[Supplementary Materials]
Beta Sampling is All You Need: Efficient Image Generation Strategy for Diffusion Models using Stepwise Spectral Analysis

1. Experiment Details and Additional Step Analysis of ADM-G

For our experiments with ADM-G on ImageNet 64 datasets, we utilized the official codebase [1] and the publicly released checkpoint. We generated 50,000 images and employed pre-computed sample batches from the reference datasets available in the ADM codebase to calculate the FID scores presented in Tables 1 and 3 of our main manuscript.

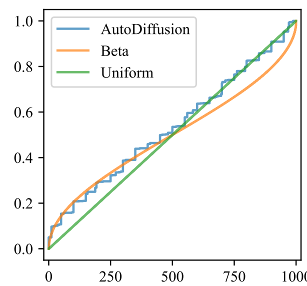
Figure 10 illustrates the cumulative histogram of occurrence numbers for 20 steps, following the same procedure outlined in Figure 8 of the main manuscript. To enhance the visibility of the histogram, the time steps were sampled 50 times. Notably, the histogram for AutoDiffusion exhibited characteristics similar to a Beta distribution, consistent with our observations for 10 and 15 steps. This consistency across different step numbers further supports the robustness of our proposed Beta Sampling approach.

2. Experiment Details and Step Analysis of Stable Diffusion

In our experiments, we employed the official codebase [2] and the “sd-v1-4.ckpt” checkpoint. For FID and IS measurements, we used the validation set of the COCO 2014 dataset. Unless otherwise specified, the Stable Diffusion experiments were conducted using the PLMS solver.

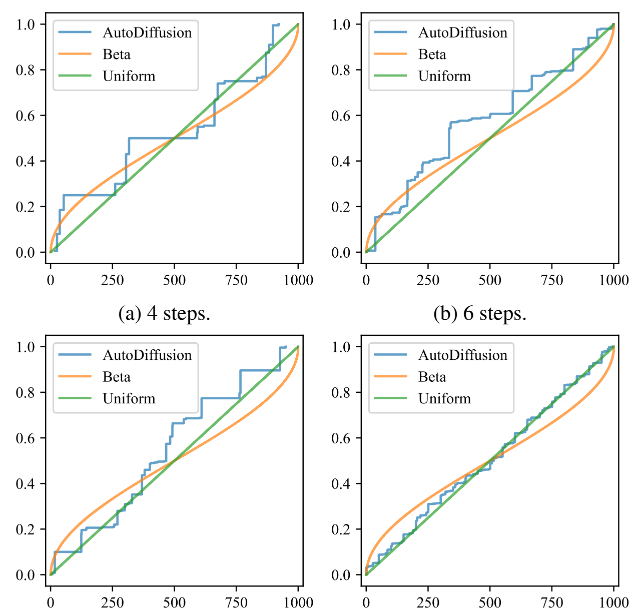
Figure 11 shows the Stable Diffusion version of the cumulative histogram of the occurrence number of time steps plot, which was originally presented in Fig. 8 of the main manuscript. We conducted 50 sampling iterations for each time step and observed that Beta Sampling in Stable Diffusion exhibits trends similar to AutoDiffusion, although less pronounced than in ADM-G. This difference in intensity is hypothesized to be the underlying cause of the performance difference observed in Stable Diffusion. Despite these intensity variations, the consistent emergence of Beta-like patterns across different architectures suggests the fundamental validity of our sampling approach.

[1] https://github.com/openai/guided-diffusion
[2] https://github.com/CompVis/stable-diffusion



(a) 20 steps.

Figure 10. A cumulative histogram of occurrence number of time steps sampled by AutoDiffusion on ADM-G with 20 time steps.



(a) 4 steps. (b) 6 steps. (c) 10 steps. (d) 20 steps.

Figure 11. A cumulative histogram of occurrence number of time steps sampled by AutoDiffusion on Stable Diffusion with various number of time steps.

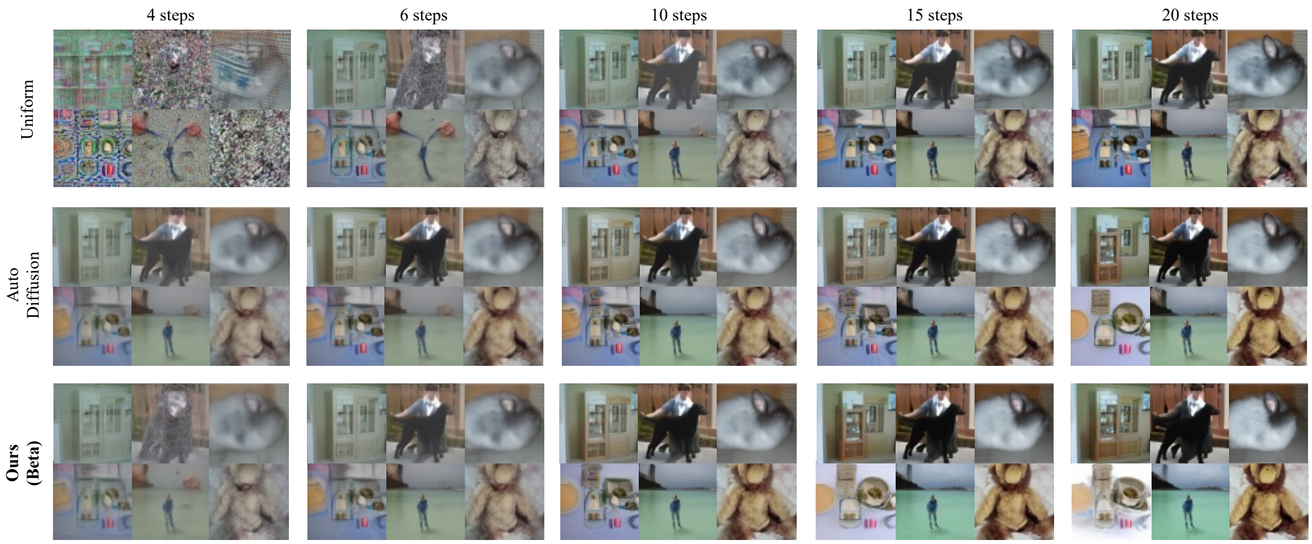


Figure 12. Examples generated by ADM-G on ImageNet 64×64 with various sampling strategies.

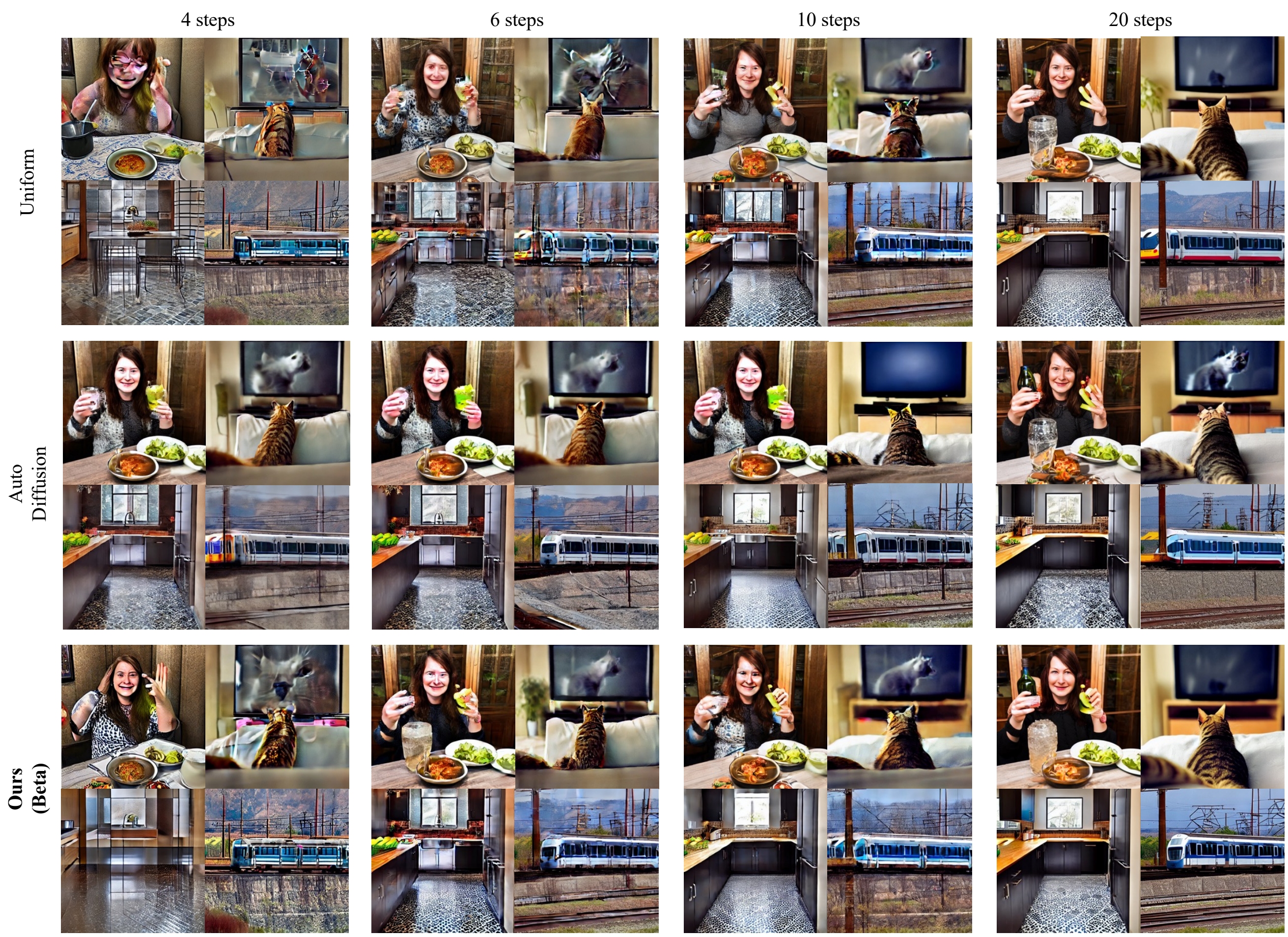


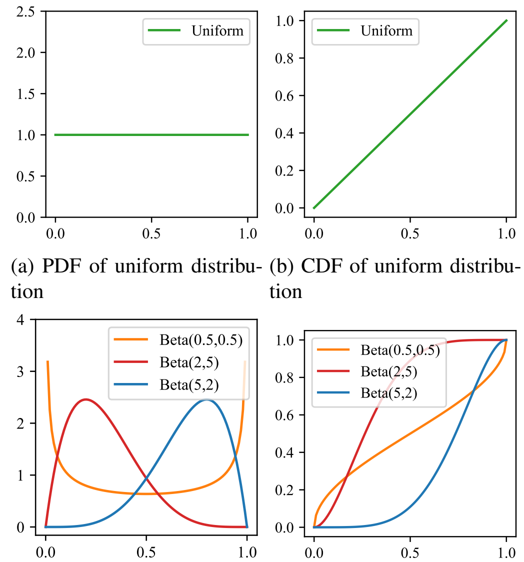
Figure 13. Examples generated by Stable Diffusion with various sampling strategies. The text prompts used for generation are “A lady sitting at a table with food and drink, holding up two fingers”, “A cat watching TV while laying in bed”, “A kitchen with a tile floor and a metallic sink” and “The transit train stretches down the track under the power lines”.

3. Additional Examples Generated by ADM-G

Figure 12 presents generated samples from ADM-G using identical initial noise across various sampling strategies. Our comprehensive analysis reveals distinct performance patterns across different step counts. At 4 steps, Beta Sampling demonstrates markedly superior results compared to uniform sampling, which exhibits significant difficulties in maintaining structural coherence and image fidelity. While Beta Sampling at this step count does not fully match AutoDiffusion's clarity and detail preservation, it achieves a favorable balance between quality and computational efficiency. At 6 and 10 steps, both Beta Sampling and AutoDiffusion produce notably sharper and more detailed images compared to uniform sampling, with Beta Sampling achieving particularly impressive results in maintaining global structure and local details. The computational advantage of Beta Sampling becomes especially apparent when considering AutoDiffusion's intensive search process, which requires substantial additional resources without proportional quality improvements.

4. Additional Examples Generated by Stable Diffusion

The supplementary results for Stable Diffusion, as shown in Fig. 13, provide valuable insights into the performance characteristics of different sampling strategies across various step counts. At 4 and 6 steps, uniform sampling demonstrates severe limitations, manifesting as significant structural defects, inconsistent object boundaries, and poor color reproduction that substantially impact the visual quality of the generated images. Beta Sampling successfully addresses many of these shortcomings, showing marked improvements in structural coherence and color fidelity, though it does not completely match the quality level achieved by AutoDiffusion when working with larger models that benefit from its more exhaustive search process. As we increase to 10 and 20 steps, Beta Sampling demonstrates particularly impressive performance, achieving sample quality that is virtually indistinguishable from AutoDiffusion while maintaining its computational efficiency advantage. This quality parity at higher step counts is especially noteworthy given the substantial computational savings offered by Beta Sampling. Throughout our experiments across all step counts, Beta Sampling consistently emerges as a highly competitive approach, delivering superior image quality compared to uniform sampling while avoiding the computational overhead associated with AutoDiffusion's search-based methodology. These results strongly suggest that Beta Sampling represents an optimal balance between generation quality and computational efficiency in practical applications.



(a) PDF of uniform distribution (b) CDF of uniform distribution

(c) PDF of Beta distribution (d) CDF of Beta distribution

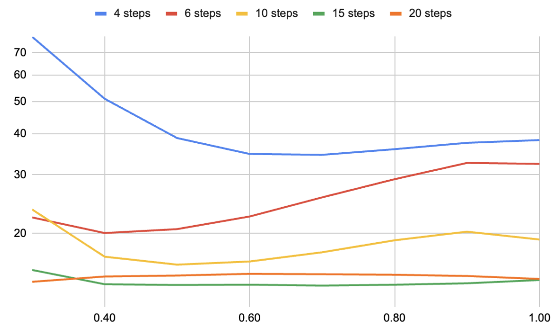
Figure 14. Probability Density Function (PDF) and Cumulative Distribution Function (CDF) of uniform and Beta distributions.

5. Beta Distribution by Different Parameters

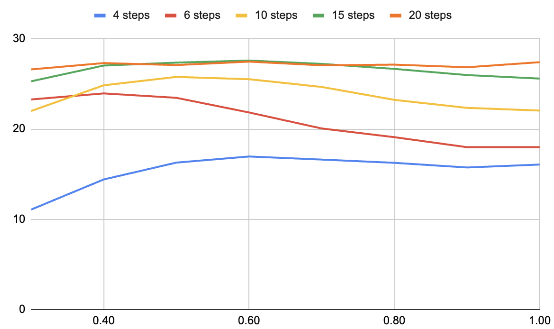
Figure 14 illustrates the Probability Density Functions (PDFs) and Cumulative Distribution Functions (CDFs) of uniform and various Beta distributions. The Beta distribution is characterized by two hyperparameters, α and β, which determine the shape of the distribution. When $\alpha > \beta$, the distribution skews to the right, meaning that sampling the denoising process based on this distribution will focus on the changes in low-frequency components during the early stages. Conversely, if $\alpha < \beta$, the distribution skews to the left, concentrating the denoising process on high-frequency component changes in the later stages. Finally, when $\alpha = \beta$, the Beta distribution forms a shape with peaks at both ends, which means that sampling according to this distribution will evenly concentrate on both low-frequency changes in the early stages and high-frequency changes in the later stages. In our proposed method, we use a Beta distribution where $\alpha = \beta$ to ensure a balanced focus on both low-frequency and high-frequency changes throughout the denoising process. This approach ensures that the denoising process effectively captures critical changes at both the beginning and end stages, leading to more efficient and high-quality image generation.

6. Ablation Study on Stable Diffusion

Figure 15 demonstrates the impact of the hyperparameter $\alpha = \beta$ on FID and IS performance in Stable Diffusion, similar to Fig. 7 in the main manuscript. When $\alpha = \beta = 1$, the distribution is uniform; as these values decrease, em-



(a) FID



(b) IS

Figure 15. FID (↓) and IS (↑) scores for Stable Diffusion with Beta Sampling $Beta(\alpha, \beta)$ of various hyperparameter $\alpha = \beta$ and various time steps.

phasis on the middle stages is reduced. The observed performance shifts in FID and IS as the hyperparameter deviates from the uniform distribution demonstrate the efficacy of Beta Sampling. The optimal parameter for maximizing FID and IS performance varied with the number of sampled steps. To achieve overall performance enhancement, we set $\alpha = \beta = 0.6$ for Stable Diffusion.

7. Additional Experiments on Stable Diffusion with DPM Solver

In Tab. 5, we present additional experiments on Stable Diffusion using the DPM solver, which supports various skip types. We tested two popular skip types as well as uniform skip types, and found that the Beta Sampling parameters $\alpha = 0.5$ and $\beta = 0.9$ work effectively for the DPM solver. The premise of Beta Sampling is to primarily sample steps at both ends of the process, where significant changes are more likely to occur, rather than the middle portion. The relative emphasis on the initial and latter parts can be adjusted using the weights of α and β. By applying greater weighting to the latter part, as derived from previous research, the effectiveness of Beta Sampling can be further enhanced.

Steps	Sampling Strategies	FID (↓)	IS (↑)
4	Uniform	*23.19*	*21.59*
	LogSNR	37.96	17.36
	Time quadratic	29.98	19.50
	AutoDiffusion	**18.53**	**24.26**
	Ours (Beta)	27.34	19.80
6	Uniform	17.76	**24.73**
	LogSNR	17.08	23.86
	Time quadratic	16.25	24.19
	AutoDiffusion	*16.15*	*24.65*
	Ours (Beta)	**15.83**	24.53
10	Uniform	16.20	26.35
	LogSNR	13.98	*26.88*
	Time quadratic	13.79	26.60
	AutoDiffusion	**12.61**	26.69
	Ours (Beta)	*13.65*	**27.10**
20	Uniform	14.39	27.35
	LogSNR	14.73	27.49
	Time quadratic	*13.99*	*27.51*
	AutoDiffusion	**13.49**	26.43
	Ours (Beta)	14.13	**27.67**

Table 5. FID (↓) and IS (↑) scores for Stable Diffusion with DPM Solver across various number of time steps and sampling strategies. In this table, Beta Sampling parameters are set to $\alpha = 0.5$ and $\beta = 0.9$. Bold indicates the **best** performance values, while italics mark the *second-best*.

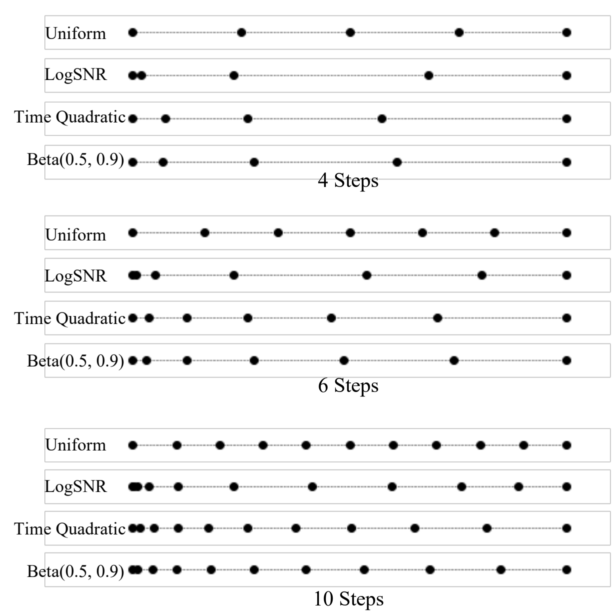


Figure 16. Sampled step distribution of Stable Diffusion with DPM solver. Beta Sampling reduces the wide gap in the early stage(right side) while maintaining step density in the later stage(left side).