Supplementary Material For
Non-Parametric Priors For Generative Adversarial Networks

Overview: In this supplemental material, we present additional qualitative results showing a variety of generated outputs from our non-parametric method as compared to the uniform, normal, Gamma (Kilcher et al., 2018), and Cauchy distributions (Leśniak et al., 2018). We compare results on four datasets: a) CelebA dataset (Liu et al., 2015), b) CIFAR10 (Krizhevsky & Hinton, 2009), c) LSUN Bedroom, and d) LSUN Kitchen (Yu et al., 2015)). We note that our non-parametric prior has visual quality that is consistent across the datasets, and is typically on-par or improved as compared to other methods.

On a particular note, we noticed that the Cauchy distribution had difficulty converging the GAN during training for the LSUN Bedroom, LSUN Kitchen and CIFAR-10 datasets. We tentatively hypothesize that it may be due to mode collapse due to instability during the GAN training. However, further investigation is needed for whether the choice of distribution affects the training of the GAN.
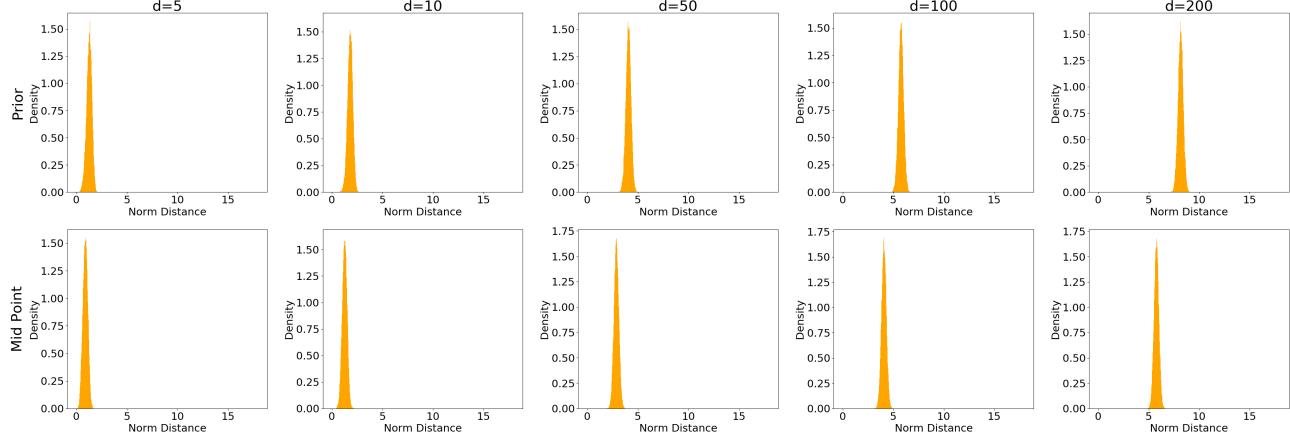
Network architecture and training details: We use the standard DCGAN model (Radford et al., 2016) using an open-source implementation in TensorFlow[1]. The generator consists of one fully connected layer and four deconvolutional layers. The discriminator consists of four convolutional layers and one fully connected layer. For the training we used learning rate of $2e^{-4}$ and Adam optimizer for the loss minimization. For CelebA, LSUN bedroom and LSUN kitchen datasets, we used 64×64 image size and trained the GAN for 25 epochs with batch size of 64. The CIFAR10 dataset is 32×32 in size and we trained it for 100 epoch with batch size of 100.

References
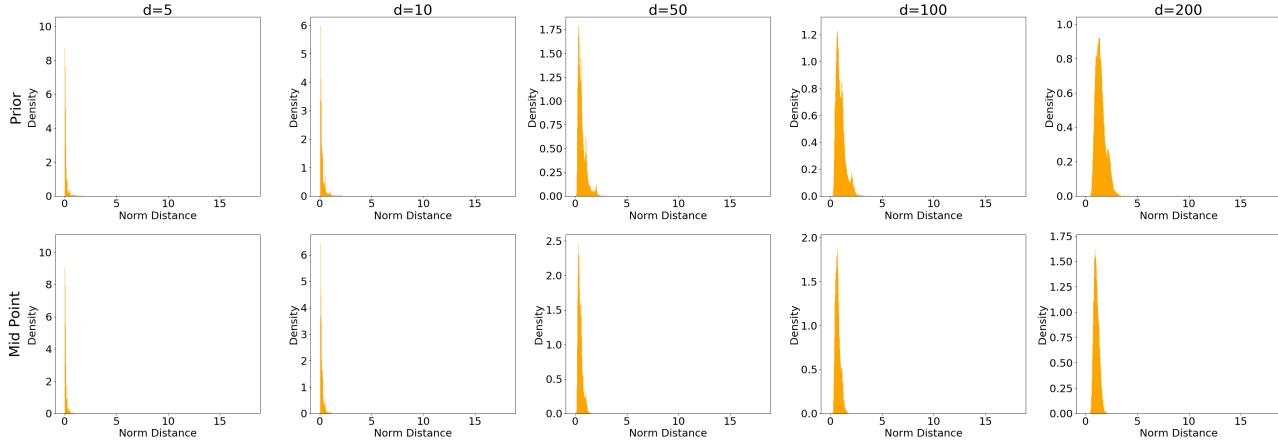
Kilcher, Y., Lucchi, A., and Hofmann, T. Semantic interpolation in implicit models. In *International Conference on Learning Representations (ICLR)*, 2018.

Krizhevsky, A. and Hinton, G. Learning multiple layers of features from tiny images. Technical report, Citeseer, 2009.

Leśniak, D., Sieradzki, I., and Podolak, I. On latent distributions without finite mean in generative models. *arXiv preprint arXiv:1806.01670*, 2018.

Liu, Z., Luo, P., Wang, X., and Tang, X. Deep learning face attributes in the wild. In *Proceedings of the IEEE International Conference on Computer Vision*, pp. 3730–3738, 2015.

Radford, A., Metz, L., and Chintala, S. Unsupervised representation learning with deep convolutional generative adversarial networks. In *International Conference on Learning Representations (ICLR)*, 2016.

Yu, F., Seff, A., Zhang, Y., Song, S., Funkhouser, T., and Xiao, J. Lsun: Construction of a large-scale image dataset using deep learning with humans in the loop. *arXiv preprint arXiv:1506.03365*, 2015.

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[1] https://github.com/carpedm20/DCGAN-tensorflow

(a) Uniform distribution

(b) Obtained non-parametric distribution

Figure 1. Euclidean norm distribution for samples drawn from uniform and our non-parametric priors and their corresponding mid-point Euclidean norm distribution for different dimensions d. Note the mid-point norm distribution for the uniform prior moves further away from the prior norm distribution as the dimension increases to $d = 200$, whereas with our non-parametric prior, the mid-point norm distribution overlaps with the prior norm distribution even at $d = 200$.

(a) Uniform distribution

(b) Normal distribution

(c) Gamma distribution

(d) Cauchy distribution

(e) Obtained non-parametric distribution
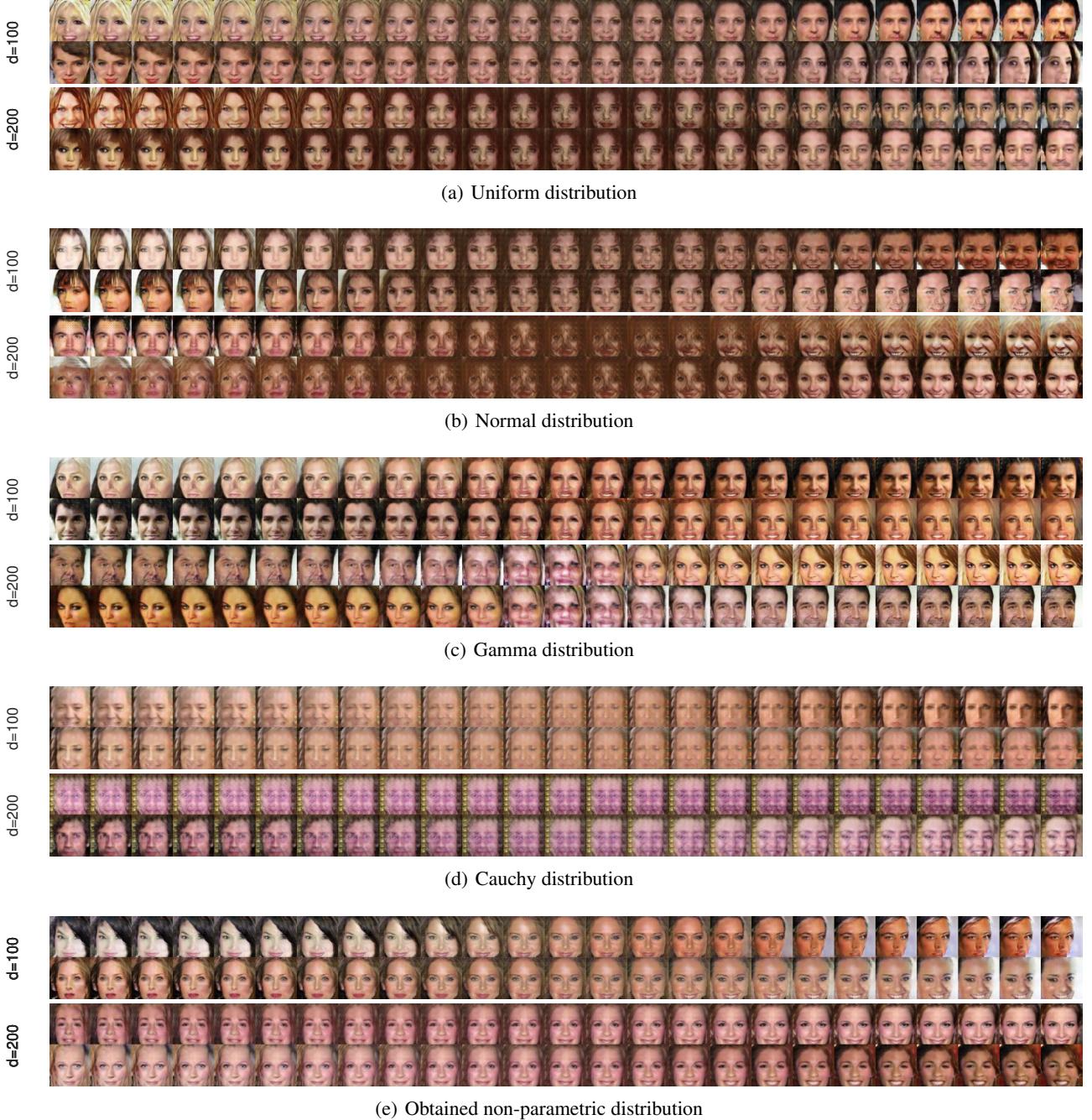
Figure 2. Interpolation (left to right) through the origin, with different dimensions d of latent-space, for all priors on CelebA dataset. Note the difference in image quality around the center of panel (origin space) at higher dimension.
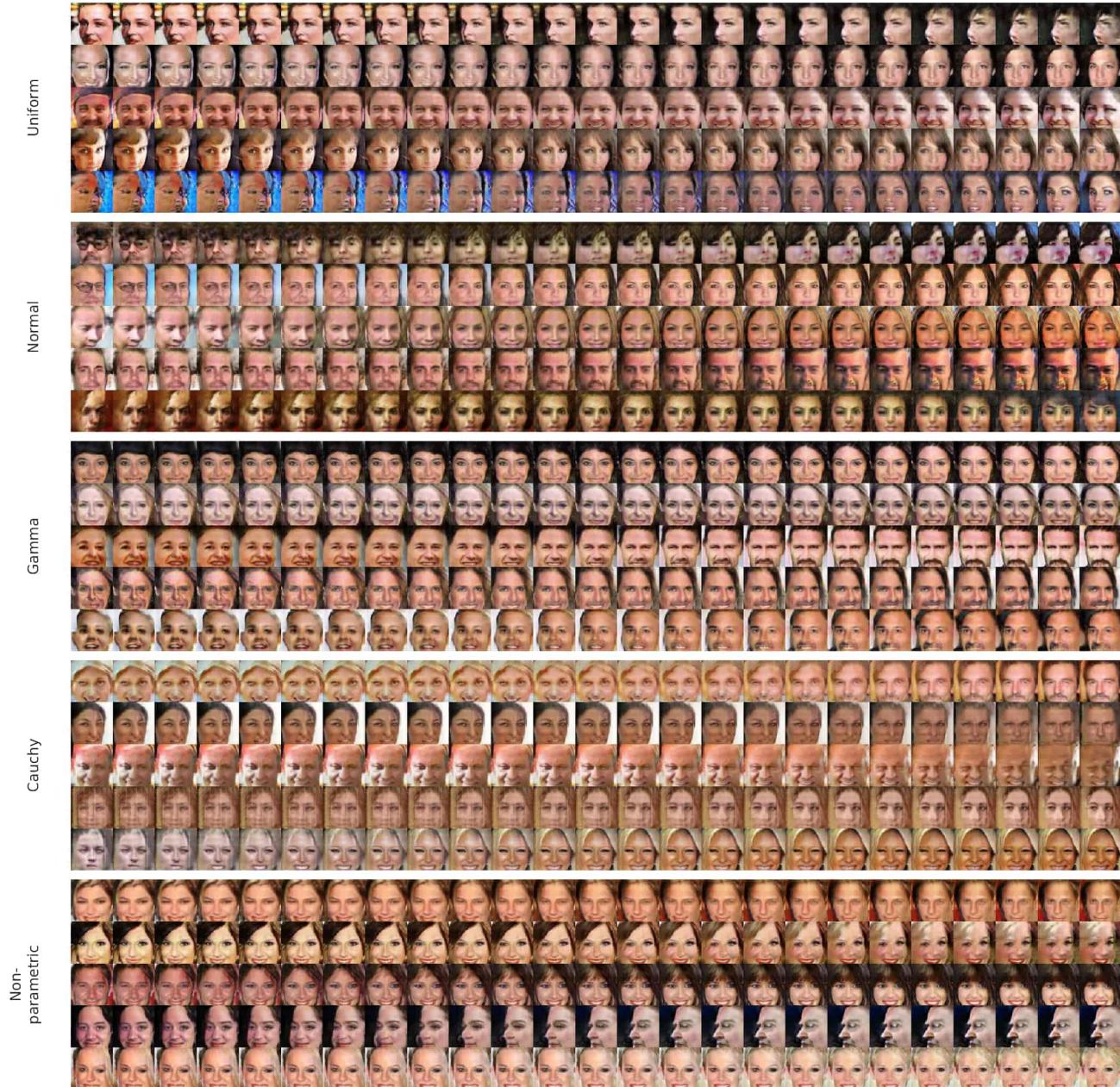
Figure 3. Interpolation (left to right) between two random points on CelebA dataset using different priors with $d = 100$.
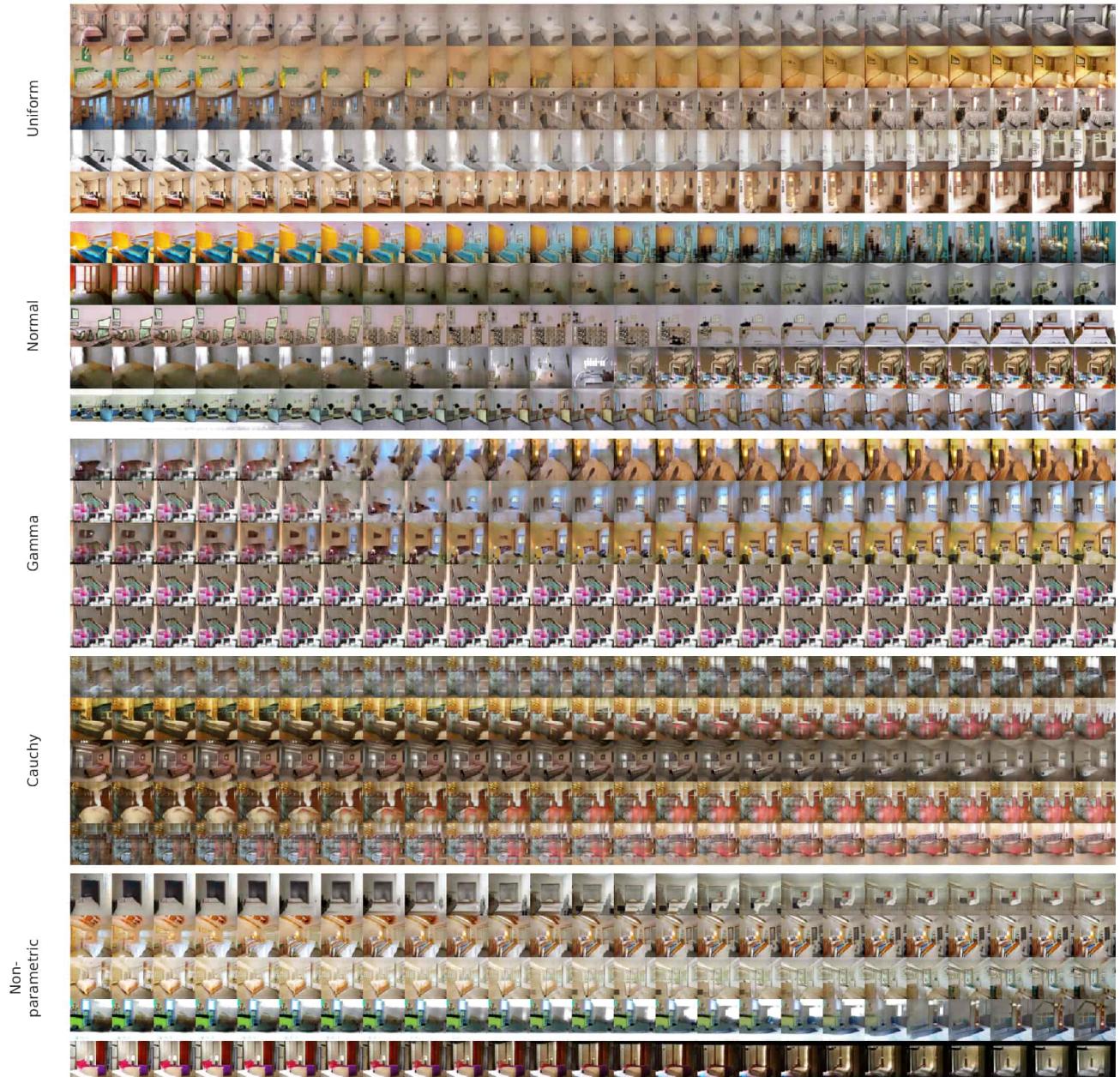
Figure 4. Interpolation (left to right) between two random points on LSUN bedroom dataset using different priors with $d = 100$.
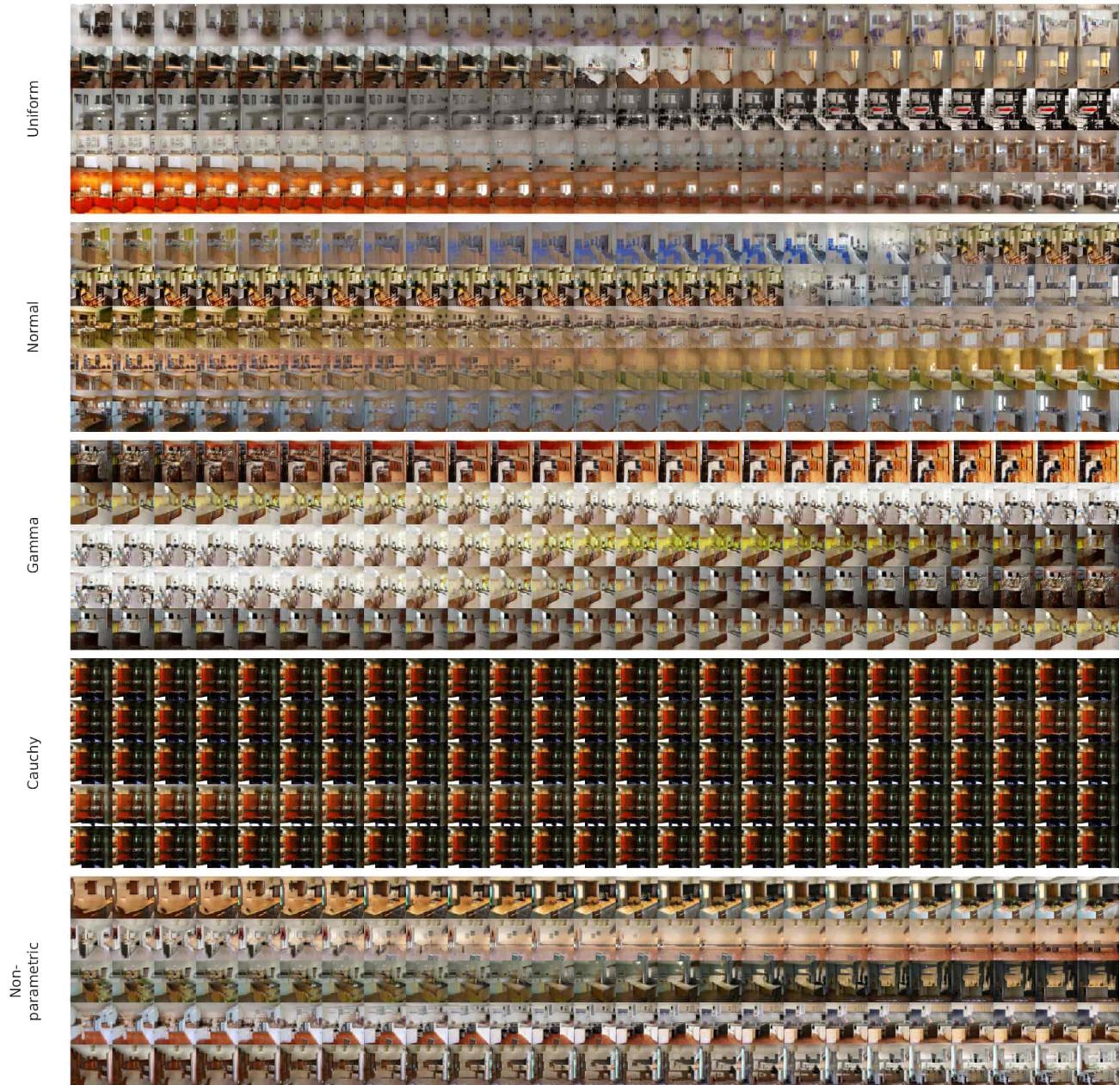
Figure 5. Interpolation (left to right) between two random points on LSUN kitchen dataset using different priors with $d = 100$.
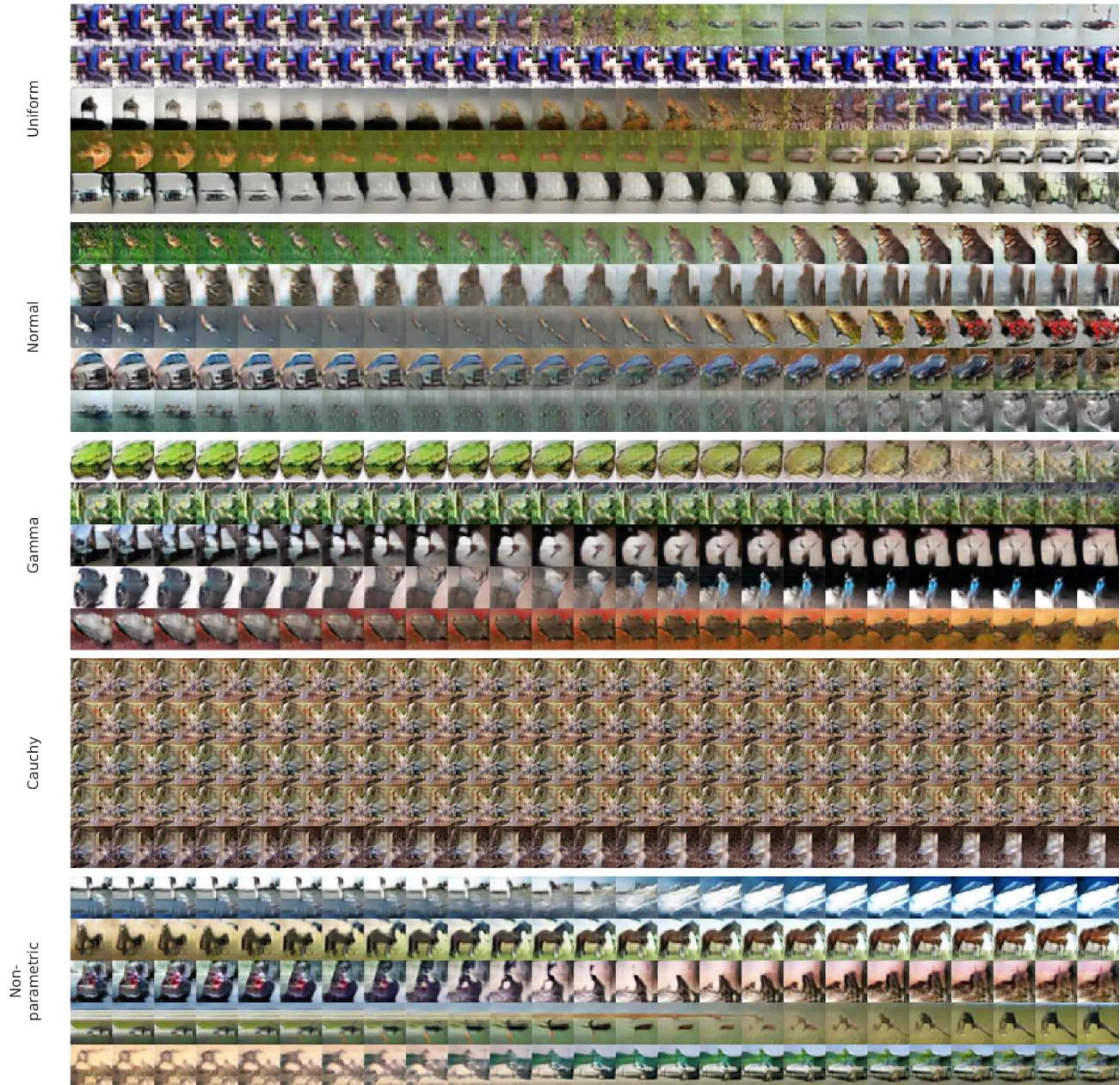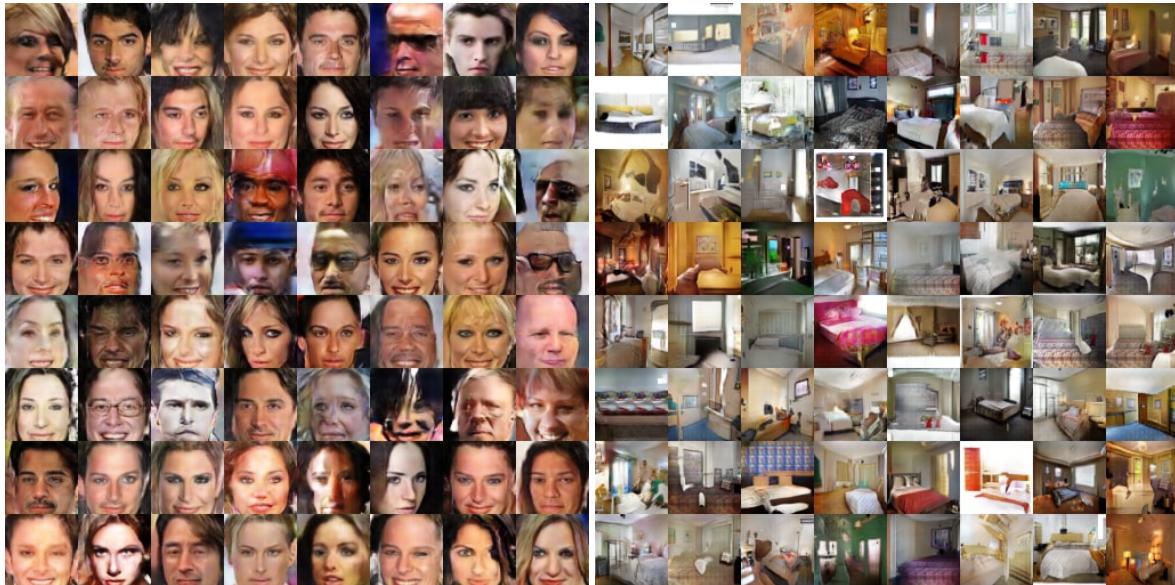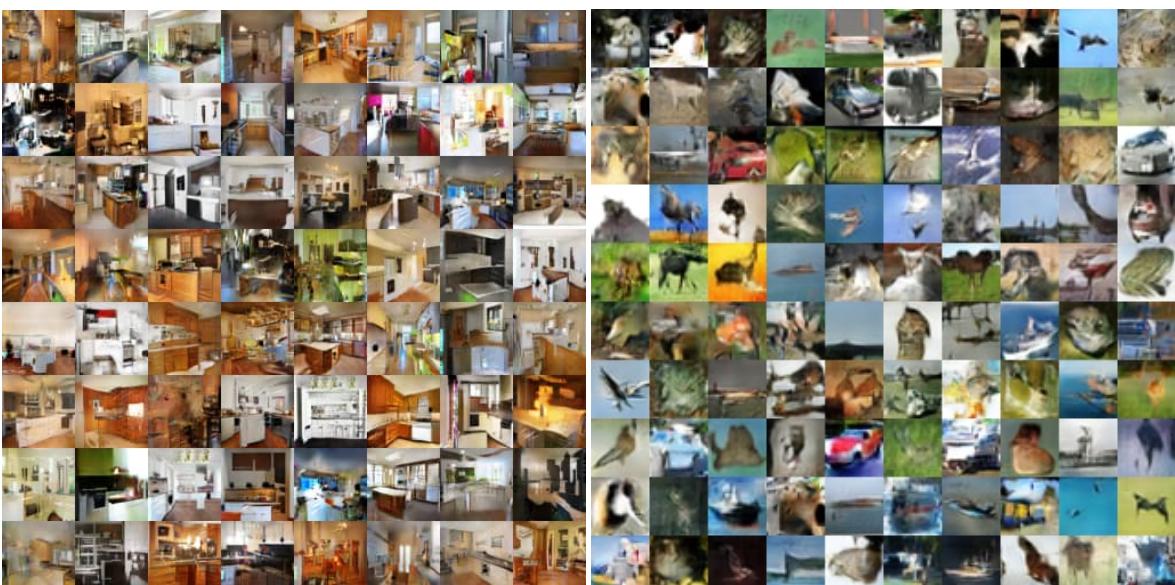
Figure 6. Interpolation (left to right) between two random points on CIFAR10 dataset using different priors with $d = 100$.

(a) CelebA dataset
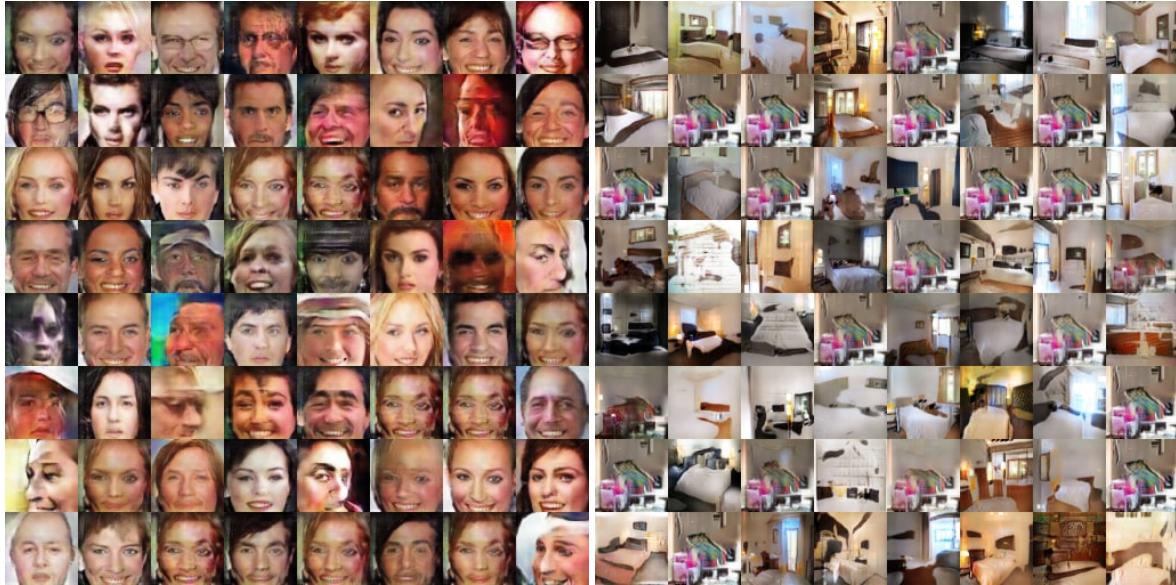
(b) LSUN bedroom
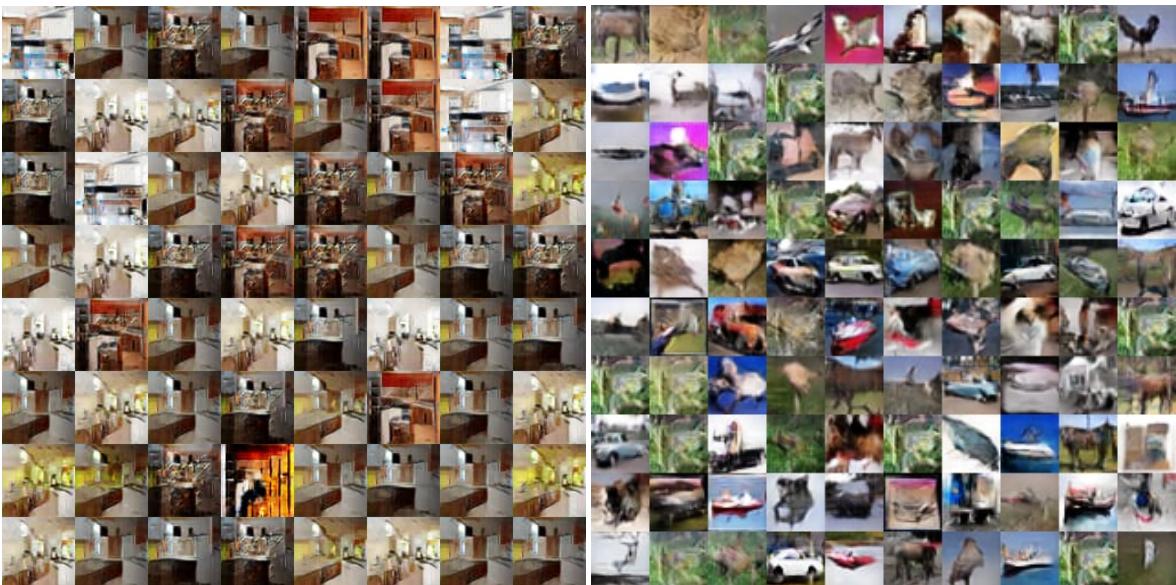
(c) LSUN kitchen

(d) CIFAR10

Figure 7. Random samples generated on the prior point with **our non-parametric distribution**.

(a) CelebA dataset
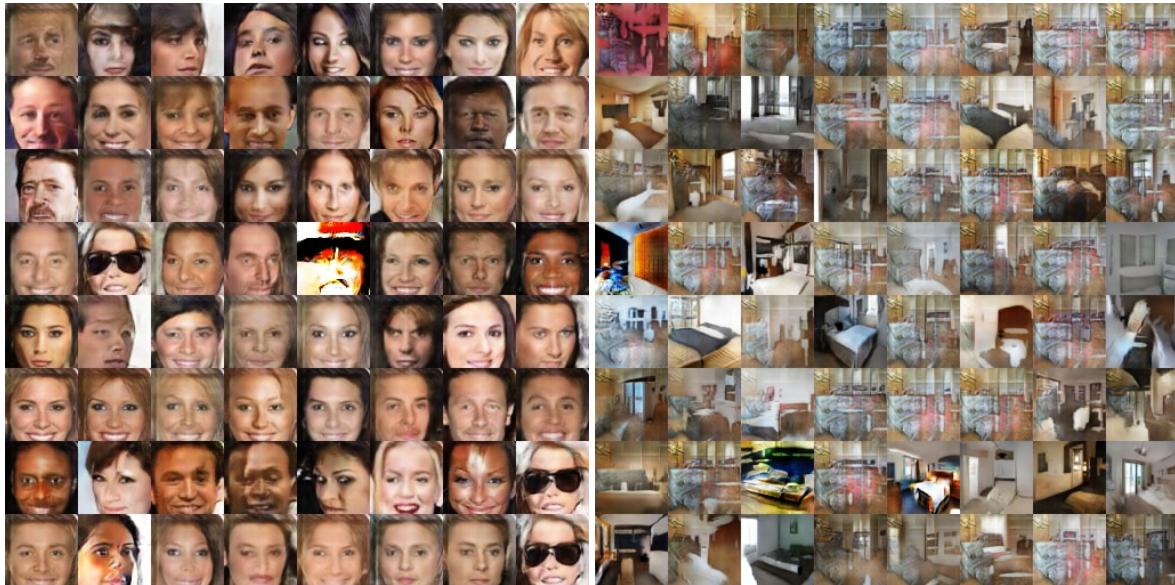
(b) LSUN bedroom
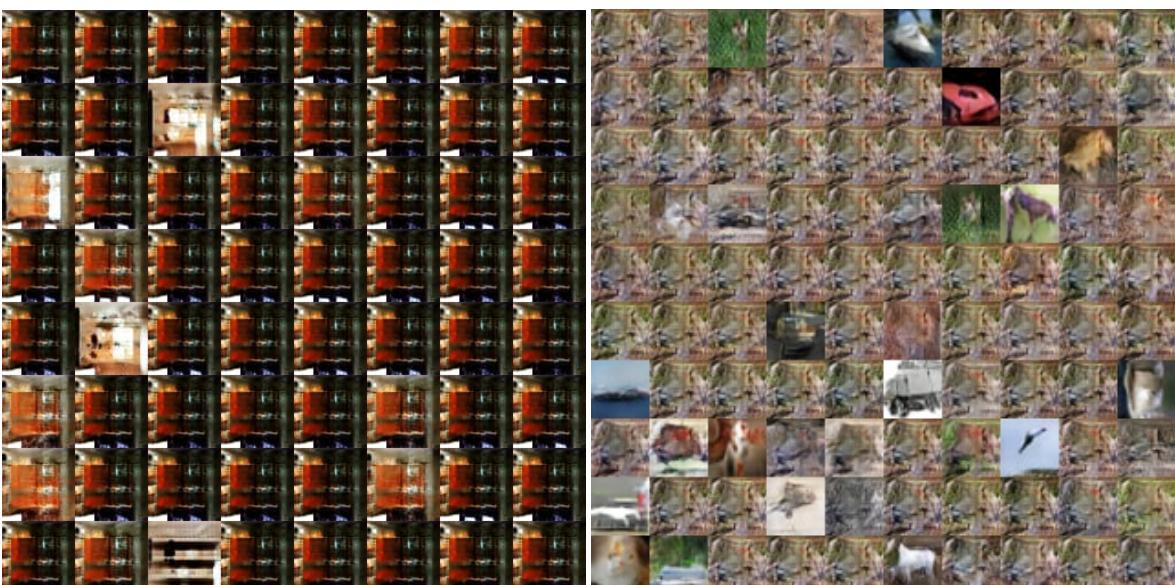
(c) LSUN kitchen

(d) CIFAR10

Figure 8. Random samples generated on the prior point with **Gamma distribution**.

(a) CelebA dataset
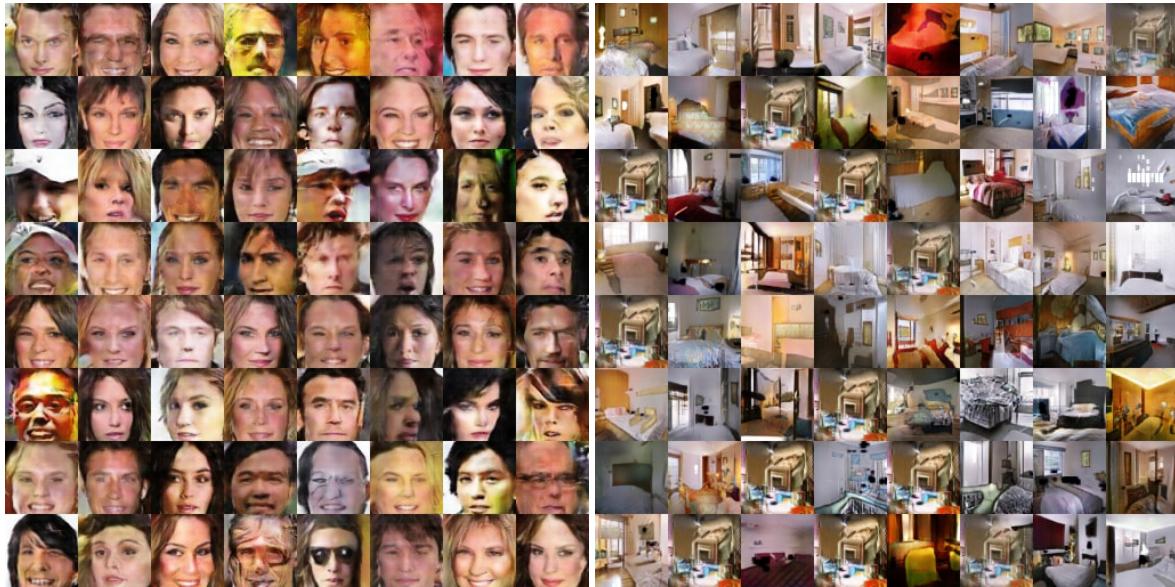
(b) LSUN bedroom

(c) LSUN kitchen

(d) CIFAR10

Figure 9. Random samples generated on the prior point with **Cauchy distribution**.

(a) CelebA dataset
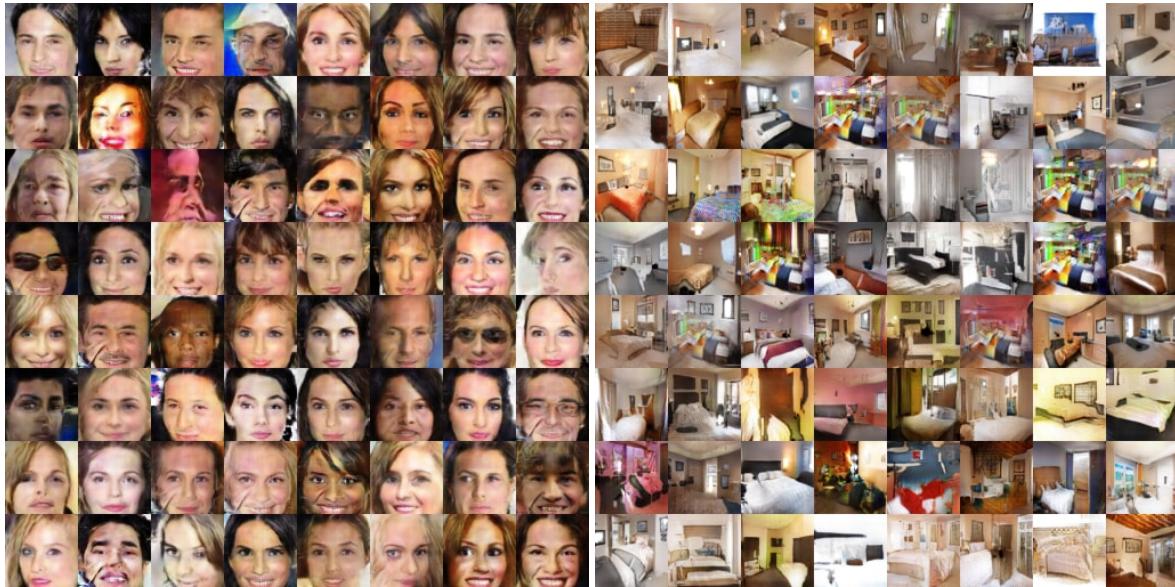
(b) LSUN bedroom
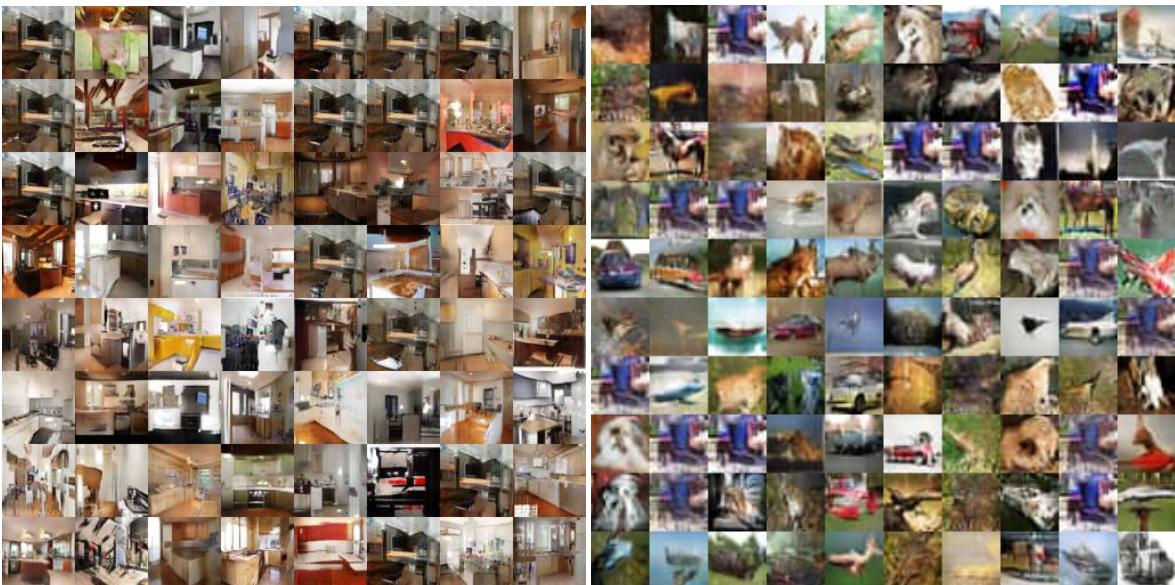
(c) LSUN kitchen

(d) CIFAR10

Figure 10. Random samples generated on the prior point with **Normal distribution**.

(a) CelebA dataset
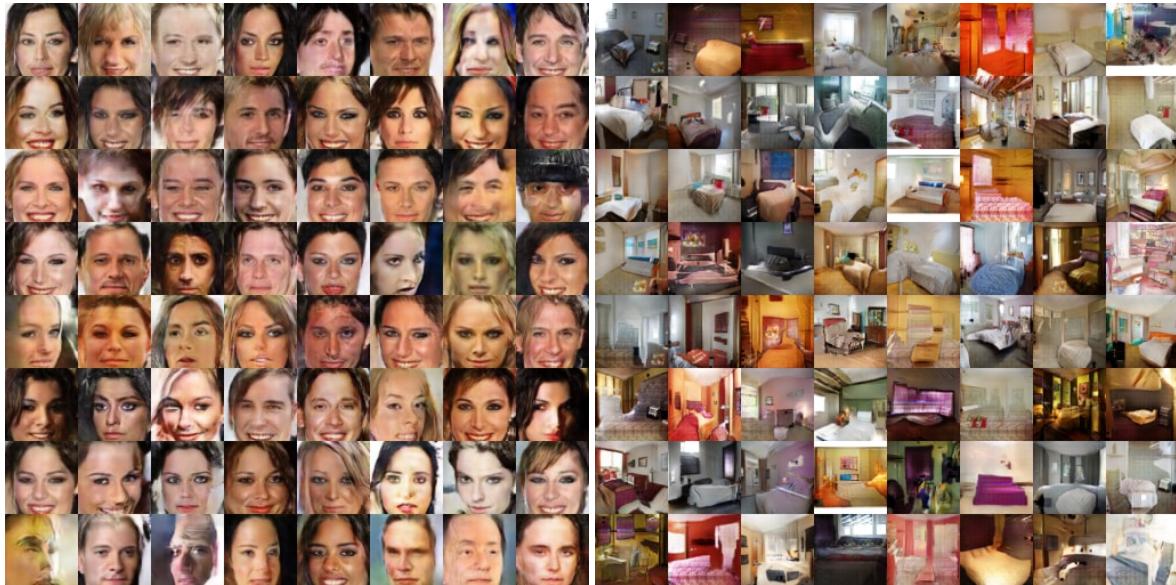
(b) LSUN bedroom
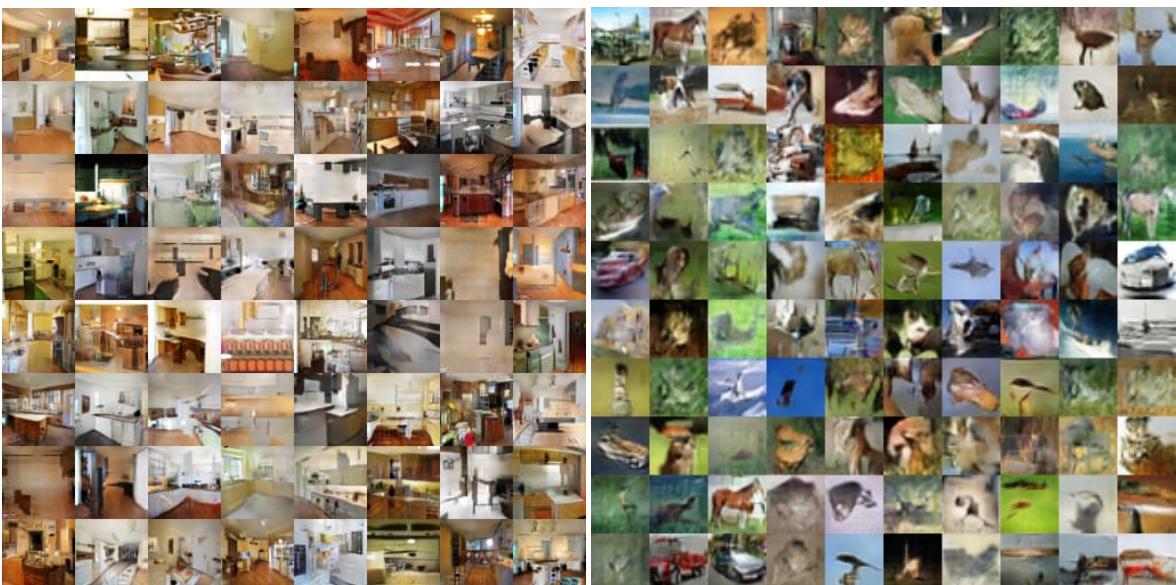
(c) LSUN kitchen

(d) CIFAR10

Figure 11. Random samples generated on the prior point with **Uniform distribution**.

(a) CelebA dataset

(b) LSUN bedroom

(c) LSUN kitchen

(d) CIFAR10

Figure 12. Random samples generated on the mid-point with **our non-parametric distribution**.