Supplementary Materials of Improving the Training of Data Efficient GANs via Quality Aware Dynamic Discriminator Rejection Sampling

Zhaoyu Zhang[1], Yang Hua[1], Guanxiong Sun[2], Hui Wang[1], Seán McLoone[1]
[1]Queen's University Belfast [2]Huawei UKRD
{zzhang55,Y.Hua,gsun02,h.wang,s.mcloone}@qub.ac.uk

1. More Details of Experiments Setup

The results of adding QADDRS of various DE-GANs in the main paper are trained by two NVIDIA A5000 GPUs ($2 \times$ 24G) with the operating system Ubuntu 20.04. To replicate our experimental environment, we recommend referring to the official open-source codes[1] for StyleGAN2-based method and open-source codes[2] for FastGAN-based method for environment settings.

1.1. More Experiments Results with Inception Score (IS)

To further show the superiority of the proposed QADDRS, we also report the experiment results using another commonly-used GANs evaluation metric, i.e., Inception Score (IS) [4]. The results on low-shot datasets compared with the state-of-the-art method, i.e., Diffusion-Projected GAN (FastGAN), are shown in Table S1. Diffusion-Projected GAN (FastGAN) + QADDRS can achieve higher IS, demonstrating the superiority of the proposed QADDRS.

1.2. More Experiments Results on CIFAR-10/100 Datasets

To further demonstrate the superiority of the proposed QADDRS, we also conduct experiments on CIFAR-10/100 datasets using StyleGAN2 + Diff-Augment [7]. The results are shown in Tables S2 and S3. StyleGAN2 + Diff-Augment + QADDRS achieves better performance on the CIFAR-10/100 datasets.

2. More Generated Images

According to the main paper, more generated results on low-shot datasets with StyleGAN2 + Diff-Augment + QADDRS, StyleGAN2 + ADA + QADDRS, InsGen + QADDRS and Diffusion-Projected GAN (FastGAN) + QADDRS are shown in Figures S1, S2, S3 and S4, respectively. More generated results on FFHQ datasets with InsGen + QADDRS, Diffusion-Projected GAN (FastGAN) + QADDRS and Diffusion-Projected GAN (FastGAN Lite) + QADDRS are shown in Figures S5, S6 and S7, respectively.

3. Discussion of Ethical Issues

This paper applies the 100-shot Obama dataset, i.e., the dataset consists of Obama faces, in the experiment section. This dataset is widely and commonly used without limitations in DE-GANs research. Furthermore, a lot of recent studies [1–3, 6, 7] on DE-GANs have applied this dataset in their experiments, demonstrating its application is reasonable and does not raise any ethical issues.

4. Limitation and Broader Impact

This paper proposes a simple yet effective method called quality aware dynamic discriminator rejection sampling (QADDRS) that can benefit the practical deployment of DE-GANs. The technical contributions of this paper do not raise any particular ethical challenges. However, because technology is usually a double-edged sword, our work may also bring potential social risks when applying GANs with limited data. For example, it may make it easier to generate fake media using only limited data.

[1] https://github.com/NVlabs/stylegan2-ada-pytorch
[2] https://github.com/autonomousvision/projected-gan

References

[1] Tianlong Chen, Yu Cheng, Zhe Gan, Jingjing Liu, and Zhangyang Wang. Data-efficient GAN training beyond (just) augmentations: A lottery ticket perspective. In *NeurIPS*, 2021. 1

[2] Kaiwen Cui, Jiaxing Huang, Zhipeng Luo, Gongjie Zhang, Fangneng Zhan, and Shijian Lu. Genco: Generative co-training for generative adversarial networks with limited data. In *AAAI*, 2022. 4

[3] Ziqiang Li, Chaoyue Wang, Heliang Zheng, Jing Zhang, and Bin Li. Fakeclr: Exploring contrastive learning for solving latent discontinuity in data-efficient gans. In *ECCV*, 2022. 1

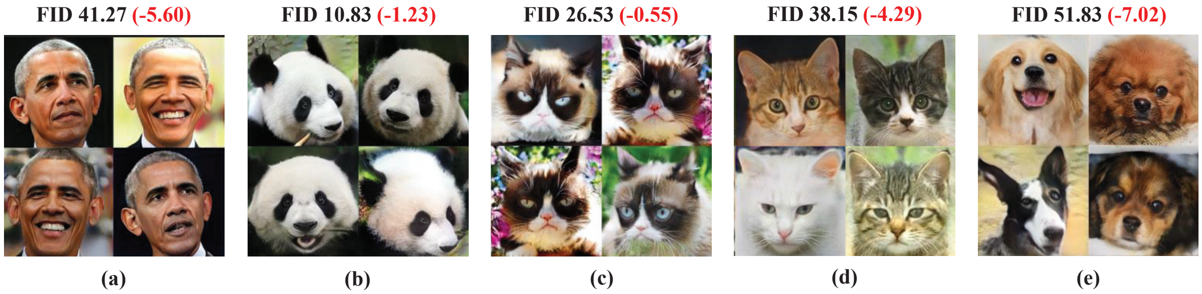

Figure S1. Images generated by StyleGAN2 + Diff-Augment + QADDRS on (a) 100-shot Obama dataset, (b) 100-shot Panda dataset, (c) 100-shot Grumpy-cat dataset, (d) AnimalFace-cat dataset and (e) AnimalFace-dog dataset. The decreasing value of FID in red color demonstrates the improvement of StyleGAN2 + Diff-Augment + QADDRS compared with baseline StyleGAN2 + Diff-Augment. *Best viewed in color.*

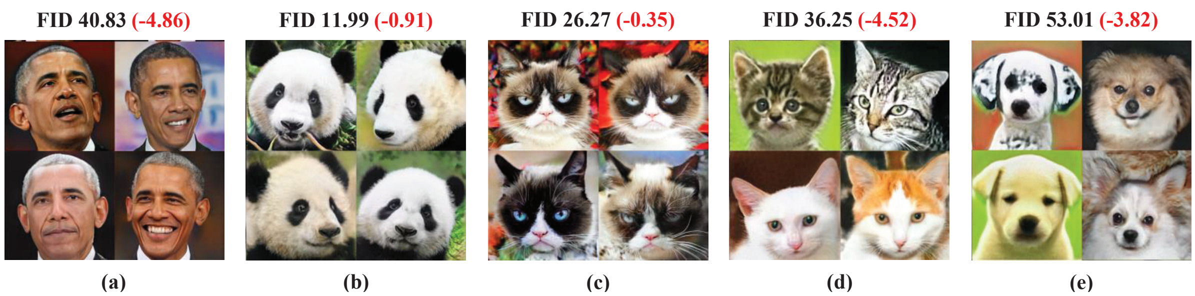

Figure S2. Images generated by StyleGAN2 + ADA + QADDRS on (a) 100-shot Obama dataset, (b) 100-shot Panda dataset, (c) 100-shot Grumpy-cat dataset, (d) AnimalFace-cat dataset and (e) AnimalFace-dog dataset. The decreasing value of FID in red color demonstrates the improvement of StyleGAN2 + ADA + QADDRS compared with baseline StyleGAN2 + ADA. *Best viewed in color.*

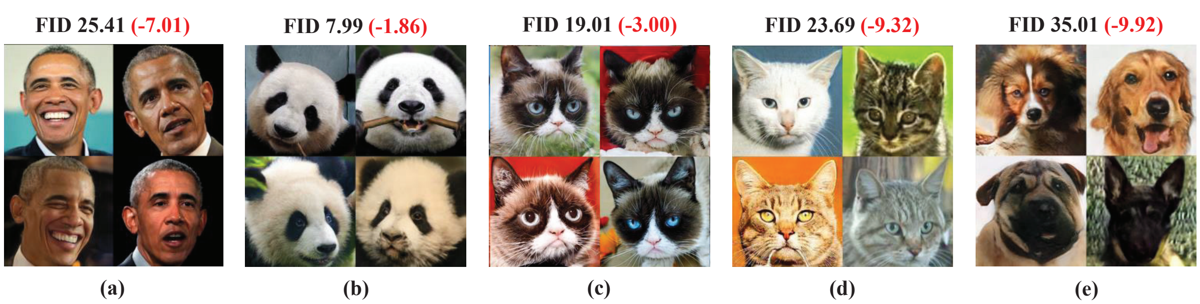

Figure S3. Images generated by InsGen + QADDRS on (a) 100-shot Obama dataset, (b) 100-shot Panda dataset, (c) 100-shot Grumpy-cat dataset, (d) AnimalFace-cat dataset and (e) AnimalFace-dog dataset. The decreasing value of FID in red color demonstrates the improvement of InsGen + QADDRS compared with baseline InsGen. *Best viewed in color.*

[4] Tim Salimans, Ian Goodfellow, Wojciech Zaremba, Vicki Cheung, Alec Radford, and Xi Chen. Improved techniques for training GANs. In *NeurIPS*, 2016. 1

[5] Zhendong Wang, Huangjie Zheng, Pengcheng He, Weizhu Chen, and Mingyuan Zhou. Diffusion-gan: Training gans with diffusion. In *ICLR*, 2023. 4

[6] Zhaoyu Zhang, Yang Hua, Guanxiong Sun, Hui Wang, and Seán McLoone. Improving the leaking of augmentations in data-efficient gans via adaptive negative data augmentation. In *WACV*, 2024. 1

[7] Shengyu Zhao, Zhijian Liu, Ji Lin, Jun-Yan Zhu, and Song Han. Differentiable augmentation for data-efficient GAN training. In *NeurIPS*, 2020. 1, 4

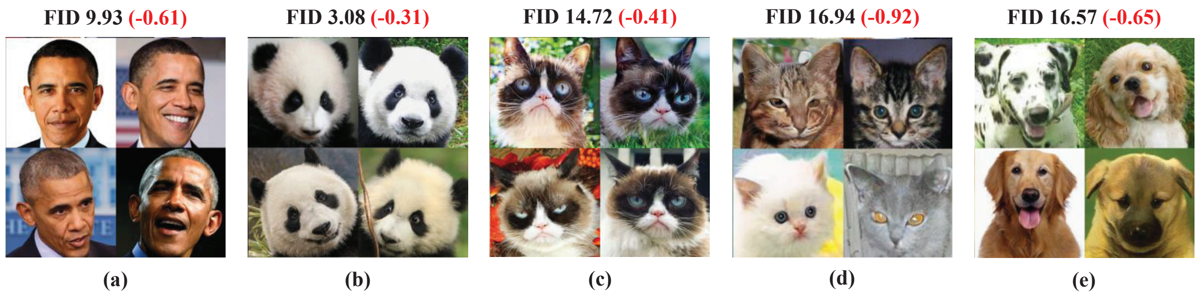

Figure S4. Images generated by Diffusion Projected GAN (FastGAN) + QADDRS on (a) 100-shot Obama dataset, (b) 100-shot Panda dataset, (c) 100-shot Grumpy-cat dataset, (d) AnimalFace-cat dataset and (e) AnimalFace-dog dataset. The decreasing value of FID in red color demonstrates the improvement of Diffusion Projected GAN (FastGAN) + QADDRS compared with baseline Diffusion Projected GAN (FastGAN). *Best viewed in color.*

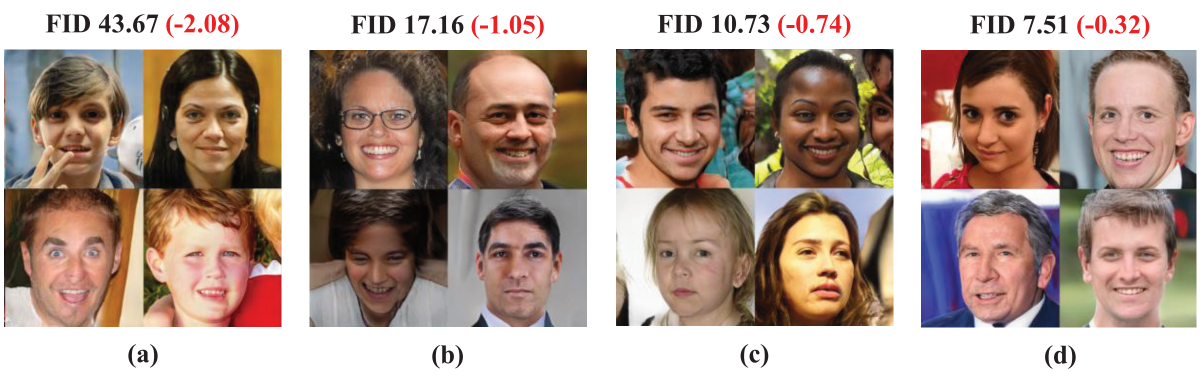

Figure S5. Images generated by InsGen + QADDRS on (a) FFHQ-100 dataset, (b) FFHQ-1K dataset, (c) FFHQ-2K dataset and (d) FFHQ-5K dataset. The decreasing value of FID in red color demonstrates the improvement of InsGen + QADDRS compared with baseline InsGen. *Best viewed in color.*

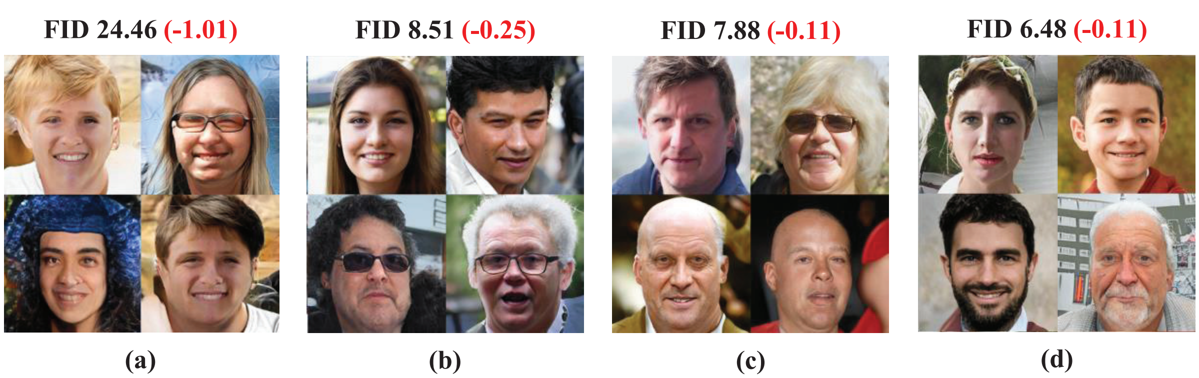

Figure S6. Images generated by Diffusion Projected GAN (FastGAN) + QADDRS on (a) FFHQ-100 dataset, (b) FFHQ-1K dataset, (c) FFHQ-2K dataset and (d) FFHQ-5K dataset. The decreasing value of FID in red color demonstrates the improvement of Diffusion Projected GAN (FastGAN) + QADDRS compared with baseline Diffusion Projected GAN (FastGAN). *Best viewed in color.*

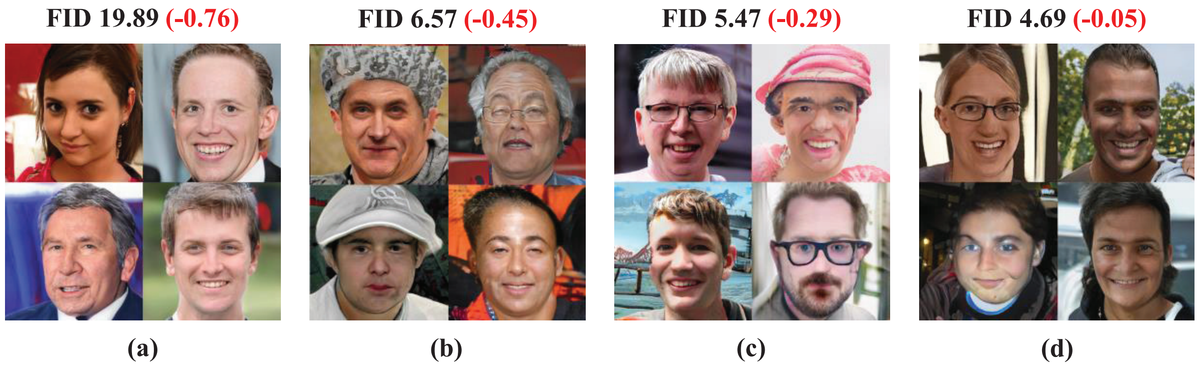

Figure S7. Images generated by Diffusion Projected GAN (FastGAN Lite) + QADDRS on (a) FFHQ-100 dataset, (b) FFHQ-1K dataset, (c) FFHQ-2K dataset and (d) FFHQ-5K dataset. The decreasing value of FID in red color demonstrates the improvement of Diffusion Projected GAN (FastGAN Lite) + QADDRS compared with baseline Diffusion Projected GAN (FastGAN Lite). *Best viewed in color.*

Method	100-shot			Animal-Face	
	Obama	Grumpy Cat	Panda	Cat	Dog
Diffusion-Projected GAN FastGAN) [5]	1.67	1.47	1.00	2.28	15.32
+ QADDRS	**1.69**	**1.50**	**1.03**	**2.33**	**15.47**

Table S1. The comparison of Inception scores (higher is better) with Diffusion-Projected GAN (FastGAN) [5] and Diffusion-Projected GAN (FastGAN) + QADDRS on low-shot datasets (256×256). We follow the setting as in [7]. Massive Augmentation [2] is applied to all of the methods. The Inception Scores are averaged over three evaluations; all standard deviations are less than 1% relatively.

Method	**MA**	100% CIFAR-10		20% CIFAR-10		10% CIFAR-10	
		IS	FID	IS	FID	IS	FID
StyleGAN2 + Diff-Augment [7]	Yes	9.40	9.89	9.21	12.15	8.84	14.50
+ QADDRS	Yes	**9.41**	**9.76**	**9.25**	**11.95**	**8.95**	**14.11**

Table S2. A comparison of StyleGAN2 + Diff-Augment + QADDRS with StyleGAN2 + Diff-Augment on the CIFAR-10 dataset (100%, 20% and 10%). Inception Score (IS) and FID are measured using 10k samples; the test set is the reference distribution. For a fair comparison, Massive Augmentation (MA) is applied to all the methods. Results are averaged over five evaluation evaluations; all standard deviations are less than 1% relatively.

Method	**MA**	100% CIFAR-100		20% CIFAR-100		10% CIFAR-100	
		IS	FID	IS	FID	IS	FID
StyleGAN2 + Diff-Augment [7]	Yes	10.04	15.22	9.82	16.65	9.06	20.75
+ QADDRS	Yes	**10.07**	**15.11**	**9.87**	**16.48**	**9.18**	**20.16**

Table S3. A comparison of StyleGAN2 + Diff-Augment + QADDRS with StyleGAN2 + Diff-Augment on the CIFAR-100 dataset (100%, 20% and 10%). Inception Score (IS) and FID are measured using 10k samples; the test set is the reference distribution. For a fair comparison, Massive Augmentation (MA) is applied to all the methods. Results are averaged over five evaluation evaluations; all standard deviations are less than 1% relatively.