of diffusion models.

2. We empirically show that *frequency diffusion* can steer models to better approximate information at particular frequencies of the underlying data distribution.

3. We provide empirical evidence that models trained with frequency-based noise schedules can outperform traditional diffusion schedules across multiple datasets.

4. We show that through frequency-denoising we can recover complex distributions after severe noise corruption at particular frequencies.

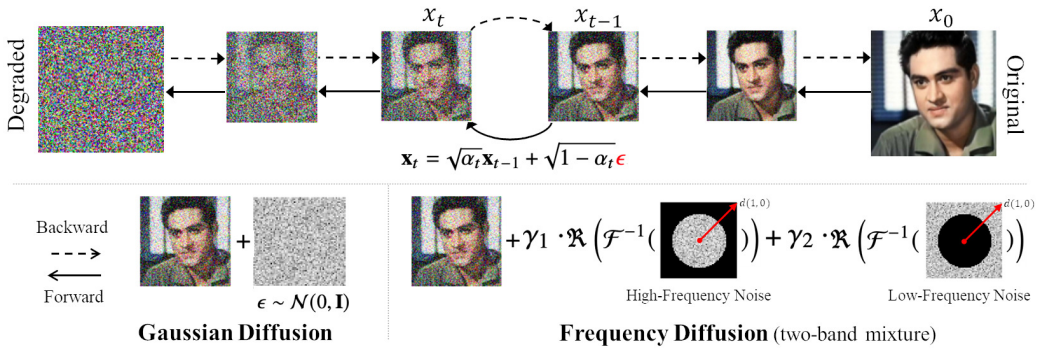

Figure 1: Frequency diffusion under a generalized framework.

2 Methods

2.1 Denoising Probabilistic Models (DPMs)

Denoising Probabilistic Models, are a class of generative models that learn to reconstruct complex data distributions by reversing a gradual noising process. DPMs are characterized by a *forward* and *backward* process. The *forward process* defines how data is corrupted, typically by Gaussian noise, over time. Given a data point $\mathbf{x}_0$ sampled from the data distribution $q(\mathbf{x}_0)$, the noisy versions of the data $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_T$ are generated according to:

$$q(\mathbf{x}_t \mid \mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x}_t; \sqrt{\alpha_t}\mathbf{x}_{t-1}, (1-\alpha_t)\mathbf{I}) \tag{1}$$

with α_t variance schedule. The *reverse process* models the denoising operation, attempting to recover $\mathbf{x}_{t-1}$ from $\mathbf{x}_t$:

$$p_\theta(\mathbf{x}_{t-1} \mid \mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \mu_\theta(\mathbf{x}_t, t), \sigma_t^2\mathbf{I}), \tag{2}$$

where $\mu_\theta(\mathbf{x}_t, t)$ is predicted by a neural network f_θ, and the variance σ_t^2 is can be fixed, learned, or precomputed based on a schedule. We often train the denoising model by minimizing a variational bound on the negative log-likelihood:

$$L = \mathbb{E}_{t,\mathbf{x}_0,\epsilon}\left[\|\epsilon - \epsilon_\theta(\mathbf{x}_t, t)\|^2\right] \tag{3}$$

where ϵ is the Gaussian noise added to $\mathbf{x}_0$, and ϵ_θ is the model's prediction of this noise. To generate new samples, we sample from a Gaussian distribution and apply the learned reverse process iteratively, often starting from a sample drawn from a simple Gaussian noise distribution.

2.2 Frequency Diffusion

The objective of this section is to generate spatial Gaussian noise whose frequency content can be systematically manipulated according to an arbitrary weighting function. In subsection 2.1, we describe how $\mathbf{x}_t$ is obtained from $\mathbf{x}_{t-1}$ by adding Gaussian noise sampled from a normal distribution to the sample at time step $t-1$. Specifically, we can sample $\epsilon_t \sim \mathcal{N}(0, \mathbf{I})$ and obtain $\mathbf{x}_t$ as:

$$\mathbf{x}_t = \sqrt{\alpha_t}\,\mathbf{x}_{t-1} + \sqrt{1-\alpha_t}\,\epsilon. \tag{4}$$

Let us denote by $\mathbf{x} \in \mathbb{R}^{H\times W}$ an image (or noise field) in the spatial domain, and by $\mathcal{F}$ the two-dimensional Fourier transform operator. We let $\mathbf{N}_{\text{freq}} \in \mathbb{C}^{H\times W}$ be a complex-valued random field whose real and imaginary parts are i.i.d. Gaussian:

$$\mathbf{N}_{\text{freq}} = \mathbf{N}_{\text{real}} + i\,\mathbf{N}_{\text{imag}}, \quad \mathbf{N}_{\text{real}}, \mathbf{N}_{\text{imag}} \sim \mathcal{N}(0, \mathbf{I}). \tag{5}$$

where each pixel (or frequency bin) in $\mathbf{N}_{\text{real}}$ and $\mathbf{N}_{\text{imag}}$ is drawn independently from a standard normal distribution. We introduce a *weighting function* $w(f_x, f_y)$ that scales the amplitude of each frequency component. Let $\mathbf{f} = (f_x, f_y)$ denote coordinates in frequency space, where $f_x = \frac{k_x}{W}$, $f_y = \frac{k_y}{H}$, and k_x, k_y are integer indices (ranging over the width and height), while H and W are the image dimensions. We define the frequency-controlled noise $\mathbf{N}_{\text{freq}}^{(w)}(\mathbf{f})$ as:

$$\mathbf{N}_{\text{freq}}^{(w)}(\mathbf{f}) \;=\; \mathbf{N}_{\text{freq}}(\mathbf{f}) \;\odot\; w(\mathbf{f}), \tag{6}$$

After applying $w(\mathbf{f})$ in the frequency domain, we invert back to the spatial domain to obtain $\epsilon^{(w)}$, our *frequency-shaped* noise:

$$\epsilon^{(w)} \;=\; \Re\Big(\mathcal{F}^{-1}\big(\mathbf{N}_{\text{freq}}^{(w)}\big)\Big), \tag{7}$$

where $\Re(\cdot)$ denotes the real part, ensuring that our final noise field is purely real.

In summary, any frequency weighting can be represented in this unified framework:

$$\epsilon \xrightarrow{\mathcal{F}} \mathbf{N}_{\text{freq}} \xrightarrow{w(\mathbf{f})} \mathbf{N}_{\text{freq}}^{(w)} \xrightarrow{\mathcal{F}^{-1}} \epsilon^{(w)}.$$

With this, we have a simple mechanism for generating noise whose power spectrum can purposefully controlled. Note that standard white Gaussian noise is a special case of this formulation, where $w(\mathbf{f}) = 1$ for all $\mathbf{f}$. In contrast, more sophisticated weightings allow one to emphasize, de-emphasize, or even remove specific bands of the frequency domain.

2.3 Frequency Noise operators

In this work, the design of $w(\mathbf{f})$ is especially important. In this section, we propose a particular choice of $w(\mathbf{f})$ to control the frequency on two frequency ranges of interest. We propose alternative formulations of w(f) in Appendix A.

Band-Pass Masking and Two-Band Mixture

A *band-pass mask* can be viewed as a special case of a more general weighting function:

$$w(\mathbf{f}) \;\in\; \{0, 1\}. \tag{8}$$

In this case, the frequency domain is split into a set of permitted and excluded regions, or radial thresholds. We this, we can construct several types of filters, including a low-pass filter retaining only frequencies below a cutoff (e.g., $\|\mathbf{f}\| \leq \omega_c$) a high-pass filter keeping only frequencies above a cutoff, or more generally a filter restricting $\|\mathbf{f}\|$ to lie between two thresholds $[a_{\min}, b_{\max}]$. We thus define a simple band pass filter as:

$$w(\mathbf{f}) \;=\; \mathbf{M}_{[a,b]}(f_x, f_y) \;=\; \begin{cases} 1, & \text{if } a \leq d(f_x, f_y) \leq b, \\ 0, & \text{otherwise.} \end{cases} \tag{9}$$

Here, $d(f_x, f_y) = \sqrt{\left(f_x - \frac{1}{2}\right)^2 + \left(f_y - \frac{1}{2}\right)^2}$ measures the radial distance in frequency space. In this special case, $w(\mathbf{f})$ is simply a *binary* mask, selecting only those frequencies within $[a, b]$.

For the experiments in this paper we formulate a simple two-band mixture, where, we limit ourselves to constructing noise as a simple linear combination of two band-pass filtered noise components. Specifically, as in the original band-based approach, we generate frequency-filtered noise ϵ_f via:

$$\epsilon_f \;=\; \gamma_l\, \epsilon_{[a_l, b_l]} \;+\; \gamma_h\, \epsilon_{[a_h, b_h]}, \tag{10}$$

where γ_l and γ_h denote the relative contributions of a low- and a high-frequency noise components, each filtering noise respectively in the ranges $[a_l, b_l]$ (low-frequency range) and $[a_h, b_h]$ (high-frequency range). We uniquely refer to $\epsilon_{[a,b]}$ as the noise filtered in the $[a, b]$ frequency range following Equation 6 and Equation 7. Standard Gaussian noise emerges as a particular instance (with $\gamma_l = 0.5$, $\gamma_h = 0.5$, $a_l = 0$, $b_l = 0.5$, $a_h = 0.5$, and $b_h = 1$) of this formulation.

2.4 DATASETS

For the experiments, we consider five datasets, namely: MNIST, CIFAR-10, Domainnet-Quickdraw, Wiki-Art and CelebA; providing examples of widely different visual distributions, scales, and domain-specific statistics.

MNIST: MNIST consists of 70,000 grayscale images of handwritten digits (0-9) (Matthey et al., 2017). MNIST provides a simple test-bed to for the hypothesis in this work, as a well understood dataset with well structured, and visually coherent samples.

CIFAR-10: CIFAR-10 contains 60,000 color images distributed across 10 object categories (Krizhevsky et al., 2009). The dataset is highly diverse in terms of object appearance, backgrounds, and colors, with the wide-ranging visual variations across classes like animals, vehicles, and other common objects.

DomainNet-Quickdraw: DomainNet-Quickdraw features 120,750 sketch-style images, covering 345 object categories (Peng et al., 2019). These images, drawn in a minimalistic, abstract style, present a distribution that is drastically different from natural images, with sparse details and heavy visual simplifications.

WikiArt: WikiArt consists of over 81,000 images of artwork spanning a wide array of artistic styles, genres, and historical periods (Saleh & Elgammal, 2015). The dataset encompasses a rich and varied distribution of textures, color palettes, and compositions, making it a challenging benchmark for generative models, which must capture both the global structure and fine-grained stylistic variations that exist across different forms of visual art.

CelebA: CelebA contains 202,599 images of celebrity faces, each 178×218 pixels in resolution (Liu et al., 2015). The dataset presents a diverse distribution of human faces with variations in pose, lighting, and facial expressions.

3 RESULTS

All experiments involve separately training and testing DPMs with various *frequency diffusion* schedules, as well as baseline standard denoising diffusion training. We use DDPM fast sampling (Ho et al., 2020a) to efficiently generate samples for all reported metrics. Across the experiments, we report FID and KID scores as similarity score estimate metrics of the generated samples with respect to a held-out set of data samples. In all relevant experiments, we compute the metrics on embeddings from block 768 of a pre-trained Inception v3 model.

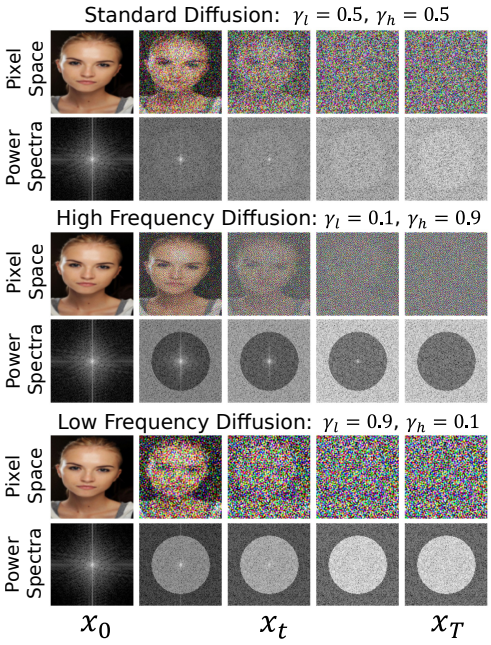

Figure 2: Power spectra and image visuals of the forward Process in standard diffusion, as compared to high and low-frequency noise settings of a two-band mixture noise parametrization.

3.1 IMPROVED DIFFUSION SAMPLING VIA FREQUENCY-BASED NOISE CONTROL

In the first set of experiments, we wish to test our main hypothesis, i.e. that appropriate manipulation of the noise frequency components can better support the learning of the distribution of interest. We follow the formulation in Equation 10 to train and compare diffusion models with a noisy operator prioritizing different parts of the frequency distribution. In these experiments we fix $a_l = 0$, $b_2 = 1$, and $b_l = a_h = 0.5$,

while performing a linear sweep of the γ_l and γ_h parameters by searching $\gamma_l \in [.1, .2, ..., .9]$ and $\gamma_h = 1 - \gamma_l$.

3.1.1 Qualitative Overview

First, we show a qualitative example of a standard linear noising schedule forward operation in Figure 2, as compared to two particular settings of our constant high and low-frequency linear schedules of the band-pass filter. With standard noise, information is uniformly removed from the image, with sample quality degrading evenly over time. In the high-frequency noising schedule, sharpness and texture are removed more prominently, while in the low-frequency schedule, general shapes and homogeneous pixel clusters are affected most, yielding qualitatively different information destruction operations. As discussed previously, we hypothesize that this will in turn purposely affect the information learned by the denoiser model, effectively focusing the diffusion sampling process on different parts of the distribution.

3.1.2 Learning Target Distributions from Frequency-Bounded Information

We conduct experiments to learn the distribution of data where, by construction, the information content lies in the low frequencies. We use the CIFAR-10 dataset, and corrupt the original data with high-frequency noise $\epsilon_{[.3,1.]}$, thus erasing the high-frequency content while predominantly preserving the low-frequency details in the range $\epsilon_{[0.,.3]}$. We train 9 diffusion models, including a standard diffusion (*baseline*) model, and 8 models trained with frequency-based noise control spanning 8 combinations of γ_l ($\gamma_h = 1 - \gamma_l$). We repeat the experiment over three seeds and report the average FID and error in Figure 3. In the figure, we observe the DPMs trained with higher amounts of low-frequency noise (higher γ_l) to perform significantly better than both the baseline ($\gamma_l = 0.5$), and higher frequency denoising models (lower γ_l). Furthermore, we see a mostly monotonically descending trend in FID for increasing values of lower frequency noise in the diffusion forward schedule, supporting the original intuition of how the frequency manipulation of the noising operator can directly steer the denoiser's learning trends, and therefor how progressively higher amount of low-frequency forward noise aid in the learning of samplers for data containing mostly low-frequency information.

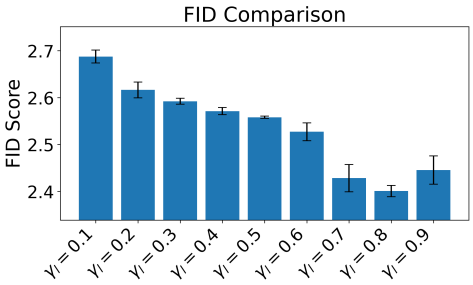

Figure 3: FID of diffusion samplers trained with various combinations of frequency noise. The settings for $\gamma_l = 0.5$ yields standard diffusion.

3.1.3 Frequency-Based noise control in natural datasets

We further test our hypothesis by training 9 models for each of the datasets considered, inclusive of all γ-variations of our two-band mixture frequency-based noise schedule. We train these models on MNIST, CIFAR-10, Domainnet-Quickdraw, Wiki-Art and CelebA, and report the FID and KID metrics for all ablations in Table 1. In the table, we observe three out of five datasets to significantly benefit from frequency-controlled noising schedules, achieving the lowest FID and KID scores across all tested models. Interestingly, the performance trends are also mostly monotonic, which together with our previous experiments is indicative of where the learned information lies. For simple datasets, such as MNIST or CIFAR-10, most frequency denoising settings perform well, with balanced high-to-low-frequency schedules performing best overall. Denoisers for Domainnet-Quickdraw and CelebA yield better performance for slightly higher frequency noising schedules, suggesting higher frequency information content for good FID and KID approximations, while Wiki-Art shows slight biases towards lower frequency schedules.

Table 1: Results for FID and KID across different settings of (γ_l, γ_h) for our frequency diffusion two-band mixture schedule across different datasets (mean ± standard error across 3 seeds). The baseline runs correspond to $\gamma_l = \gamma_h = 0.5$.

Dataset →	**MNIST**		**CIFAR-10**		**Domainnet-Quickdraw**		**Wiki-Art**		**CelebA**	
Algo ↓ Metric →	FID (↓)	KID (↓)	FID (↓)	KID (↓)	FID (↓)	KID (↓)	FID (↓)	KID (↓)	FID (↓)	KID (↓)
baseline	0.0168±0.0010	0.0000±0.0000	0.1055±0.0042	0.0001±0.0000	0.0875±0.0060	1.69e-04±1.61e − 05	0.1622±0.0133	2.53e-04±1.80e − 05	0.0863±0.0094	0.0001±0.0000
$\gamma_l = 0.1, \gamma_h = 0.9$	0.2624±0.2184	7.90e-04±6.85e − 04	0.2648±0.0691	4.31e-04±1.30e − 04	0.5250±0.3907	1.46e-03±1.21e − 03	0.2673±0.0273	4.31e-04±4.56e − 05	0.1555±0.0273	2.97e-04±6.93e − 05
$\gamma_l = 0.2, \gamma_h = 0.8$	0.0432±0.0187	1.10e-04±5.24e − 05	0.2191±0.0223	3.86e-04±6.72e − 05	0.1843±0.0723	4.20e-04±2.15e − 04	0.2048±0.0063	3.43e-04±1.27e − 05	0.1024±0.0045	1.85e-04±2.72e − 06
$\gamma_l = 0.3, \gamma_h = 0.7$	0.0267±0.0029	6.40e-05±8.63e − 06	0.1506±0.0168	2.28e-04±3.34e − 05	0.1248±0.0375	2.70e-04±1.13e − 04	0.1865±0.0181	2.86e-04±2.46e − 05	0.0838±0.0107	1.44e-04±1.89e − 05
$\gamma_l = 0.4, \gamma_h = 0.6$	0.0224±0.0032	5.29e-05±8.15e − 06	0.1131±0.0079	1.64e-04±2.15e − 05	0.0799±0.0166	0.0001±0.0000	0.1597±0.0122	2.62e-04±3.23e − 05	0.0875±0.0020	1.49e-04±1.71e − 06
$\gamma_l = 0.6, \gamma_h = 0.4$	0.0253±0.0039	5.81e-05±7.63e − 06	0.1131±0.0074	1.56e-04±1.95e − 05	0.1128±0.0174	2.57e-04±5.56e − 05	0.1348±0.0126	0.0002±0.0000	0.1068±0.0039	2.04e-04±1.07e − 05
$\gamma_l = 0.7, \gamma_h = 0.3$	0.0363±0.0075	9.14e-05±2.04e − 05	0.1432±0.0203	2.19e-04±3.66e − 05	0.1353±0.0223	2.91e-04±6.08e − 05	0.1561±0.0123	2.32e-04±2.46e − 05	0.0990±0.0082	1.84e-04±2.12e − 05
$\gamma_l = 0.8, \gamma_h = 0.2$	0.0512±0.0119	1.36e-04±3.60e − 05	0.1898±0.0095	2.88e-04±1.85e − 05	0.2288±0.0737	5.85e-04±2.21e − 04	0.2256±0.0096	3.86e-04±3.08e − 05	0.1053±0.0185	1.95e-04±4.34e − 05
$\gamma_l = 0.9, \gamma_h = 0.1$	0.3403±0.1513	9.74e-04±4.47e − 04	0.3226±0.0660	5.31e-04±1.20e − 04	0.9827±0.4229	2.84e-03±1.29e − 03	0.3250±0.0270	5.57e-04±3.22e − 05	0.2291±0.0605	4.86e-04±1.52e − 04

3.2 Selective Learning: Frequency-Based Noise Control to Omit Targeted Information

Following our original intuition, a denoising model has pressure to learn the very information that is erased by the forward noising operator to achieve successful reconstruction. Conversely, when the noising operator is crafted to leave parts of the original distribution intact, no such pressure exists, and the denoising model can effectively discard the left-out statistics during generation.

In this section, we perform experiments whereby the original data is corrupted with noise at different frequency ranges. The objective is to manipulate the inductive biases of diffusion denoisers to avoid learning the corruption noise, while correctly approximating the relevant information in the data. We formulate our noising process as $\mathbf{x}' = A_c(\mathbf{x})$, where:

$$A_c(\mathbf{x}) = \mathbf{x} + \gamma_c \epsilon_{f[a_c, b_c]} \tag{11}$$

Here, $\epsilon_{[a_c, b_c]}$ denotes noise in the $[a_c, b_c]$ frequency range. We default $\gamma_c = 1.$ and show samples of the original and corrupted distributions in Figure 4. For any standard DPM training procedure, the denoiser would make no distinction of which information to learn, and thus would approximate the corrupted distribution presented at training time. As such, the recovery of the original, noiseless, distribution would normally be impossible. Assuming knowledge of the corruption process, we frame the frequency diffusion learning procedures as a noiseless distribution recovery process, and set $a_l = 0$, $b_h = 1$, $b_l = a_c$, and $a_h = b_c$. This formulation effectively allows for the forward frequency noising operator to omit the range of frequencies in which the noise lies. In line with our previous rationale, this would effectively put no pressure on the denoiser to learn the noise part of the distribution at hand, and focus instead on the frequency ranges where the true information lies.

We compare original and corrupted samples from MNIST, as well as samples from standard and frequency diffusion-trained models in Figure 4. In line with our hypothesis, we observe frequency diffusion DPMs trained with an appropriate frequency noise operator to be able to discard the corrupting information and recover the original distribution after severe noisy corruption. We further measure the FID and KID of the samples generated by the baseline and frequency DPMs against the original (uncorrupted) data samples in Table 2. We perform 8 ablation studies, considering noises at 0.1 non-overlapping intervals in the $[0.1, .9]$ frequency range. We observe *frequency diffusion* to outperform standard diffusion training across all tested ranges. Interestingly, we observe better performance (lower FID) for data corruption in the high-frequency ranges, and reduced performance for data corruptions in low-frequency ranges, suggesting a marginally higher information content in the low frequencies for the MNIST dataset.

4 Discussion and Conclusion

In this work, we studied the potential to build inductive biases in the training and sampling of Diffusion Probabilistic Models by purposeful manipulation of the forward, noising, process. We introduced *frequency diffusion*, an approach that enables us to guide DPMs toward learning specific statistics of the data distribution. We compare *frequency diffusion* to DPS trained with standard gaussian noise on generative visual tasks set by several datasets, with significant varying structure and scales. We show several key findings. First, we show that appropriate manipulation of the forward noising process can serve as a stong inductive bias for diffusion models to better learn the information

Table 2: Resulting FID and KID between standard diffusion and frequency diffusion DPMs trained on noise-corrupted data, with respect to samples from the true uncorrupted distribution (mean ± standard error across 3 seeds). We report eight ablation experiments across different non-overlapping corruption noise schemes.

Dataset →	**Baseline**		**Ours**	
Corruption ↓	FID (↓)	KID (↓)	FID (↓)	KID (↓)
$\epsilon_{[0.1,0.2]}$	$3.2273_{\pm 8.50e-03}$	$0.0114_{\pm 3.13e-05}$	$2.7572_{\pm 3.56e-02}$	$0.0095_{\pm 1.47e-04}$
$\epsilon_{[0.2,0.3]}$	$3.6601_{\pm 4.43e-03}$	$0.0132_{\pm 1.67e-05}$	$3.0416_{\pm 4.47e-02}$	$0.0107_{\pm 1.79e-04}$
$\epsilon_{[0.3,0.4]}$	$3.4771_{\pm 4.79e-03}$	$0.0125_{\pm 1.89e-05}$	$2.9952_{\pm 3.35e-02}$	$0.0106_{\pm 1.23e-04}$
$\epsilon_{[0.4,0.5]}$	$3.4281_{\pm 5.46e-03}$	$0.0123_{\pm 1.98e-05}$	$2.9218_{\pm 2.54e-02}$	$0.0105_{\pm 8.79e-05}$
$\epsilon_{[0.5,0.6]}$	$3.3638_{\pm 6.31e-03}$	$0.0121_{\pm 2.32e-05}$	$2.8267_{\pm 2.81e-02}$	$0.0102_{\pm 9.32e-05}$
$\epsilon_{[0.6,0.7]}$	$3.2444_{\pm 7.10e-03}$	$0.0116_{\pm 2.55e-05}$	$2.7026_{\pm 3.90e-02}$	$0.0097_{\pm 1.28e-04}$
$\epsilon_{[0.7,0.8]}$	$3.0442_{\pm 6.32e-03}$	$0.0109_{\pm 2.29e-05}$	$2.5469_{\pm 6.39e-02}$	$0.0091_{\pm 2.00e-04}$
$\epsilon_{[0.8,0.9]}$	$3.4660_{\pm 7.90e-03}$	$0.0124_{\pm 2.96e-05}$	$2.5138_{\pm 9.63e-02}$	$0.0090_{\pm 3.07e-04}$

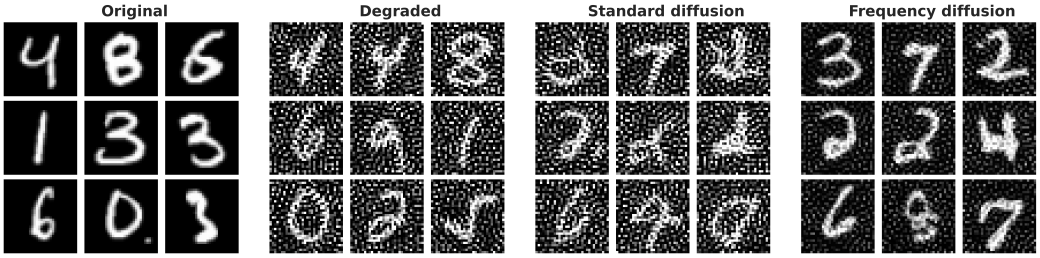

Figure 4: Samples from the original data distribution, the degraded data distribution, a standard diffusion sampler trained on the degraded data distribution, and a *frequency diffusion* sampler trained on the degraded data distribution. We generate noise for data corruption in the frequency range $[a_c = 0.5, b_c = 0.6)]$.

of the distribution at particular frequencies. Second, we show that this important characteristic can be readily used when training diffusion models on natural dataset, some of which may be better supported by appropriate frequency diffusion schedules, yielding higher sampling quality. Third, we show how this processes can be used to discard unwanted information at particular frequency ranges, yielding DPMs capable of extract noiseless signals from the remaining ranges.

In our approach, we have limited the results to a simple two-band pass frequency filter. We propose in Appendix A several other alternatives, which may serve as more flexible tools to inject useful inductive biases for similar tasks. Moreover, the approach can be extended beyond constant schedules. For instance, it may prove useful to introduce dynamic frequency noise strategies that shift the focus from low-frequency (general shapes) to high-frequency (sharp edges and textures) components over the time discretization of the sampling process. Such methods could more closely align with human visual processing, which progressively sharpens details over time, offering a more natural sampling process. Additionally, other domains of noise manipulation—outside of the frequency domain may also present new opportunities for further improving DPMs across various tasks.

Finally, a current limitation of this approach lies in the complexity of understanding the relationship between visual data in spatial and frequency domains. The perception of information in the frequency domain does not always translate straightforwardly to visual content, complicating the process of designing optimal noise schedules. As such, it is not trivial to design appropriate frequency schedules for a particular distribution. In practice, empirical validation may still be required to identify the best inductive biases for a given dataset. Future work could focus on refining analytical tools for frequency analysis or exploring alternative inductive bias mechanisms that extend beyond frequency-based manipulations.

Overall, this work opens the door for more targeted and flexible diffusion generative modeling by building inductive biases through the manipulation of the forward nosing process. The ability to design noise schedules that align with specific data characteristics holds promise for advancing the state of the art in generative modeling.

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A FREQUENCY NOISE OPERATORS

In this section, we propose two alternatives to the design of $w(\mathbf{f})$, which can be considered as viable alternatives for frequency manipulations of the noise.

POWER-LAW WEIGHTING.

A natural alternative choice is the power-law weighting, expressed as:

$$w(\mathbf{f}) \;=\; \|\mathbf{f}\|^{\alpha}, \tag{12}$$

where $\mathbf{f} = (f_x, f_y)$ denotes a frequency coordinate, and the exponent α determines which frequencies are amplified or suppressed. Power-law weighting is popular in the modeling if natural phenomena (e.g., fractal landscapes, turbulence) where the energy distribution often follows an approximate power spectrum (Van der Schaaf & van Hateren, 1996).

EXPONENTIAL DECAY WEIGHTING

Another alternative is an exponential decay function, defined as as:

$$w(\mathbf{f}) \;=\; \exp\!\big(-\beta\,\|\mathbf{f}\|^2\big), \tag{13}$$

where $\beta > 0$, and frequencies with larger norms $\|\mathbf{f}\|$ are exponentially suppressed. This weighting effectively imposes spatial correlations, e.g. for β close to 0 the function induces the retention of more high-frequency components, while for large β, the function quickly damps out high frequencies, resulting in a smoothing of the spatial domain.