Ensembling Off-the-shelf Models for GAN Training

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Abstract

The advent of large-scale training has produced a cornucopia of powerful visual recognition models. However, generative models, such as GANs, have traditionally been trained from scratch in an unsupervised manner. Can the collective "knowledge" from a large bank of pretrained vision models be leveraged to improve GAN training? If so, with so many models to choose from, which one(s) should be selected, and in what manner are they most effective? We find that pretrained computer vision models can significantly improve performance when used in an ensemble of discriminators. Notably, the particular subset of selected models greatly affects performance. We propose an effective selection mechanism, by probing the linear separability between real and fake samples in pretrained model embeddings, choosing the most accurate model, and progressively adding it to the discriminator ensemble. Interestingly, our method can improve GAN training in both limited data and large-scale settings. Given only 10k training samples, our FID *on* LSUN CAT *matches the StyleGAN2 trained on 1.6M images. On the full dataset, our method improves* FID *by* 1.5 *to* 2× *on cat, church, and horse categories of* LSUN.

1. Introduction

Image generation inherently requires being able to capture and model complex statistics in real-world visual phenomena. Computer vision models, driven by the success of supervised and self-supervised learning techniques [16, 18, 34, 70, 83], have proven effective at capturing useful representations when trained on large-scale data [73, 98, 111]. What potential implications does this have on generative modeling? If one day, perfect computer vision systems could answer any question about any image, could this capability be leveraged to improve image synthesis models?

Surprisingly, despite the aforementioned connection between synthesis and analysis, state-of-the-art generative adversarial networks (GANs) [9, 41, 42, 109] are trained in an unsupervised manner without the aid of such pretrained networks. With a plethora of useful models easily available in the research ecosystem, this presents a missed opportunity to explore. Can the knowledge of pretrained visual represen-
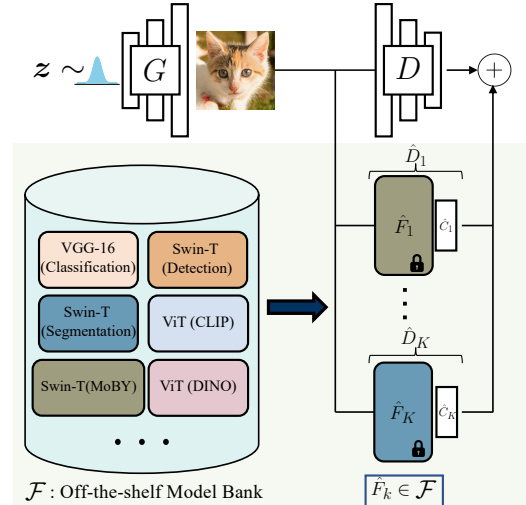

Figure 1. **Vision-aided GAN training**. The model bank $\mathcal{F}$ consists of widely used and state-of-the-art pretrained networks. We automatically select a subset $\{\hat{F}\}_{k=1}^{K}$ from $\mathcal{F}$, which can best distinguish between real and fake distribution. Our training procedure consists of creating an ensemble of the original discriminator D and discriminators $\hat{D}_k = \hat{C}_k \circ \hat{F}_k$ based on the feature space of selected off-the-shelf models. $\hat{C}_k$ is a shallow trainable network over the frozen pretrained features.

tations actually benefit GAN training? If so, with so many models, tasks, and datasets to choose from, which models should be used, and in what manner are they most effective?

In this work, we study the use of a "bank" of pretrained deep feature extractors to aid in generative model training. Specifically, GANs are trained with a discriminator, aimed at continuously learning the relevant statistics differentiating real and generated samples, and a generator, which aims to reduce this gap. Naïvely using such strong, pretrained networks as a discriminator leads to the overfitting and overwhelming the generator, especially in limited data settings. We show that freezing the pretrained network (with a small, lightweight learned classifier on top, as shown in Figure 1) provides stable training when used with the original, learned discriminator. In addition, ensembling multiple pretrained networks encourages the generator to match the real distribution in different, complementary feature spaces.

To choose which networks work best, we propose to use

an automatic model selection strategy based on the linear separability of real and fake images in the feature space, and progressively add supervision from a set of available pretrained networks. In addition, we use label smoothing [76] and differentiable augmentation [41, 109] to stabilize the model training further and reduce overfitting.

We experiment on several datasets in both limited and large-scale sample setting to show the effectiveness of our method. We improve the state-of-the-art on FFHQ [43] and LSUN [98] datasets given 1k training samples by 2-3× on the FID metric [36]. For LSUN CATs, we match the FID of StyleGAN2 trained on the full dataset (1.6M images) with only 10k samples, as shown in Figure 2. In the full-scale data setting, our method improves FID for LSUN CATs from 6.86 to 3.98, LSUN CHURCH from 4.28 to 1.72, and LSUN HORSE from 4.09 to 2.11. Finally, we visualize the internal representation of our learned models as well as training dynamics. Our code is available on our website.

2. Related Work

Improving GAN training. Since the introduction of GANs [31], significant advances have been induced by architectural changes [42, 43, 71], training schemes [40, 102], as well as objective functions [4, 5, 22, 25, 57, 58]. In previous works, the learning objectives often aim to minimize different types of divergences between real and fake distribution. The discriminators are typically trained from scratch and do not use external pretrained networks. As a result, the discriminator is prone to overfit the training set, especially for the limited data setting [41, 96, 109].

Use of pretrained models in image synthesis. Pretrained models have been widely used as perceptual loss functions [24, 28, 39] to measure the distance between an output image and a target image in deep feature space. The loss has proven effective for conditional image synthesis tasks such as super-resolution [50], image-to-image translation [15, 66, 91], and neural style transfer [28]. Zhang et al. [106] show that deep features can indeed match the human perception of image similarity better than classic metrics. Sungatullina et al. [85] propose a perceptual discriminator to combine perceptual loss and adversarial loss for unpaired image-to-image translation. This idea was recently used by a concurrent work on CG2real [72]. Another recent work [27] proposes the use of pretrained objects detectors to detect regions in the image and train object-specific discriminators during GAN training. Our work is inspired by the idea of perceptual discriminators [85] but differs in three ways. First, we focus on a different application of unconditional GAN training rather than image-to-image translation. Second, instead of using a single VGG model, we ensemble a diverse set of feature representations that complement each other. Finally, we propose an automatic model selection method to find models useful for a given domain. A concurrent work [78] propose

to reduce overfitting of perceptual discriminators [85] using random projection and achieve better and faster GAN training.

Loosely related to our work, other works have used pretrained models for clustering, encoding, and nearest neighbor search during their model training. Logo-GAN [75] uses deep features to get synthetic clustering labels for conditional GAN training. InclusiveGAN [99] improves the recall of generated samples by enforcing each real image to be close to a generated image in deep feature space. Shocher et al. [81] uses an encoder-decoder based generative model with pretrained encoder for image-to-image translation tasks. Pretrained features have also been used to condition the generator in GANs [13, 56]. Different from the above work, our method empowers the discriminator with pretrained models and requires no changes to the backbone generator.

Use of pretrained models in image editing. Pretrained models have also been used in image editing once the generative model has been trained. Notable examples include image projection with a perceptual distance [1, 113], text-driven image editing with CLIP [68], finding editable directions using attribute classifier models [80], and extracting semantic editing regions with pretrained segmentation networks [114]. In our work, we focus on using the rich knowledge of computer vision models to improve model training.

Transfer learning. Large-scale supervised and self-supervised models learn useful feature representations [11, 16, 35, 47, 70, 95] that can transfer well to unseen tasks, datasets, and domains [23, 37, 45, 65, 74, 89, 97, 100, 101]. In generative modeling, recent works propose transferring the weights of pretrained generators and discriminators from a source domain (e.g., faces) to a new domain (e.g., portraits of one person) [32, 53, 60, 63, 64, 92, 93, 107]. Together with differentiable data augmentation techniques [41, 88, 109, 110], they have shown faster convergence speed and better sampling quality for limited-data settings. Different from them, we transfer the knowledge of learned feature representations of computer vision models. This enables us to leverage the knowledge from a diverse set of sources at scale.

3. Method

Generative Adversarial Networks (GANs) aim to approximate the distribution of real samples from a finite training set $x \sim \mathbb{P}_{\mathcal{X}}$. The generator network G, maps latent vectors $z \sim \mathbb{P}(z)$ (e.g., a normal distribution) to samples $G(z) \sim \mathbb{P}_{\theta}$. The discriminator network D is trained adversarially to distinguish between the continuously changing generated distribution $\mathbb{P}_{\theta}$ and target real distribution $\mathbb{P}_{\mathcal{X}}$. GANs perform the minimax optimization $\min_G \max_D V(D, G)$, where

$$V(D, G) = \mathbb{E}_{x \sim \mathbb{P}_{\mathcal{X}}}[\log D(x)] + \mathbb{E}_{z \sim \mathbb{P}(z)}[\log(1 - D(G(z)))].$$
(1)

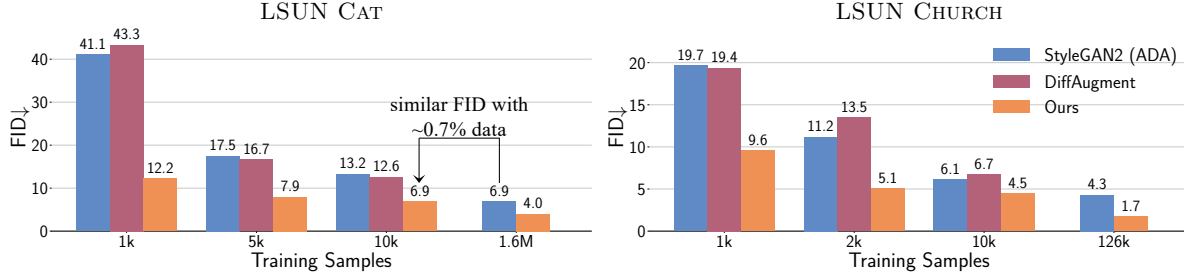Ideally, the discriminator should measure the gap be-

Figure 2. **Performance on LSUN CAT and LSUN CHURCH**. We compare with the leading methods StyleGAN2-ADA [41] and DiffAugment [109] on different sizes of training samples and full-dataset. Our method outperforms them by a large margin, especially in limited sample setting. For LSUN CAT we achieve similar FID as StyleGAN2 [44] trained on full-dataset using only 0.7% of the dataset.
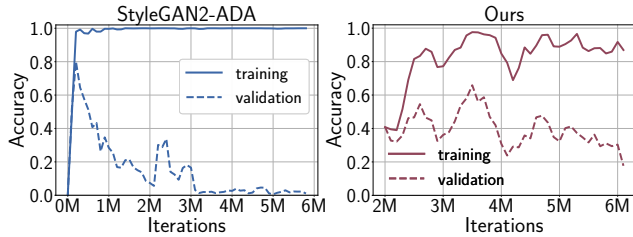

Figure 3. Training and validation accuracy w.r.t. training iterations for our DINO [11] based discriminator vs. baseline StyleGAN2-ADA discriminator on FFHQ 1k dataset. Our discriminator based on pretrained features has higher accuracy on validation real images and thus shows better generalization. In the above training, vision-aided adversarial loss is added at the 2M iteration.

tween $\mathbb{P}_{\mathcal{X}}$ and $\mathbb{P}_\theta$ and guide the generator towards $\mathbb{P}_{\mathcal{X}}$. However, in practice, large capacity discriminators can easily overfit on a given training set, especially in the limited-data regime [41, 109]. Unfortunately, as shown in Figure 3, even when we adopt the latest differentiable data augmentation [41] to reduce overfitting, the discriminator still tends to overfit, failing to perform well on a validation set. In addition, the discriminator can potentially focus on artifacts that are indiscernible to humans but obvious for machines [90].

To address the above issues, we propose ensembling a diverse set of deep feature representations as our discriminator. This new source of supervision can benefit us in two manners. First, training a shallow classifier over pretrained features is a common way to adapt deep networks to a small-scale dataset, while reducing overfitting [17,30]. As shown in Figure 3, our method reduces the discriminator overfitting significantly. Second, recent studies [6,101] have shown that deep networks can capture meaningful visual concepts from low-level visual cues (edges and textures) to high-level concepts (objects and object parts). A discriminator built on these features may better match human perception [106].

3.1. Formulation

Given a set of pretrained feature extractors $\mathcal{F} = \{F_n\}_{n=1}^N$, which learns to tackle different vision tasks, we

train corresponding discriminators $\{D_n\}_{n=1}^N$. We add small classifier heads $\{C_n\}_{n=1}^N$ to measure the gap between $\mathbb{P}_{\mathcal{X}}$ and $\mathbb{P}_\theta$ in the pretrained models' feature spaces. During discriminator training, the feature extractor F_n is frozen, and only the classifier head is updated. The generator G is updated with the gradients from D and the discriminators $\{D_n\}$ based on pretrained feature extractors. In this manner, we propose to leverage pretrained models in an adversarial fashion for GAN training, which we refer to as *Vision-aided Adversarial* training:

$$\min_G \max_{D,\{C_n\}_{n=1}^N} V(D,G) + \overbrace{\sum_{n=1}^N V(D_n, G)}^{\text{vision-aided adversarial loss}} , \quad (2)$$

where $D_n = C_n \circ F_n$.

Here, C_n is a small trainable head over the pretrained features. The above training objective involves the sum of discriminator losses based on all available pretrained models $\{F_n\}$. Solving for this at each training iteration would be computationally and memory-intensive. Using all pretrained models would force a significant reduction in batch size to fit all models into memory, potentially hurting performance [9]. To bypass the computational bottleneck, we automatically select a small subset of K models, where $K < N$:

$$\min_G \max_{D,\{\hat{C}_k\}_{k=1}^K} V(D,G) + \sum_{k=1}^K V(\hat{D}_k, G), \quad (3)$$

where $\hat{D}_k = \hat{C}_k \circ \hat{F}_k$ denotes the discriminator corresponding to k^{th} selected model, and $k \in \{1, \ldots, K\}$.

3.2. Model Selection

We choose the models whose off-the-shelf feature spaces best distinguish samples from real and fake distributions. Given the pretrained model's features of real and fake images, the strongest adversary from the set of models is $\hat{F}_k$, where

$$k = \arg\max_n \{ \max_{C'_n} V(D'_n, G)\},$$
$$\text{where } D'_n = C'_n \circ F_n. \quad (4)$$

3

Algorithm 1 GAN training with *Vision-aided Adversarial* loss.

Input: G, D trained with standard GAN loss for baseline number of iterations. Off-the-shelf model bank $\mathcal{F} = \{F_n\}_{n=1}^N$. Training data $\{\boldsymbol{x}_i\}$.

Hyperparameters: K: maximum number of pretrained models to use. $\{T_k : k = 1 \cdots K\}$: training intervals before adding next pretrained model.

1: Selected model set $\hat{\mathcal{F}} = \emptyset$
2: **for** $k = 1$ to K **do**
3:     Select best model $\hat{F}_k \in \mathcal{F}$ using Eqn. 4
4:     $\hat{\mathcal{F}} = \hat{\mathcal{F}} \cup \{\hat{F}_k\}$
5:     $\hat{D}_k = \hat{C}_k \circ \hat{F}_k$ ▷ $\hat{C}_k$ is a shallow trainable network
6:     $\mathcal{F} = \mathcal{F} \setminus \hat{F}_k$
7:     **for** $t = 1$ to T_k **do**
8:        Sample $\boldsymbol{x} \sim \{\boldsymbol{x}_i\}$
9:        Sample $\boldsymbol{z} \sim \mathbb{P}(\boldsymbol{z})$
10:       Update $D, \hat{D}_j \,\forall j = 1, \cdots, k$ using Eqn. 3
11:       Sample $\boldsymbol{z} \sim \mathbb{P}(\boldsymbol{z})$
12:       Update G using Eqn. 3
13:     **end for**
14: **end for**

Output: G with best training set FID

Here F_n is frozen, and C'_n is a linear trainable head over the pretrained features. In the case of limited real samples available and for computational efficiency, we use linear probing to measure the separability of real and fake images in the feature space of F_n.

We split the union of real training samples $\{\boldsymbol{x}_i\}$ and generated images $\{G(\boldsymbol{z}_i)\}$ into training and validation sets. For each pretrained model F_n, we train a logistic linear discriminator head to classify whether a sample comes from $\mathbb{P}_\mathcal{X}$ or $\mathbb{P}_\theta$ and measure $V(D'_n, G)$ on the validation split. The above term measures the negative binary cross-entropy loss and returns the model with the lowest error. A low validation error correlates with higher accuracy of the linear probe, indicating that the features are useful for distinguishing real from generated samples and using these features will provide more useful feedback to the generator. We empirically validate this on GAN training with 1k training samples of FFHQ and LSUN Cat datasets. Figure 4 shows that the GANs trained with the pretrained model F_n with higher linear probe accuracy in general achieve better FID metrics.

To incorporate feedback from multiple off-the-shelf models, we explore two variants of model selection and ensembling strategies – (1) **K-fixed** model selection strategy chooses the K best off-the-shelf models at the start of training and trains until convergence and (2) **K-progressive** model selection strategy iteratively selects and adds the best, unused off-the-shelf model after a fixed number of iterations.

K-progressive model selection. We find including multiple models in a progressive manner has lower computational complexity compared to the K-fixed strategy. This also helps in the selection of pretrained models, which captures differ-
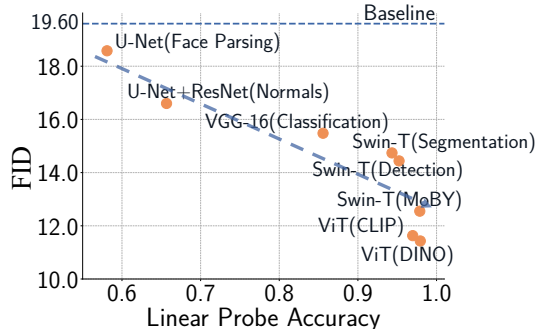

Figure 4. **Model selection using linear probing of pretrained features**. We show correlation of FID with the accuracy of a logistic linear model trained for real vs fake classification over the features of off-the-shelf models. Top dotted line is the FID of StyleGAN2-ADA generator used in model selection and from which we finetune with our proposed vision-aided adversarial loss. Similar analysis for LSUN Cat is shown in Figure 12 in the appendix.

ent aspects of the data distribution. For example, the first two models selected through the progressive strategy are usually a pair of self-supervised and supervised models. For these reasons, we primarily perform all of our experiments using the progressive strategy. We also show a comparison between the two strategies in Section 4.4.

Discussion. The idea of linear separability as a metric has been previously used for evaluating GAN via classifier two-sample tests [55, 108]. We adopt this in our work to evaluate the usefulness of available off-the-shelf discriminators, rather than evaluating generators. "Linear probing" is also a common technique for measuring the effectiveness of intermediate features spaces in both self-supervised [16, 33, 105] and supervised [3] contexts, and model selection has been explored in previous works to predict expert models for transfer learning [26, 62, 69]. We explore this in context of generative modeling and propose a progressive addition of next best model to create an ensemble [12] of discriminators.

3.3. Training Algorithm

As shown in Algorithm 1, our final algorithm consists of first training a GAN with standard adversarial loss [31, 44]. Given this baseline generator, we search for the best off-the-shelf models using linear probing and introduce our proposed loss objective during training. In the K-progressive strategy, we add the next vision-aided discriminator after training for a fixed number of iterations proportional to the number of available real training samples. The new vision-aided discriminator is added to the snapshot with the best training set FID in the previous stage. During training, we perform data augmentation through horizontal flipping and use differentiable augmentation techniques [41, 109] and one-sided label smoothing [76] as a regularization. We also observe that only using off-the-shelf models as the discriminator leads to divergence. Thus, the benefit is brought by ensembling

Dataset		StyleGAN2	DiffAugment	ADA	Ours (w/ ADA)			Ours (w/ DiffAugment)		
					+1st D	+2nd D	+3rd D	+1st D	+2nd D	+3rd D
FFHQ	1k	62.16	27.20	19.57	11.43	**10.39**	10.58	**12.33**	13.39	12.76
	2k	42.62	16.63	16.06	10.17	8.73	**8.18**	10.01	**9.24**	10.99
	10k	16.07	8.15	8.38	6.90	6.39	**5.90**	6.94	**6.26**	6.43
LSUN CAT	1k	185.75	43.32	41.14	15.49	12.90	**12.19**	13.52	12.52	**11.01**
	2k	68.03	25.70	23.32	13.44	13.35	**11.51**	12.20	11.79	**11.33**
	10k	18.59	12.56	13.25	8.37	7.13	**6.86**	8.19	7.90	**7.79**
LSUN CHURCH	1k	-	19.38	19.66	11.39	9.78	**9.56**	10.15	**9.87**	9.94
	2k	-	13.46	11.17	5.25	**5.06**	5.26	6.09	6.37	**5.56**
	10k	-	6.69	6.12	4.80	4.82	**4.47**	3.42	3.41	**3.25**

Table 1. **FFHQ and LSUN results** with varying training samples from 1k to 10k. FID↓ is measured with complete dataset as reference distribution. We select the best snapshot according to training set FID, and report mean of 3 FID evaluations. In Ours (w/ ADA) we finetune the StyleGAN2-ADA model, and in Ours (w/ DiffAugment) we finetune the model trained with DiffAgument while using the corresponding policy for augmentation. Our method works with both ADA and DiffAugment strategy for augmenting images input to the discriminators.

the original discriminator and the newly added off-the-shelf models. We show results with the use of three pretrained models and observe minimal benefit with the progressive addition of next model if the linear probe accuracy is low and worse than the models already in the selected set.

4. Experiments

Here we conduct extensive experiments on multiple datasets of different resolutions with the StyleGAN2 architecture. We show results on FFHQ [43], LSUN CAT, and LSUN CHURCH datasets [98] while varying training sample size from 1k to 10k, as well as with the full dataset. For real-world limited sample datasets, we perform experiments on the cat, dog, and wild categories of AFHQ [19] dataset at 512 resolution and METFACES [41] at 1024 resolution. In 100-400 low-shot settings, we perform experiments on AnimalFace cat and dog [82], and 100-shot Bridge-of-Sighs [109] dataset. We also show results with BigGAN [9] architecture on CIFAR [46] datasets in Appendix B.

Baseline and metrics. We compare with state-of-the-art methods for limited dataset GAN training, StyleGAN2-ADA [41] and DiffAugment [109]. We compute the commonly used Fréchet Inception Distance (FID) metric [36] using the `clean-fid` library [67] to evaluate models. In low-shot settings we evaluate on KID [8] metric as well. We report more evaluation metrics like precision and recall [49], and SwAV-FID [48, 61] using feature space of SwAV [10] model which was not used during our training in Appendix C.

Off-the-shelf models. We include eight large-scale self-supervised and supervised networks. Specifically, we perform experiments with CLIP [70], VGG-16 [83] trained for ImageNet [20] classification, and self-supervised models, DINO [11] and MoBY [95]. We also include face parsing [51] and face normals prediction networks [2]. Finally, we have Swin-Transformer [54] based segmentation model trained on ADE-20K [112] and object detection model
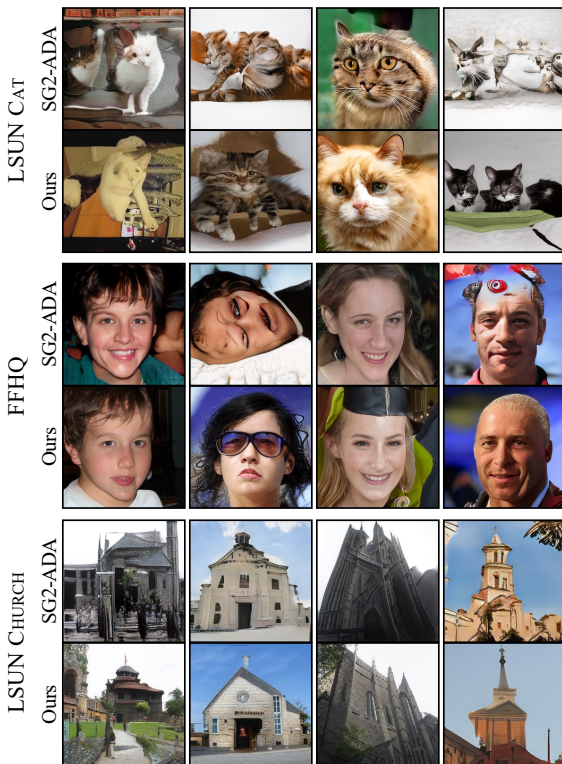

Figure 5. **LSUN CAT, FFHQ, and LSUN CHURCH paired sample comparison in 1k training dataset setting**. For each dataset, the top row shows the baseline StyleGAN2-ADA samples, and the bottom row shows the samples by Our method for the same randomly sample latent code. We fine-tune the StyleGAN2-ADA model with our vision-aided adversarial loss. For the same latent code image quality improves with our method on average.

trained on MS-COCO [52]. Full details of all models is given in Table 16 in Appendix D. We exclude the Inception model [86] trained on ImageNet since Inception features have already been used to calculate the FID metric.

Vision-aided discriminator's architecture. For discriminator $\hat{D}_k$ based on pretrained model features, we
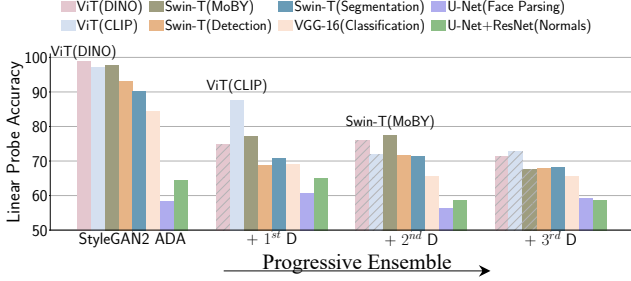
Figure 6. **Linear probe accuracy of off-the-shelf models during our K-progressive ensemble training** on FFHQ 1k. For the StyleGAN2-ADA, ViT (DINO) model has the highest accuracy and is selected first, then ViT (CLIP) and then Swin-T (MoBY). As we train with vision-aided discriminators, linear probe accuracy decreases for most of the pretrained models. Similar trend for all our experiments are shown in the Appendix D.

extract spatial features from the last layer and use a small `Conv-LeakyReLU-Linear-LeakyReLU-Linear` architecture for binary classification. In the case of big transformer networks, such as CLIP and DINO, we explore a multi-scale architecture that works better. For all experiments, we use three pretrained models selected by the model selection strategy during training. Details about the architecture, model training, memory requirements, and hyperparameters are provided in Appendix D.

4.1. FFHQ and LSUN datasets

Table 1 shows the results of our method when the training sample is varied from 1k to 10k for FFHQ, LSUN CAT, and LSUN CHURCH datasets. The considerable gain in FID for all settings shows the effectiveness of our method in the limited data scenario. To qualitatively analyze the difference between our method and StyleGAN2-ADA, we show randomly generated samples from both models given the same latent code in Figure 5. Our method improves the quality of the worst samples, especially for FFHQ and LSUN CAT (also see Figure 13, 14 in Appendix A). Figure 6 shows the accuracy of linear probe over the pretrained models' features as we progressively add the next discriminator.

To analyze the overfitting behavior of discriminators, we evaluate its training and validation accuracy across iterations. Compared to the baseline StyleGAN2-ADA discriminator, our vision-aided discriminator shows better generalization on the validation set specifically for limited-data regime as shown in Figure 3 for FFHQ 1k setting.

Full-dataset training. In the full-dataset setting, we fine-tune the trained StyleGAN2 (config-F) [44] model with our method. Table 2 shows the comparison of StyleGAN2 and ADM [21] with our method trained using three vision-aided discriminators. We report both FID and Perceptual Path Length (PPL) [43] (W space) metric. On LSUN CAT, our method improves FID from 6.86 to 3.98, on LSUN

Dataset	StyleGAN2 (F)		Ours (w/ ADA)		ADM
	FID ↓	PPL ↓	FID ↓	PPL ↓	FID ↓
FFHQ-1024	**2.98**	144.62	3.01	**127.58**	-
LSUN CAT-256	6.86	437.13	**3.98**	420.15	5.57*
LSUN CHURCH-256	4.28	**343.02**	**1.72**	388.94	-
LSUN HORSE-256	4.09	337.98	**2.11**	307.12	2.57*

Table 2. **Results on full-dataset setting**. we improve the FID metric on LSUN categories by a significant margin. On the FFHQ dataset we improve the PPL metric. ∗ means directly reported from the ADM paper [21].
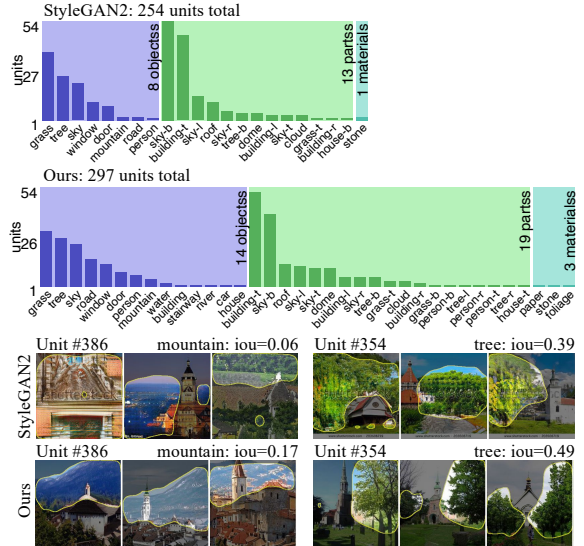

Figure 7. **GAN Dissection visualization of improved units.** We analyze StyleGAN2 and our model trained on LSUN CHURCH using GAN Dissection [7] and show here qualitative examples of units with improved IoU to a semantic category. The total number of detected units also increases from 254 to 297 for our model.

CHURCH from 4.28 to 1.72, and on LSUN HORSE from 4.09 to 2.11. For FFHQ dataset, our method improves the PPL metric from 144.62 to 127.58 and has similar performance on FID metric. Perceptual path length has been shown to correlate with image quality and indicates a smooth mapping in generator latent space [44]. Random generated samples for all models are shown in Figure 18 in Appendix A.

GAN Dissection analysis on LSUN CHURCH. How does the generator change with the use of off-the-shelf models as discriminators? To analyze this, we use the existing technique of GAN Dissection [6, 7], which calculates the correlation between convolutional feature maps of the generator and scene parts obtained through a semantic segmentation network [94]. Specifically, we select the convolutional layer with 32 resolution in the generator trained with our method and StyleGAN2 on the full LSUN CHURCH dataset. The total number of interpretable units [7] increases from 254 to 297 by our method, suggesting that our model may learn a richer representation of semantic concepts. Figure 7 shows

Dataset	Transfer	StyleGAN2			StyleGAN2-ADA			Ours (w/ ADA)		
		FID ↓	KID ↓	Recall ↑	FID ↓	KID ↓	Recall ↑	FID ↓	KID ↓	Recall ↑
AFHQ Dog	✗	22.35	10.05	0.20	7.60	1.29	0.47	**4.73**	**0.39**	**0.60**
	✓	9.28	3.13	0.42	7.52	1.22	0.43	**4.81**	**0.37**	**0.61**
AFHQ Cat	✗	5.16	1.72	0.26	3.29	0.72	0.41	**2.53**	**0.47**	**0.52**
	✓	3.48	1.07	0.47	3.02	**0.38**	0.45	**2.69**	0.62	**0.50**
AFHQ Wild	✗	3.62	0.84	0.15	3.00	0.44	0.14	**2.36**	**0.38**	**0.29**
	✓	**2.11**	**0.17**	0.35	2.72	0.17	0.29	2.18	0.28	**0.38**
MetFaces	✓	57.26	2.50	**0.34**	17.56	1.55	0.22	**15.44**	**1.03**	0.30

Table 3. **Results on AFHQ and METFACES**. Our method, in general, results in lower FID and higher Recall. In transfer setup we fine-tune from a FFHQ trained model of similar resolution with D updated according to FreezeD technique [60] similar to [41]. We select the snapshot with the best FID and show an average of three evaluations. KID is shown in $\times 10^3$ units following [41].

Figure 8. **Qualitative comparison of our method with StyleGAN2-ADA on AFHQ.** *Left:* randomly generated samples for both methods. *Right:* For both our model and StyleGAN2-ADA, we independently generate 5k samples and find the worst-case samples compared to real image distribution. We first fit a Gaussian model using the Inception [86] feature space of real images. We then calculate the log-likelihood of each sample given this Gaussian prior and show the images with minimum log-likelihood (maximum Mahalanobis distance). We show more samples in Figure 19 and Figure 20 in Appendix A.

the complete statistics of detected units corresponding to each semantic category and some of the example images of improved units by our method. We observe an overall

Method	Bridge		AnimalFace Cat		AnimalFace Dog	
	FID ↓	KID↓	FID ↓	KID ↓	FID↓	KID↓
DiffAugment	54.50	15.68	43.87	7.56	60.50	20.13
ADA	-	-	38.01	5.61	52.59	14.32
Ours +1st D	44.18	9.27	30.62	1.15	34.23	2.01
Ours +2nd D	**33.89**	**2.35**	28.01	0.37	33.03	**1.37**
Ours +3rd D	34.35	2.96	**27.35**	**0.34**	**32.56**	1.67

Table 4. **Low-shot generation results** on 100-shot Bridge dataset [109], AnimalFace cat and dog [82] categories. Our method significantly improves FID and KID compared to leading methods for few-shot GAN training. KID is shown in $\times 10^3$ units.

increase in the number of detected units as well as units corresponding to new semantic categories.

Human preference study. As suggested by [48] we perform a human preference study on Amazon Mechanical Turk (AMT) to verify that our results agree with the human judgment regarding the improved sample quality. We compare StyleGAN2-ADA and our method trained on 1k samples of LSUN CAT, LSUN CHURCH, and FFHQ datasets. Since we fine-tune StyleGAN2-ADA with our method, the same latent code corresponds to similar images for the two models, as also shown in Figure 5. For randomly sampled latent codes, we show the two images generated by our method and StyleGAN2-ADA for six seconds to the test subject and ask to select the more realistic image. We perform this study for 50 test subjects per dataset, and each subject is shown a total of 55 images. On the FFHQ dataset, human preference for our method is $53.8\% \pm 1.3$. For the LSUN CHURCH dataset, our method is preferred over StyleGAN2-ADA with $60.5\% \pm 1.7$, and for the LSUN CAT dataset $63.5\% \pm 1.6$. These results correlate with the improved FID metric. Example images from our study are shown in Figure 15.

4.2. AFHQ and METFACES

To further evaluate our method on real-world limited sample datasets, we perform experiments on METFACES (1336 images) and AFHQ dog, cat, wild categories with $\sim$ 5k images per category. We compare with StyleGAN2-ADA under
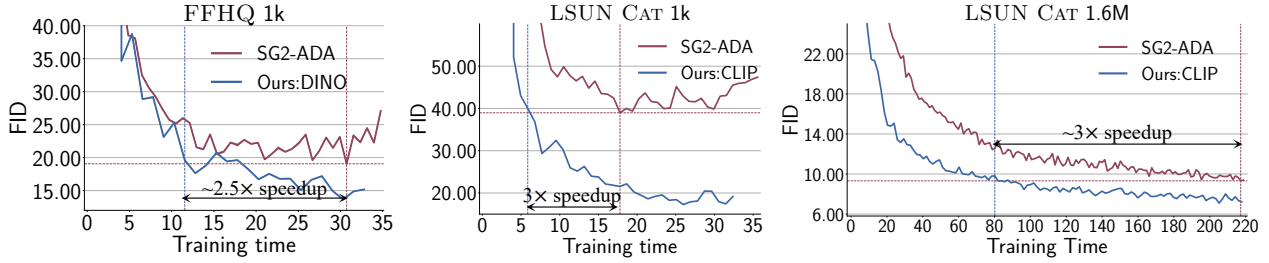
Figure 9. **FID↓ w.r.t. training time comparison** between StyleGAN2-ADA and our method (w/ ADA and one pretrained model) when applied from the start for FFHQ, LSUN CAT 1k, and LSUN CAT full-dataset setting. There is a warm-up of 0.5M images, and then our loss is added. Our method results in similar FID at more than twice the speedup. We show training time in hours measured on one RTX 3090.

two settings, (1) Fine-tuning StyleGAN2-ADA model with our loss (2) Fine-tuning from a StyleGAN2 model trained on FFHQ dataset of same resolution (transfer setup) using FreezeD [60]. The second setting evaluates the transfer learning capability when fine-tuned from a generator trained on a different domain. Table 3 shows the comparison of our method with StyleGAN2 and StyleGAN2-ADA on multiple metrics. We outperform or perform on-par compared to the existing methods in general. Figure 8 shows the qualitative comparison between our method and StyleGAN2-ADA.

4.3. Low-shot Generation

To test our method to the limit of low-shot samples, we evaluate our method when only 100-400 samples are available. We finetune StyleGAN2 model with our method on AnimalFace cat (169 images) and dog (389 images) [82], and 100-shot Bridge-of-Sighs [109] datasets. For differentiable augmentation, we use ADA except for the 100-shot dataset where we find that the DiffAugment [109] works better than ADA [41], and therefore employ that. Our method leads to considerable improvement over existing methods on both FID and KID metrics as shown in Table 4. We show nearest neighbour test and latent space interpolations in Figure 23 and Figure 24 of Appendix A.

4.4. Ablation Study

Fine-tuning vs. training from scratch. In all our experiments, we fine-tuned a well-trained StyleGAN2 model (both generator and discriminator) with our additional loss. We show here that our method works similarly well when training from scratch. Figure 9 shows the plot of FID with training time for StyleGAN2-ADA and our method with a single vision-aided discriminator on FFHQ and LSUN CAT trained with 1k samples, and LSUN CAT full-dataset setting. Our method results in better FID and converges more than $2\times$ faster. During training from scratch, we train with the standard adversarial loss for the first 0.5M images and then introduce the discriminator selected by the model selection strategy. Training with three vision-aided discriminators for same number of iterations as Table 1 we get similar FID of
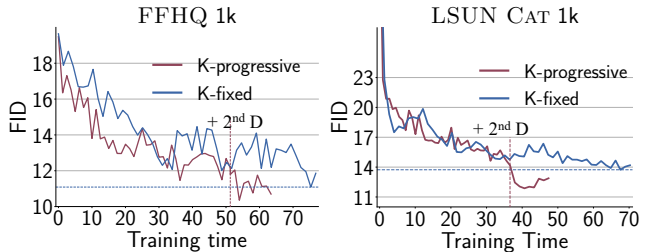

Figure 10. **K-progressive vs K-fixed comparison** on FFHQ and LSUN CAT 1k setting. Progressive addition of the next best model is computationally efficient and results in similar FID at lower run time. We show training time in hours measured on one RTX 3090.

Model	FFHQ 1k			LSUN CAT 1k		
Selection	+1st D	+2nd D	+3rd D	+1st D	+2nd D	+3rd D
Best	11.43	**10.39**	10.58	15.49	12.90	**12.19**
Random	15.48	12.54	11.92	19.02	15.12	14.28
Worst	15.48	15.45	13.88	19.02	17.53	17.66

Table 5. **FID↓ metric for models trained with different model selection strategies in K-progressive vision-aided training.** 1st *Row:* model selection with best linear probe accuracy. 2nd *Row:* randomly selecting from the bank of off-the-shelf models. 3rd *Row:* model selection with least linear probe accuracy.

10.60 and 12.24 for FFHQ and LSUN CAT 1k respectively.

K-progressive vs. K-fixed model selection. We compare the K-progressive and K-fixed model selection strategies in this section. Figure 10 shows the comparison for FFHQ 1k and LSUN CAT 1k trained for the same number of iterations with two models from our model bank. We observe that training with two fixed pretrained models from the start results in a similar or slightly worse FID at the cost of extra training time compared to the progressive addition.

Our model selection vs. random selection. We showed in Figure 4 that FID correlates with model selection ranking in vision-aided GAN training with a single pretrained model. To show the effectiveness of model selection in K-progressive strategy, we compare it with (1) random selection of models during progressive addition and (2) selection of models with
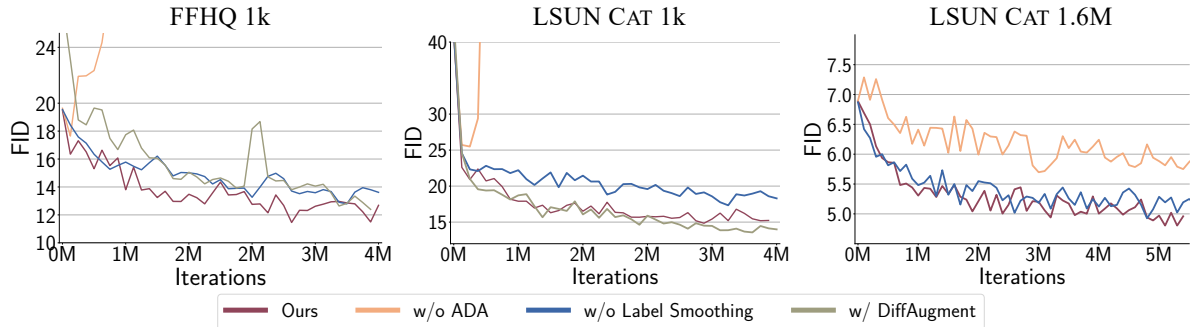
8

Figure 11. **Ablation of augmentation and label smoothing** on FFHQ and LSUN CAT with 1k training samples and LSUN CAT full-dataset setting. We show the plot of FID w.r.t training iterations when ADA [41] augmentation and label smoothing [76] are individually removed from our training. Without differentiable augmentation, model training quickly collapses in limited sample setting. Even for full-dataset, using differentiable augmentation for vision-aided discriminator results in better FID. Label smoothing has a reasonable effect in case of LSUN CAT 1k and is marginally helpful for FFHQ 1k. We also change the augmentation technique to DiffAugment [109] for both original and vision-aided discriminator and observe that it performs comparable to ADA [41].

Method	FFHQ 1k	LSUN CAT 1k	LSUN CAT 1.6M
StyleGAN2-ADA	19.57	41.14	6.86
Ours (w/ ViT (CLIP))	**11.63**	**15.49**	**4.61**
Ours w/ fine-tune ViT (CLIP)	✗	✗	✗
Ours w/ ViT random weights	19.10	33.77	6.35
Ours w/ multi-discriminator	17.59	37.01	✗
Longer StyleGAN2-ADA	19.07	39.36	6.52

Table 6. **Additional ablation studies evaluated on FID↓ metric**. Having two discriminators during training (frozen with random weights or trainable) or standard adversarial training for more iterations leads to only marginal benefits in FID. Thus the improvement is through an ensemble of original and vision-aided discriminators. ✗ means FID increased to twice the baseline, and therefore, we stop the training run.

least linear probe accuracy. The results are as shown in Table 5. We observe that random selection of pretrained models from the model bank already provides benefit in FID, but with our model selection, it can be improved further. Details of selected models are given in Appendix D.

Role of data augmentation and label smoothing. Here, we investigate the role of differentiable augmentation [41, 88, 109, 110] which is one of the important factors that enable the effective use of pretrained features. Label smoothing [76] further improves the training dynamics, especially in a limited sample setting. We ablate each of these component and show its contribution in Figure 11 on FFHQ and LSUN CAT dataset in 1k sample setting, and LSUN CAT full-dataset setting. Figure 11 shows that replacing ADA [41] augmentation strategy with DiffAugment [109] in our method also performs comparably. Moreover, in the limited sample setting, without data augmentation, model collapses very early in training, and FID diverges. The role of label smoothing is more prominent in limited data setting e.g. LSUN CAT 1k.

Additional ablation study. Here we further analyze the im-

portance of our design choice. All the experiments are done on LSUN CAT and FFHQ. We compare our method with the following settings: (1) Fine-tuning ViT (CLIP) network as well in our vision-aided adversarial loss; (2) Randomly initializing the feature extractor network ViT (CLIP); (3) Training with two discriminators, where the 2nd discriminator is of same architecture as StyleGAN2 original discriminator; (4) Training the StyleGAN2-ADA model longer for the same number of iterations as ours with standard adversarial loss. The results are as shown in Table 6. We observe that the baseline methods provide marginal improvement, whereas our method offers significant improvement over StyleGAN2-ADA, as measured by FID.

5. Limitations and Discussion

In this work, we propose to use available off-the-shelf models to help in the unconditional GAN training. Our method significantly improves the quality of generated images, especially in the limited-data setting. While the use of multiple pretrained models as discriminators improves the generator, it has a few limitations. First, this increases memory requirement for training. Exploring the use of efficient computer vision models [77, 87] will potentially make our method more accessible. Second, our model selection strategy is not ideal in the low-shot settings when only a dozen samples are available. We observe increased variance in the linear probe accuracy with sample size ∼ 100 which can lead to ineffective model selection. We plan to adopt few-shot learning [29, 84] methods for these settings in future.

Nonetheless, as more and more self-supervised and supervised computer vision models are readily available, they should be used to good advantage for generative modeling. This paper serves as a small step towards improving generative modeling by transferring the knowledge from large-scale representation learning.

References

[1] Rameen Abdal, Yipeng Qin, and Peter Wonka. Image2stylegan: How to embed images into the stylegan latent space? In *ICCV*, 2019. 2

[2] Victoria Fernández Abrevaya, Adnane Boukhayma, Philip HS Torr, and Edmond Boyer. Cross-modal deep face normals with deactivable skip connections. In *CVPR*, 2020. 5, 18

[3] Guillaume Alain and Yoshua Bengio. Understanding intermediate layers using linear classifier probes. *arXiv preprint arXiv:1610.01644*, 2016. 4

[4] Isabela Albuquerque, João Monteiro, Thang Doan, Breandan Considine, Tiago Falk, and Ioannis Mitliagkas. Multi-objective training of generative adversarial networks with multiple discriminators. In *ICML*, 2019. 2

[5] Martin Arjovsky, Soumith Chintala, and Léon Bottou. Wasserstein Generative Adversarial Networks. In *ICML*, 2017. 2

[6] David Bau, Jun-Yan Zhu, Hendrik Strobelt, Agata Lapedriza, Bolei Zhou, and Antonio Torralba. Understanding the role of individual units in a deep neural network. *Proceedings of the National Academy of Sciences*, 2020. 3, 6

[7] David Bau, Jun-Yan Zhu, Hendrik Strobelt, Bolei Zhou, Joshua B Tenenbaum, William T Freeman, and Antonio Torralba. Gan dissection: Visualizing and understanding generative adversarial networks. In *ICLR*, 2019. 6

[8] Mikołaj Bińkowski, Danica J Sutherland, Michael Arbel, and Arthur Gretton. Demystifying mmd gans. In *ICLR*, 2018. 5

[9] Andrew Brock, Jeff Donahue, and Karen Simonyan. Large scale gan training for high fidelity natural image synthesis. In *ICLR*, 2019. 1, 3, 5, 14

[10] Mathilde Caron, Ishan Misra, Julien Mairal, Priya Goyal, Piotr Bojanowski, and Armand Joulin. Unsupervised learning of visual features by contrasting cluster assignments. In *NeurIPS*, 2020. 5

[11] Mathilde Caron, Hugo Touvron, Ishan Misra, Hervé Jégou, Julien Mairal, Piotr Bojanowski, and Armand Joulin. Emerging properties in self-supervised vision transformers. In *ICCV*, 2021. 2, 3, 5, 18

[12] Rich Caruana, Alexandru Niculescu-Mizil, Geoff Crew, and Alex Ksikes. Ensemble selection from libraries of models. In *ICML*, 2004. 4

[13] Arantxa Casanova, Marlène Careil, Jakob Verbeek, Michal Drozdzal, and Adriana Romero. Instance-conditioned gan. In *NeurIPS*, 2021. 2

[14] Lucy Chai, David Bau, Ser-Nam Lim, and Phillip Isola. What makes fake images detectable? understanding properties that generalize. In *European Conference on Computer Vision*, pages 103–120. Springer, 2020. 17

[15] Qifeng Chen and Vladlen Koltun. Photographic image synthesis with cascaded refinement networks. In *ICCV*, 2017. 2

[16] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. A simple framework for contrastive learning of visual representations. In *ICML*, 2020. 1, 2, 4

[17] Wei-Yu Chen, Yen-Cheng Liu, Zsolt Kira, Yu-Chiang Frank Wang, and Jia-Bin Huang. A closer look at few-shot classification. In *ICLR*, 2019. 3

[18] Xinlei Chen, Haoqi Fan, Ross Girshick, and Kaiming He. Improved baselines with momentum contrastive learning. *arXiv preprint arXiv:2003.04297*, 2020. 1

[19] Yunjey Choi, Youngjung Uh, Jaejun Yoo, and Jung-Woo Ha. Stargan v2: Diverse image synthesis for multiple domains. In *CVPR*, 2020. 5

[20] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *CVPR*, 2009. 5, 18

[21] Prafulla Dhariwal and Alexander Nichol. Diffusion models beat gans on image synthesis. In *NeurIPS*, 2021. 6

[22] Thang Doan, Joao Monteiro, Isabela Albuquerque, Bogdan Mazoure, Audrey Durand, Joelle Pineau, and R Devon Hjelm. On-line adaptative curriculum learning for gans. In *AAAI*, 2019. 2

[23] Jeff Donahue, Yangqing Jia, Oriol Vinyals, Judy Hoffman, Ning Zhang, Eric Tzeng, and Trevor Darrell. Decaf: A deep convolutional activation feature for generic visual recognition. In *ICML*, 2014. 2

[24] Alexey Dosovitskiy and Thomas Brox. Generating images with perceptual similarity metrics based on deep networks. In *NeurIPS*, 2016. 2

[25] Ishan Durugkar, Ian Gemp, and Sridhar Mahadevan. Generative multi-adversarial networks. In *ICLR*, 2017. 2

[26] Kshitij Dwivedi and Gemma Roig. Representation similarity analysis for efficient task taxonomy & transfer learning. In *CVPR*, 2019. 4

[27] Raghudeep Gadde, Qianli Feng, and Aleix M Martinez. Detail me more: Improving gan's photo-realism of complex scenes. In *ICCV*, 2021. 2

[28] Leon A Gatys, Alexander S Ecker, and Matthias Bethge. Image style transfer using convolutional neural networks. In *CVPR*, 2016. 2

[29] Spyros Gidaris, Andrei Bursuc, Nikos Komodakis, Patrick Pérez, and Matthieu Cord. Boosting few-shot visual learning with self-supervision. In *ICCV*, 2019. 9

[30] Ross Girshick, Jeff Donahue, Trevor Darrell, and Jitendra Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. In *CVPR*, 2014. 3

[31] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial networks. *Communications of the ACM*, 63(11):139–144, 2020. 2, 4

[32] Zheng Gu, Wenbin Li, Jing Huo, Lei Wang, and Yang Gao. Lofgan: Fusing local representations for few-shot image generation. In *ICCV*, 2021. 2

[33] Kaiming He, Haoqi Fan, Yuxin Wu, Saining Xie, and Ross Girshick. Momentum contrast for unsupervised visual representation learning. In *CVPR*, 2020. 4

[34] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *CVPR*, 2016. 1

[35] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *CVPR*, 2016. 2

[36] Martin Heusel, Hubert Ramsauer, Thomas Unterthiner, Bernhard Nessler, and Sepp Hochreiter. Gans trained by a two time-scale update rule converge to a local nash equilibrium. In *NeurIPS*, 2017. 2, 5

[37] Minyoung Huh, Pulkit Agrawal, and Alexei A Efros. What makes imagenet good for transfer learning? *arXiv preprint arXiv:1608.08614*, 2016. 2

[38] Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A Efros. Image-to-image translation with conditional adversarial networks. In *CVPR*, 2017. 15

[39] Justin Johnson, Alexandre Alahi, and Li Fei-Fei. Perceptual losses for real-time style transfer and super-resolution. In *ECCV*, 2016. 2

[40] Tero Karras, Timo Aila, Samuli Laine, and Jaakko Lehtinen. Progressive growing of gans for improved quality, stability, and variation. In *ICLR*, 2018. 2

[41] Tero Karras, Miika Aittala, Janne Hellsten, Samuli Laine, Jaakko Lehtinen, and Timo Aila. Training generative adversarial networks with limited data. In *NeurIPS*, 2020. 1, 2, 3, 4, 5, 7, 8, 9, 14, 15, 16, 18, 22, 23

[42] Tero Karras, Miika Aittala, Samuli Laine, Erik Härkönen, Janne Hellsten, Jaakko Lehtinen, and Timo Aila. Alias-free generative adversarial networks. In *NeurIPS*, 2021. 1, 2

[43] Tero Karras, Samuli Laine, and Timo Aila. A style-based generator architecture for generative adversarial networks. In *CVPR*, 2019. 2, 5, 6

[44] Tero Karras, Samuli Laine, Miika Aittala, Janne Hellsten, Jaakko Lehtinen, and Timo Aila. Analyzing and improving the image quality of stylegan. In *CVPR*, 2020. 3, 4, 6, 16, 17, 24

[45] Simon Kornblith, Jonathon Shlens, and Quoc V Le. Do better imagenet models transfer better? In *CVPR*, 2019. 2

[46] Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. 2009. 5, 14, 15

[47] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In *NeurIPS*, 2012. 2

[48] Tuomas Kynkäänniemi, Tero Karras, Miika Aittala, Timo Aila, and Jaakko Lehtinen. The role of imagenet classes in fr\'echet inception distance. *arXiv preprint arXiv:2203.06026*, 2022. 5, 7, 14

[49] Tuomas Kynkäänniemi, Tero Karras, Samuli Laine, Jaakko Lehtinen, and Timo Aila. Improved precision and recall metric for assessing generative models. In *NeurIPS*, 2019. 5, 14

[50] Christian Ledig, Lucas Theis, Ferenc Huszár, Jose Caballero, Andrew Cunningham, Alejandro Acosta, Andrew Aitken, Alykhan Tejani, Johannes Totz, Zehan Wang, et al. Photorealistic single image super-resolution using a generative adversarial network. In *CVPR*, 2017. 2

[51] Cheng-Han Lee, Ziwei Liu, Lingyun Wu, and Ping Luo. Maskgan: Towards diverse and interactive facial image manipulation. In *CVPR*, 2020. 5, 18

[52] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *ECCV*, 2014. 5

[53] Bingchen Liu, Yizhe Zhu, Kunpeng Song, and Ahmed Elgammal. Towards faster and stabilized gan training for high-fidelity few-shot image synthesis. In *ICLR*, 2021. 2

[54] Ze Liu, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin, and Baining Guo. Swin transformer: Hierarchical vision transformer using shifted windows. In *ICCV*, 2021. 5, 18

[55] David Lopez-Paz and Maxime Oquab. Revisiting classifier two-sample tests. In *ICLR*, 2017. 4

[56] Puneet Mangla, Nupur Kumari, Mayank Singh, Balaji Krishnamurthy, and Vineeth N Balasubramanian. Data instance prior (disp) in generative adversarial networks. *arXiv preprint arXiv:2012.04256*, 2020. 2

[57] Xudong Mao, Qing Li, Haoran Xie, Raymond YK Lau, Zhen Wang, and Stephen Paul Smolley. Least squares generative adversarial networks. In *CVPR*, 2017. 2

[58] Lars Mescheder, Andreas Geiger, and Sebastian Nowozin. Which training methods for gans do actually converge? In *ICML*, 2018. 2

[59] Takeru Miyato and Masanori Koyama. cgans with projection discriminator. In *ICLR*, 2018. 14, 18

[60] Sangwoo Mo, Minsu Cho, and Jinwoo Shin. Freeze the discriminator: a simple baseline for fine-tuning gans. In *CVPRW*, 2020. 2, 7, 8, 16, 18

[61] Stanislav Morozov, Andrey Voynov, and Artem Babenko. On self-supervised image representations for gan evaluation. In *ICLR*, 2021. 5, 14, 16, 17

[62] Basil Mustafa, Carlos Riquelme, Joan Puigcerver, André Susano Pinto, Daniel Keysers, and Neil Houlsby. Deep ensembles for low-data transfer learning. *arXiv preprint arXiv:2010.06866*, 2020. 4

[63] Atsuhiro Noguchi and Tatsuya Harada. Image generation from small datasets via batch statistics adaptation. In *ICCV*, 2019. 2

[64] Utkarsh Ojha, Yijun Li, Jingwan Lu, Alexei A Efros, Yong Jae Lee, Eli Shechtman, and Richard Zhang. Fewshot image generation via cross-domain correspondence. In *CVPR*, 2021. 2

[65] Maxime Oquab, Leon Bottou, Ivan Laptev, and Josef Sivic. Learning and transferring mid-level image representations using convolutional neural networks. In *CVPR*, 2014. 2

[66] Taesung Park, Ming-Yu Liu, Ting-Chun Wang, and Jun-Yan Zhu. Semantic image synthesis with spatially-adaptive normalization. In *CVPR*, 2019. 2

[67] Gaurav Parmar, Richard Zhang, and Jun-Yan Zhu. On buggy resizing libraries and surprising subtleties in fid calculation. *arXiv preprint arXiv:2104.11222*, 2021. 5, 14

[68] Or Patashnik, Zongze Wu, Eli Shechtman, Daniel Cohen-Or, and Dani Lischinski. Styleclip: Text-driven manipulation of stylegan imagery. In *ICCV*, 2021. 2

11

[69] Joan Puigcerver, Carlos Riquelme, Basil Mustafa, Cedric Renggli, André Susano Pinto, Sylvain Gelly, Daniel Keysers, and Neil Houlsby. Scalable transfer learning with expert models. In *ICLR*, 2021. 4

[70] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *ICML*, 2021. 1, 2, 5, 18

[71] Alec Radford, Luke Metz, and Soumith Chintala. Unsupervised representation learning with deep convolutional generative adversarial networks. In *ICLR*, 2016. 2

[72] Stephan R Richter, Hassan Abu AlHaija, and Vladlen Koltun. Enhancing photorealism enhancement. *arXiv preprint arXiv:2105.04619*, 2021. 2

[73] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, et al. Imagenet large scale visual recognition challenge. *IJCV*, 115(3):211–252, 2015. 1

[74] Kate Saenko, Brian Kulis, Mario Fritz, and Trevor Darrell. Adapting visual category models to new domains. In *ECCV*, 2010. 2

[75] Alexander Sage, Eirikur Agustsson, Radu Timofte, and Luc Van Gool. Logo synthesis and manipulation with clustered generative adversarial networks. In *CVPR*, 2018. 2

[76] Tim Salimans, Ian Goodfellow, Wojciech Zaremba, Vicki Cheung, Alec Radford, and Xi Chen. Improved techniques for training gans. In *NeurIPS*, 2016. 2, 4, 9, 15

[77] Mark Sandler, Andrew Howard, Menglong Zhu, Andrey Zhmoginov, and Liang-Chieh Chen. Mobilenetv2: Inverted residuals and linear bottlenecks. In *CVPR*, 2018. 9, 17

[78] Axel Sauer, Kashyap Chitta, Jens Müller, and Andreas Geiger. Projected gans converge faster. In *NeurIPS*, 2021. 2

[79] Edgar Schonfeld, Bernt Schiele, and Anna Khoreva. A u-net based discriminator for generative adversarial networks. In *CVPR*, 2020. 14

[80] Yujun Shen, Ceyuan Yang, Xiaoou Tang, and Bolei Zhou. Interfacegan: Interpreting the disentangled face representation learned by gans. *IEEE TPAMI*, 2020. 2

[81] Assaf Shocher, Yossi Gandelsman, Inbar Mosseri, Michal Yarom, Michal Irani, William T Freeman, and Tali Dekel. Semantic pyramid for image generation. In *CVPR*, 2020. 2

[82] Zhangzhang Si and Song-Chun Zhu. Learning hybrid image templates (hit) by information projection. *PAMI*, 34(7):1354–1367, 2011. 5, 7, 8, 30, 35

[83] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. In *ICLR*, 2015. 1, 5

[84] Jake Snell, Kevin Swersky, and Richard S Zemel. Prototypical networks for few-shot learning. In *NeurIPS*, 2017. 9

[85] Diana Sungatullina, Egor Zakharov, Dmitry Ulyanov, and Victor Lempitsky. Image manipulation with perceptual discriminators. In *ECCV*, 2018. 2

[86] Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna. Rethinking the inception architecture for computer vision. In *CVPR*, 2016. 5, 7, 25

[87] Mingxing Tan and Quoc Le. Efficientnet: Rethinking model scaling for convolutional neural networks. In *ICML*, 2019. 9, 17

[88] Ngoc-Trung Tran, Viet-Hung Tran, Ngoc-Bao Nguyen, Trung-Kien Nguyen, and Ngai-Man Cheung. Towards good practices for data augmentation in gan training. *arXiv preprint arXiv:2006.05338*, 2, 2020. 2, 9

[89] Eric Tzeng, Judy Hoffman, Kate Saenko, and Trevor Darrell. Adversarial discriminative domain adaptation. In *CVPR*, 2017. 2

[90] Sheng-Yu Wang, Oliver Wang, Richard Zhang, Andrew Owens, and Alexei A Efros. Cnn-generated images are surprisingly easy to spot... for now. In *CVPR*, 2020. 3, 17

[91] Ting-Chun Wang, Ming-Yu Liu, Jun-Yan Zhu, Andrew Tao, Jan Kautz, and Bryan Catanzaro. High-resolution image synthesis and semantic manipulation with conditional gans. In *CVPR*, 2018. 2

[92] Yaxing Wang, Abel Gonzalez-Garcia, David Berga, Luis Herranz, Fahad Shahbaz Khan, and Joost van de Weijer. Minegan: effective knowledge transfer from gans to target domains with few images. In *CVPR*, 2020. 2

[93] Yaxing Wang, Chenshen Wu, Luis Herranz, Joost van de Weijer, Abel Gonzalez-Garcia, and Bogdan Raducanu. Transferring gans: generating images from limited data. In *ECCV*, 2018. 2

[94] Tete Xiao, Yingcheng Liu, Bolei Zhou, Yuning Jiang, and Jian Sun. Unified perceptual parsing for scene understanding. In *ECCV*, pages 418–434, 2018. 6

[95] Zhenda Xie, Yutong Lin, Zhuliang Yao, Zheng Zhang, Qi Dai, Yue Cao, and Han Hu. Self-supervised learning with swin transformers. *arXiv preprint arXiv:2105.04553*, 2021. 2, 5, 18

[96] Ceyuan Yang, Yujun Shen, Yinghao Xu, and Bolei Zhou. Data-efficient instance generation from instance discrimination. In *NeurIPS*, 2021. 2

[97] Jason Yosinski, Jeff Clune, Yoshua Bengio, and Hod Lipson. How transferable are features in deep neural networks? In *NeurIPS*, 2014. 2

[98] Fisher Yu, Ari Seff, Yinda Zhang, Shuran Song, Thomas Funkhouser, and Jianxiong Xiao. Lsun: Construction of a large-scale image dataset using deep learning with humans in the loop. *arXiv preprint arXiv:1506.03365*, 2015. 1, 2, 5

[99] Ning Yu, Ke Li, Peng Zhou, Jitendra Malik, Larry Davis, and Mario Fritz. Inclusive gan: Improving data and minority coverage in generative models. In *ECCV*, 2020. 2

[100] Amir R Zamir, Alexander Sax, William Shen, Leonidas J Guibas, Jitendra Malik, and Silvio Savarese. Taskonomy: Disentangling task transfer learning. In *CVPR*, 2018. 2

[101] Matthew D Zeiler and Rob Fergus. Visualizing and understanding convolutional networks. In *ECCV*, 2014. 2, 3

[102] Han Zhang, Tao Xu, Hongsheng Li, Shaoting Zhang, Xiaogang Wang, Xiaolei Huang, and Dimitris N Metaxas. Stackgan: Text to photo-realistic image synthesis with stacked generative adversarial networks. In *ICCV*, 2017. 2

[103] Han Zhang, Zizhao Zhang, Augustus Odena, and Honglak Lee. Consistency regularization for generative adversarial networks. In *ICLR*, 2020. 15

[104] Richard Zhang. Making convolutional networks shift-invariant again. In *ICML*, 2019. 18

[105] Richard Zhang, Phillip Isola, and Alexei A Efros. Split-brain autoencoders: Unsupervised learning by cross-channel prediction. In *CVPR*, 2017. 4

[106] Richard Zhang, Phillip Isola, Alexei A Efros, Eli Shechtman, and Oliver Wang. The unreasonable effectiveness of deep features as a perceptual metric. In *CVPR*, 2018. 2, 3

[107] Miaoyun Zhao, Yulai Cong, and Lawrence Carin. On leveraging pretrained gans for generation with limited data. In *ICML*, 2020. 2

[108] Shengyu Zhao, Jonathan Cui, Yilun Sheng, Yue Dong, Xiao Liang, Eric I Chang, and Yan Xu. Large scale image completion via co-modulated generative adversarial networks. In *ICLR*, 2021. 4

[109] Shengyu Zhao, Zhijian Liu, Ji Lin, Jun-Yan Zhu, and Song Han. Differentiable augmentation for data-efficient gan training. In *NeurIPS*, 2020. 1, 2, 3, 4, 5, 7, 8, 9, 14, 15, 22, 23, 30, 35

[110] Zhengli Zhao, Zizhao Zhang, Ting Chen, Sameer Singh, and Han Zhang. Image augmentations for gan training. *arXiv preprint arXiv:2006.02595*, 2020. 2, 9

[111] Bolei Zhou, Agata Lapedriza, Aditya Khosla, Aude Oliva, and Antonio Torralba. Places: A 10 million image database for scene recognition. *IEEE TPAMI*, 40(6):1452–1464, 2017. 1

[112] Bolei Zhou, Hang Zhao, Xavier Puig, Tete Xiao, Sanja Fidler, Adela Barriuso, and Antonio Torralba. Semantic understanding of scenes through the ade20k dataset. *International Journal of Computer Vision*, 127(3):302–321, 2019. 5

[113] Jun-Yan Zhu, Philipp Krähenbühl, Eli Shechtman, and Alexei A Efros. Generative visual manipulation on the natural image manifold. In *ECCV*, 2016. 2

[114] Peihao Zhu, Rameen Abdal, John Femiani, and Peter Wonka. Barbershop: Gan-based image compositing using segmentation masks, 2021. 2

Appendix

We show more visualizations and quantitative results to show the efficacy of our method. Namely, Section A shows qualitative comparisons between our method and leading methods for GAN training i.e. StyleGAN2-ADA [41] and DiffAugment [109]. In Section B we show results of our vision-aided adversarial training with BigGAN architecture on CIFAR-10 and CIFAR-100 datasets. In Section C, we show more evaluation of our model on other metrics. Section D details our training hyperparameters, discriminator architectures, and selected models in each experiment. In Section E, we discuss the societal impact of our work.

A. Qualitative Image Analysis

In Figure 13, we show more randomly generated images by StyleGAN2-ADA and our method with the same latent code for FFHQ, LSUN CAT, and LSUN CHURCH 1k training sample setting similar to Figure 5 of the main paper. Figure 14 shows similar comparison between DiffAugment and our method. In many cases, our method improves the visual quality of samples compared to the baseline.

For the human preference study conducted on the 1k sample setting, Figure 15 shows the sample images for the cases where users preferred our generated images or StyleGAN2-ADA generated images. Figure 16 and Figure 17 show randomly generated images by our method, StyleGAN2-ADA, and DiffAugment for varying training sample settings of FFHQ, LSUN CAT, and LSUN CHURCH.

For AFHQ and METFACES, Figure 19 and Figure 20 show the qualitative comparison between StyleGAN2-ADA and our method (similar to Figure 8 in the main paper). Figure 21 and Figure 22 show similar comparison for FFHQ, LSUN CAT, and LSUN CHURCH 1k training sample setting. We also qualitatively evaluate our low-shot trained models on nearest neighbour test from training images in Figure 23. Figure 24 shows the latent interpolation of models trained by our method in the low-shot setting with $100 - 400$ real samples. The smooth interpolation shows that the model is probably not overfitting on the few real samples.

B. Vision-aided BigGAN

Here, we perform experiments with BigGAN architecture [9] on CIFAR-10 and CIFAR-100 datasets [46]. Table 7 shows the comparison of vision-aided adversarial training with the current leading method DiffAugment [109] in both unconditional and conditional settings, with varying training dataset sizes. We outperform DiffAugment across all settings according to the FID metric. In the case of unconditional training with BigGAN, we use self-modulation in the generator layers [61, 79]. During conditional training, we use projection discriminator [59] in the vision-aided discriminator as well. The training is done for the same number of
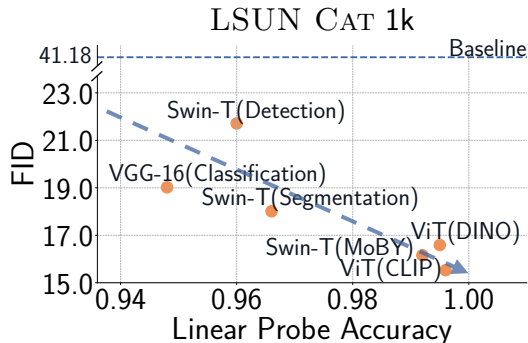

Figure 12. **Model selection using linear probing of pretrained features** on LSUN CAT 1k training sample setting. We show correlation of FID with the accuracy of a logistic linear model trained for real vs fake classification over the features of off-the-shelf models. Top dotted line is the FID of StyleGAN2-ADA generator used in model selection and from which we finetune with our proposed vision-aided adversarial loss. Thus, selecting models with higher linear probe accuracy in general results in better generative model with respect to FID metric.

iterations as DiffAugment [109].

C. Evaluation

We measure FID using `clean-fid` library [67] with $50k$ generated samples and complete training dataset as the reference distribution in all our experiments similar to StyleGAN2-ADA [41] except in low-shot setting. For low-shot 100-400 sample setting we compute FID and KID with $5k$ generated samples and full available real dataset as the reference following DiffAugment [109]. In addition to the FID metric reported in the main paper, we report in Table 9 and Table 10, precision and recall metrics [49] for FFHQ and LSUN experiments with varying training sample size and full-dataset. We observe that our method improves the recall metric in all cases and has similar or better precision, particularly in the limited sample settings. Recent studies [48, 61] suggest reporting FID metrics in different feature spaces, in order to avoid "attacking" the evaluation metric. As such, we also report FID, but using the feature space of a self-supervised model trained on ImageNet via SwAV [61], in Table 11 to Table 14, and observe consistent improvements. Moreover, as shown in Table 1 and Table 8, when using CLIP (which is not trained on ImageNet) or using DINO (a self-supervised method that does not require ImageNet labels) in our vision-aided training, we also improve FID scores. Table 15 shows the results on progressive addition of vision-aided discriminator on METFACES and AFHQ.

D. Training and Hyperparameter details

Off-the-shelf models and discriminator head architecture. We provide network details of off-the-shelf mod-

BigGAN	Conditional				Unconditional			
	CIFAR-10		CIFAR-100		CIFAR-10		CIFAR-100	
	100 %	10 %	100 %	10 %	100 %	10 %	100 %	10 %
DiffAugment [109]	10.09	27.81	13.60	39.59	15.23	32.63	19.20	33.75
DiffAugment + CR [103]	9.68	22.89	12.65	30.53			-	
Ours +1ˢᵗ D	9.93	17.03	12.46	23.30	12.41	21.17	16.08	25.13
+2ⁿᵈ D	9.25	14.28	11.50	20.05	11.59	17.39	15.05	20.89
+3ʳᵈ D	**8.75**	**13.11**	**10.88**	**15.71**	**11.17**	**16.34**	**14.10**	**19.13**

Table 7. Vision-aided GAN training on CIFAR-10 and CIFAR-100 [46] with the BigGAN architecture. We improve FID on both conditional and unconditional training setups. FID is calculated using `clean-fid` with 10k generated samples and test set as the reference distribution. The three off-the-shelf models selected by model selection are CLIP, DINO, and MoBY (Swin-T), respectively, in all settings.

Discriminator Architecture	Dataset	
	LSUN CAT 1k	FFHQ 1k
Single-scale (MLP)	17.21	13.31
Multi-scale	**15.49**	**11.63**

Table 8. **FID↓ on Single-scale vs Multi-scale discriminator head for ViT (CLIP)**. We observe slightly better FID with a multi-scale discriminator head compared to a 2-layer MLP head on final classification token feature, without any significant increase in training time. Therefore, we select the multi-scale discriminator head for all our experiments on both CLIP and DINO with ViT-B architecture.

els we used in our experiments in Table 16. For extracting features, we resize both real and fake images to the resolution that the pretrained network was trained on. For the trainable discriminator head, we use a `Conv-LeakyReLU-Linear-LeakyReLU-Linear` architecture over the spatial features after $2\times$ downsampling for all pretrained models except CLIP and DINO. In the case of CLIP and DINO with ViT-B architecture, we observed that a multi-scale architecture leads to marginally better results (as shown in Table 8). We extract the spatial features at 4 and 8 layers and the final classifier token feature. For each spatial feature, we use a `Conv-LeakyReLU-Conv` with downsampling to predict a 3×3 real vs fake logits similar to PatchGAN [38], and the loss is averaged over the 3×3 spatial grid. On the classifier token, we use `Linear-LeakyReLU-Linear` discriminator head for a global real vs. fake prediction. The final loss is the sum of losses at the three scales. Extracted feature size for each model and exact architecture of the trainable discriminator head is detailed in Table 16.

Linear accuracy analysis of all experiments Figure 25 - Figure 29 show the linear probe accuracy of the pretrained models and the selected model based on that. We calculate linear probe accuracy on the average of 3 runs (variance is always less than 1.% except in 100-400 low-sample setting where it increases to $\sim 5 - 8\%$). For the limited sample setting, we use the complete set of real training samples and

the same amount of generated samples. For the full-dataset setting, we randomly sample a subset of 10k real and generated samples during linear probe accuracy calculation. We observe diminished variance in the linear classifier validation accuracy with the increase in sample size. The computational cost of calculating linear probe accuracy for a model varies with the sample size and dataset resolution but is always in the order of $5 - 10$ minutes, including the time for fake image generation for training linear classifier as measured on one RTX 3090.

Details of our model selection vs random selection experiment in Section 4.4 In FFHQ 1k, our method selects DINO, CLIP, and Swin-T (MoBY) during training. Random selection consists of VGG-16, Swin-T (MoBY), and U-Net (Face Parsing) networks and worst selection consists of VGG-16, U-Net (Face Parsing), and U-Net (Face Normals) networks. For LSUN CAT 1k setting, CLIP, DINO, and Swin-T (Segmentation) networks are selected by our method during training. In random selection VGG-16, CLIP, and Swin-T (Segmentation) networks are selected and worst selection consists of VGG-16, Swin-T (Segmentation), and Swin-T (Detection) networks.

Training hyperparameters and memory requirement. We keep similar architecture and training hyperparameters as StyleGAN2-ADA [41]. For experiments on FFHQ, LSUN CAT, and LSUN CHURCH with varying sample size, number of feature maps at shallow layers is halved [41]. For 256 resolution datasets, the weight of R_1 regularization (γ) in the original discriminator is 1, learning rate is 0.002 and path length regularization is 2. For datasets with 512 resolution, γ is 0.5 and learning rate is 0.0025. When using ADA in our vision-aided adversarial loss, we employ cutout + bgc [41] policy for augmentation, and if the linear probe accuracy of the selected model is above 90% one-sided label smoothing [76] is used as a regularization. The ADA target value for the original discriminator in StyleGAN2-ADA is kept the same at 0.6. For vision-aided discriminators, we use 0.3 as the target probability for ADA in all limited data experiments. In case of finetuning from the StyleGAN2 model

Dataset		StyleGAN2		DiffAugment		ADA		Ours (w/ ADA)					
								+1st D		+2nd D		+3rd D	
		P ↑	R ↑	P ↑	R ↑	P ↑	R ↑	P ↑	R ↑	P ↑	R ↑	P ↑	R ↑
FFHQ	1k	0.580	0.000	0.681	0.034	0.675	0.088	0.719	0.139	**0.740**	0.139	0.694	**0.173**
	2k	0.586	0.025	0.709	0.099	0.676	0.137	0.701	0.242	0.719	0.251	**0.719**	**0.251**
	10k	0.669	0.191	0.704	0.256	0.700	0.255	0.683	0.334	0.687	0.342	**0.697**	**0.351**
LSUN CAT	1k	0.290	0.000	0.539	0.015	0.468	0.012	**0.653**	0.033	0.627	0.053	0.624	**0.058**
	2k	0.527	0.001	0.607	0.032	0.617	0.066	**0.667**	0.084	.645	0.105	0.652	**0.120**
	10k	0.632	0.099	0.628	0.188	0.598	0.111	**0.639**	0.152	0.615	0.181	0.599	**0.203**
LSUN Church	1k	-	-	0.593	0.015	0.554	0.038	**0.652**	0.047	0.609	**0.065**	0.645	0.063
	2k			0.613	0.042	0.604	0.075	0.637	0.100	0.626	0.107	**0.649**	0.114
	10k	-	-	0.567	0.256	0.617	0.108	**0.662**	0.132	0.645	0.112	0.643	**0.133**

Table 9. **Precision (P) and Recall (R) metrics for experiments on FFHQ and LSUN datasets** with varying training samples from 1k to 10k. Complete training dataset is used as the reference distribution for calculating the above metrics and average of 3 evaluation runs is reported. Our method results in higher recall and precision in all settings. In addition, we observe that as we add vision-aided discriminators, recall increases at the cost of slight decrease in precision.

Dataset	Resolution	StyleGAN2 (F)			Ours (w/ ADA)								
					+1st D			+2nd D			+3rd D		
		FID ↓	P ↑	R ↑	FID ↓	P↑	R ↑	FID ↓	P↑	R ↑	FID ↓	P↑	R ↑
FFHQ	1024 × 1024	**2.98**	**0.684**	0.495	3.11	0.656	**0.519**	3.01	0.678	0.499	3.09	0.665	0.507
LSUN CAT	256 × 256	6.86	0.606	0.318	4.61	**0.626**	0.341	4.19	0.608	0.355	**3.98**	0.598	**0.381**
LSUN CHURCH	256 × 256	4.28	0.594	0.391	2.05	0.596	0.447	1.81	0.603	0.451	**1.72**	**0.612**	0.451
LSUN HORSE	256 × 256	4.09	0.609	0.357	2.79	**0.636**	0.369	2.38	0.614	0.406	**2.11**	0.611	**0.416**

Table 10. **FID**, **Preicison (P), and Recall (R) metrics on full-dataset setting**. Our method results in improved recall for most cases and has similar precision compared to StyleGAN2. A higher recall is usually preferred as with truncation precision can be recovered [44].

Dataset		StyleGAN2	DiffAugment	ADA	Ours (w/ ADA)	Ours (w/ DiffAugment)
FFHQ	1k	14.42	6.31	4.15	**1.18**	1.95
	2k	7.72	3.53	3.32	**0.91**	1.27
	10k	3.85	1.95	1.59	**0.61**	0.73
LSUN CAT	1k	22.71	10.74	10.33	3.27	**2.82**
	2k	14.97	7.90	6.23	3.10	**2.57**
	10k	6.92	4.97	4.50	**1.78**	1.96
LSUN CHURCH	1k	-	7.66	6.49	**2.50**	2.87
	2k	-	6.28	4.54	**1.49**	1.57
	10k	-	3.43	3.25	1.24	**0.98**

Table 11. **SwAV-FID [61] of models trained on FFHQ, LSUN datasets with varying training samples**. FID↓ is measured in SwAV ResNet-50 feature space with complete dataset as reference distribution. We select the best snapshot according to training set FID, and report mean of 3 FID evaluations. In Ours (w/ ADA) we finetune the pretrained StyleGAN2-ADA model, and in Ours (w/ DiffAugment) we finetune the model trained with DiffAgument while using the corresponding policy for augmentation.

Dataset	Transfer	StyleGAN2-ADA	Ours (w/ ADA)
AFHQ DOG	✗	2.02	**1.04**
	✓	1.89	**1.03**
AFHQ CAT	✗	1.17	**0.62**
	✓	0.98	**0.70**
AFHQ WILD	✗	1.89	**1.10**
	✓	1.23	**0.97**
METFACES	✓	2.14	**1.72**

Table 12. **SwAV-FID [61] of models trained on AFHQ categories and METFACES**. FID↓ is measured in SwAV ResNet-50 feature space with complete dataset as reference distribution. We select the best snapshot according to training set FID, and report mean of 3 FID evaluations. In transfer setup we fine-tune from a FFHQ trained model of similar resolution with D updated according to FreezeD technique [60] similar to [41].

in the full-dataset setting on FFHQ and LSUN categories, the original discriminator has non-augmented real and fake images as input and ADA target for additional discriminators is 0.1. In case of training with DiffAugment, we always

use one-sided label smoothing and all three augmentations color, translation, and cutout. All experiments are done with a batch size of 16 (mini-batch std 4) on a single RTX 3090 GPU for 256 resolution, and 4 GPUs for 512, 1024 resolution datasets. In the case of LSUN HORSE, we fine-tuned StyleGAN2 (config F) model with a batch size of 64 and use

Dataset	StyleGAN2 (F)	Ours (w/ ADA)
FFHQ-1024	0.57	**0.38**
LSUN CAT-256	2.65	**1.03**
LSUN CHURCH-256	1.81	**0.58**
LSUN HORSE-256	1.65	**0.71**

Table 13. **SwAV-FID [61] of models trained on full dataset of FFHQ and LSUN categories**. FID↓ is measured in SwAV ResNet-50 feature space with complete dataset as reference distribution. We select the best snapshot according to training set FID, and report mean of 3 FID evaluations.

Method	Bridge		AnimalFace Cat		AnimalFace Dog	
	FID ↓	KID ↓	FID ↓	KID ↓	FID ↓	KID ↓
DiffAugment	8.83	4.96	12.14	5.62	18.48	7.56
ADA	-	-	10.87	4.55	15.60	5.41
Ours	**3.46**	**0.22**	**5.18**	**0.29**	**6.47**	**0.35**

Table 14. **SwAV-FID [61] and KID of models trained on low-shot datasets**. FID and KID are measured in SwAV ResNet-50 feature space with complete dataset as reference distribution and 5k generated images. We select the best snapshot according to training set FID, and report mean of 3 FID and KID evaluations. KID is shown in $\times 10^3$ units.

γ value of 100 following [44].

In all experiments, we train with an ensemble of three vision-aided discriminators. The number of training iterations after which we add the second model is 1 million (1M) in low-shot generation settings, 4M for 1k training sample setting, and 8M for the rest. With the second and third pretrained model, we train for 1M training iterations on < 1k training sample setting and 2M otherwise. The GPU memory requirement of our method is maximum when using VGG-16 model at $\sim$ 2.5GB. Next, CLIP and DINO model with ViT-B architecture have a memory requirement of $\sim$ 2GB. Pretrained models based on tiny Swin-T architecture and face normals and parsing model lead to < 1GB of overhead in GPU memory during training. Compared to training the StyleGAN2 (config F) model architecture on 256 resolution images which required $\sim$ 10.5GB of GPU memory on a single RTX 3090, the overhead in memory with a single pretrained model is $10 - 25\%$ approximately. The maximum overhead in memory is when CLIP, DINO, and Swin-T based models are selected by model selection strategy. This results in $\sim$ 4.5GB of additional memory requirement as measured on one RTX 3090 while training with our default batch-size of 16 on 256 resolution dataset. In the future, we hope to explore the use of efficient [77, 87] computer vision models to reduce the increased memory requirement of our method.

E. Societal Impact

Our proposed method is towards improving the image quality of GANs, specifically in the limited sample setting.

This can help users in novel content creation where usually only few relevant samples are available for inspiration. Also, the faster convergence of our method when used in training from scratch makes it accessible to a broad set of people as the model can be trained at a lower computational cost. This can lead to negative societal impact as well through the creation of fake data and disinformation. One of the possible solutions to mitigate this can be to ensure reliable detection of fake generated data [14, 90].

F. Change log

v1: Original draft.

v2: We included additional visualization and revised text in experiments and appendix section. Specifically, we added Figure 14 to show qualitative comparison between our method and DiffAugment. We also added Table 15 in Appendix to show intermediate results with progressive addition of pretrained models for METFACES and AFHQ categories. Figure 25 - Figure 29 in Appendix is updated to include linear probe accuracy plots corresponding to experiments with DiffAugment. We also updated relevant citations.

v3: We included additional results on CIFAR datasets with BigGAN in Table 7. We also added the FID evaluation using SwAV model in Table 11 to Table 14 and nearest neighbour test for low-shot models in Figure 23.

| Dataset | Transfer | Ours (w/ ADA) | | | | | | | | |
| | | +1$^{\text{st}}$ D | | | +2$^{\text{nd}}$ D | | | +3$^{\text{rd}}$ D | | |
		FID ↓	KID ↓	Recall ↑	FID ↓	KID ↓	Recall ↑	FID ↓	KID ↓	Recall ↑
AFHQ Dog	✗	5.67	0.61	0.54	4.82	**0.33**	0.58	**4.73**	0.39	**0.60**
	✓	5.86	0.70	0.54	5.08	0.41	0.59	**4.81**	**0.37**	**0.61**
AFHQ Cat	✗	2.95	0.57	0.46	2.70	0.61	0.49	**2.53**	**0.47**	**0.52**
	✓	2.93	0.82	0.48	2.93	0.94	0.50	**2.69**	**0.62**	0.50
AFHQ Wild	✗	2.82	0.38	0.18	2.51	0.41	0.24	**2.36**	**0.38**	**0.29**
	✓	2.26	0.34	0.35	2.18	0.28	0.34	**2.18**	**0.28**	**0.38**
MetFaces	✓	17.10	2.18	0.30	15.82	1.37	0.29	**15.44**	**1.03**	**0.30**

Table 15. **Results on AFHQ and MetFaces** with progressive addition of vision-aided discriminators. In transfer setup we fine-tune from a FFHQ trained model of similar resolution with D updated according to FreezeD technique [60] similar to [41]. We select the snapshot with the best FID and show an average of three evaluations. KID is shown in $\times 10^3$ units following [41].

Vision task	Network	Params	Extracted feature size	D_i Architecture
ImageNet [20] classifier	VGG-16 [104]	138M	$512 \times 7 \times 7$	2 × avg. downsampling
MoBY [95]	tiny Swin-T	29M	$768 \times 7 \times 7$	Conv3x3: ch → 256
Face parsing [51]	U-Net	1.9M	$256 \times 8 \times 8$	LeakyReLU(0.2)
Face normals [2]	U-Net + ResNet	35M	$512 \times 8 \times 8$	Linear: 256 × h × w → 256
Segmentation [54]	tiny Swin-T	29M	$768 \times 8 \times 8$	LeakyReLU(0.2)
Object detection [54]	tiny Swin-T	29M	$768 \times 8 \times 8$	Linear: 256 → 1
CLIP [70]	ViT-B32	86M	$768 \times 7 \times 7$ $768 \times 7 \times 7$ 512	2× { Conv3x3: ch → 256; LeakyReLU(0.2); 2 × avg. downsample; Conv3x3: 256 → 1 }, { Linear: 512 → 256; LeakyReLU(0.2); Linear: 256 → 1 }
DINO [11]	ViT-B16	85M	$768 \times 14 \times 14$ $768 \times 14 \times 14$ 768	2× { 2 × avg. downsample; Conv3x3: ch → 128; LeakyReLU(0.2); 2 × avg. downsample; Conv3x3: 128 → 1 }, { Linear: 768 → 128; LeakyReLU(0.2); Linear: 128 → 1 }

Table 16. **Off-the-shelf Model Bank.** We select state-of-the-art feature extractors and task specific networks to use as an ensemble of off-the-shelf discriminators during GAN training. We keep the discriminator head architecture small and fairly similar across different models. In the multi-scale architecture of CLIP and DINO, we extract the spatial features from 4 and 8 layers and final classification token feature. In case of conditional training for CIFAR-10 and CIFAR-100 we use an additional embedding layer for number of classes and employ projection discriminator [59].
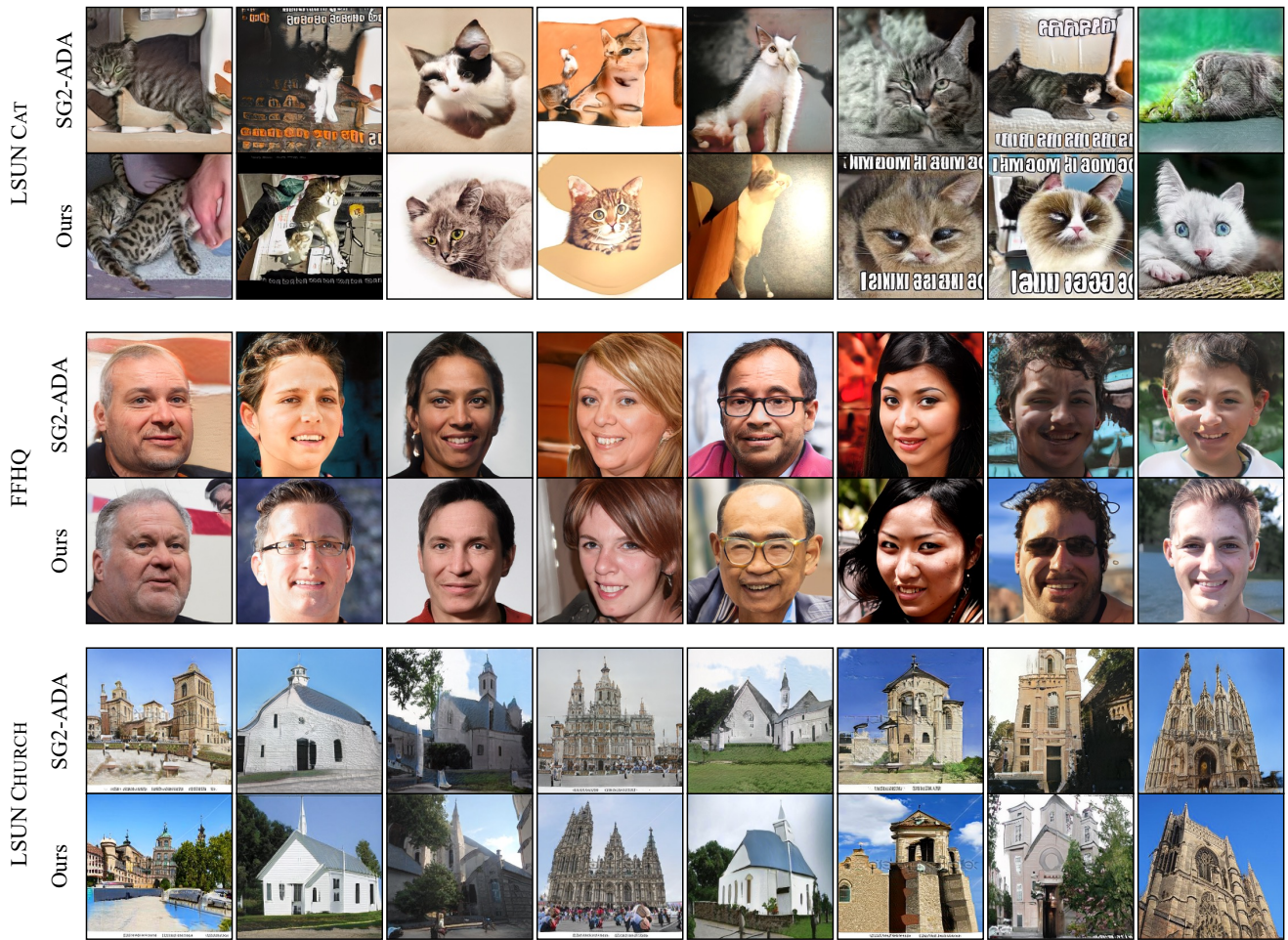
Figure 13. **LSUN Cat, FFHQ, and LSUN Church paired sample comparison in 1k training dataset setting with ADA**. For each dataset, the top row shows random samples of the baseline StyleGAN2-ADA, and the bottom row shows the samples by our method for the same latent code. We fine-tune StyleGAN2-ADA model with our vision-aided adversarial loss. On average we observe improved image quality with our method for the same latent code.
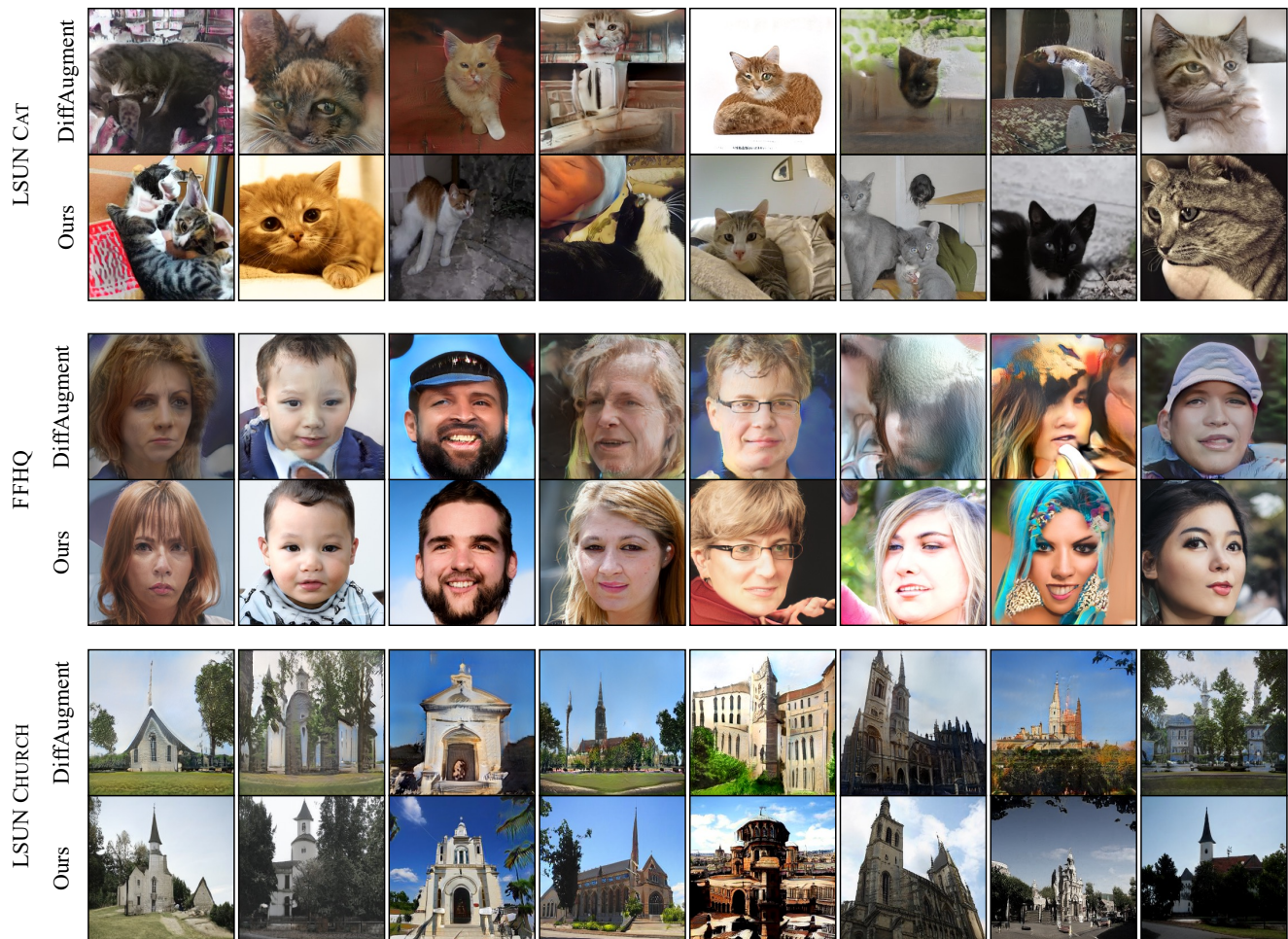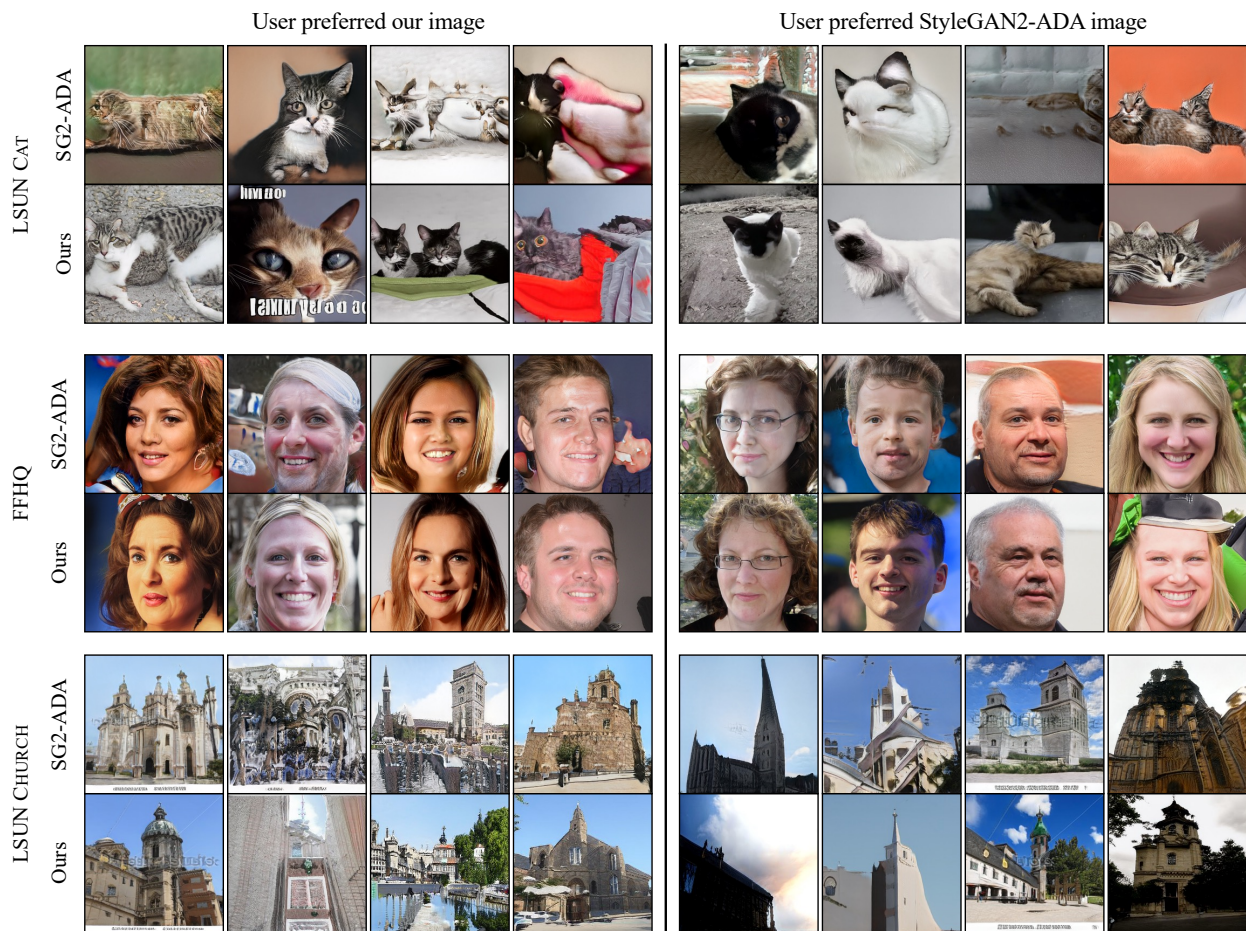
Figure 14. **LSUN Cᴀᴛ, FFHQ, and LSUN Cʜᴜʀᴄʜ paired sample comparison in 1k training dataset setting with DiffAugment**. For each dataset, the top row shows random samples of the baseline DiffAugment model with StyleGAN2 architecture, and the bottom row shows the samples by our method for the same latent code. We fine-tune StyleGAN2-DiffAugment model with our vision-aided adversarial loss. On average we observe improved image quality with our method for the same latent code.

Figure 15. **Example images shown to users in the human preference study between our method (w/ ADA) and StyleGAN2-ADA** on LSUN CAT, FFHQ, and LSUN CHURCH 1k training sample setting. *Left:* example instances where images generated by our method is preferred by users. *Right:* where images generated by StyleGAN2-ADA is preferred. For each dataset, top and bottom row show the two images generated by StyleGAN2-ADA and our method from the same random latent code and shown to the user. For LSUN CAT, FFHQ, and LSUN CHURCH our method is preferred with 63.5%, 53.8%, and 60.5% as mentioned in the main paper.

Figure 16. **Randomly generated samples** by DiffAugment [109], StyleGAN2-ADA [41] and Our method (w/ ADA) on 2k and 10k sample setting of FFHQ and LSUN CAT.

Figure 17. **Randomly generated samples** by DiffAugment [109], StyleGAN2-ADA [41] and Our method (w/ ADA) on LSUN CHURCH 2k and 10k training sample setting.

Figure 18. **Uncurated samples** generated by StyleGAN2 [44] and Our method (w/ ADA) trained on full-dataset of FFHQ, LSUN CAT, LSUN CHURCH, and LSUN HORSE.
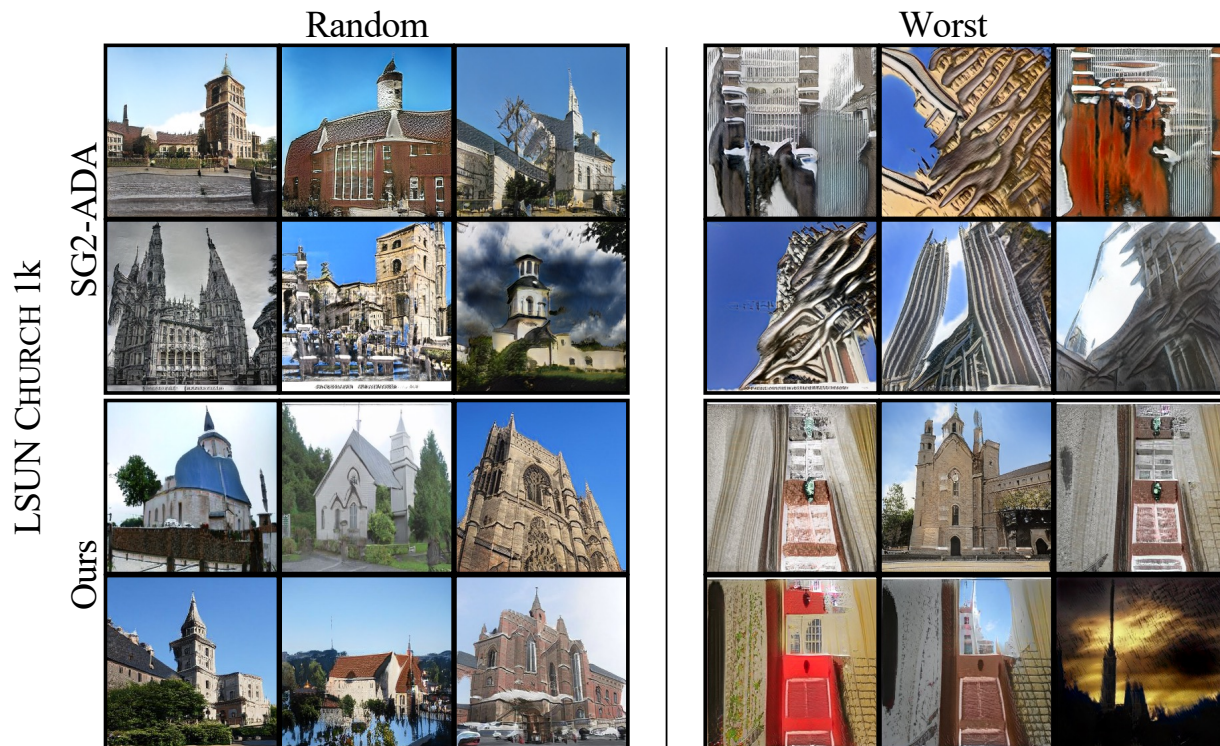
Figure 19. **Qualitative comparison of our method (w/ ADA) with StyleGAN2-ADA on AFHQ Dog and AFHQ Cat.** *Left:* randomly generated samples for both methods. *Right:* **Worst FID samples**. For both our model and StyleGAN2-ADA, we independently generate 5k samples and find the worst-case samples compared to real image distribution. We first fit a Gaussian model using the Inception [86] feature space of real images. We then calculate the log-likelihood of each sample given this Gaussian prior and show the images with minimum log-likelihood (maximum Mahalanobis distance). Our method shows better image quality on average compared to StyleGAN2-ADA.

Figure 20. **Qualitative comparison of our method (w/ ADA) with StyleGAN2-ADA on AFHQ WILD and METFACES** *Left:* randomly generated samples for both methods. *Right:* samples with maximum Mahalanobis distance as described in Figure 19.

Figure 21. **Qualitative comparison of our method (w/ ADA) with StyleGAN2-ADA on FFHQ and LSUN Cat 1k training sample setting** *Left:* randomly generated samples for both methods. *Right:* samples with maximum Mahalanobis distance as described in Figure 19. Our method to a large extent prevents generation of rotated images with extreme artifacts in case of FFHQ 1k training sample setting.

Figure 22. **Qualitative comparison of our method (w/ ADA) with StyleGAN2-ADA on LSUN Church 1k** *Left:* randomly generated samples for both methods. *Right:* samples with maximum Mahalanobis distance as described in Figure 19. Our method has relatively better worst case samples compared to StyleGAN2-ADA.

Figure 23. Nearest neighbor test on low-shot data settings. *Left column*: generated images by our model. *Middle column*: LPIPS based nearest neighbors from the training set. *Right column*: pixel wise L_1 distance based nearest neighbors. We observe that the generated images are different from the training set. Thus our model is not simply memorizing the training set.

Figure 24. **Latent interpolation results** of models trained with our method on AnimalFace Cat (169 images), AnimalFace Dog (389 images) [82] and 100-shot Bridge-of-Sighs [109] datasets. The smooth interpolation suggests that there is probably little overfitting in the trained generator.

Figure 25. **Linear probe accuracy of off-the-shelf models during our K-progressive ensemble training** on FFHQ with different training sample setting for both ADA and DiffAugment. The selected model at each stage is annotated at the top of the bar-plot. As we include more vision-aided discriminators during GAN training, linear probe accuracy of the pretrained models decreases.
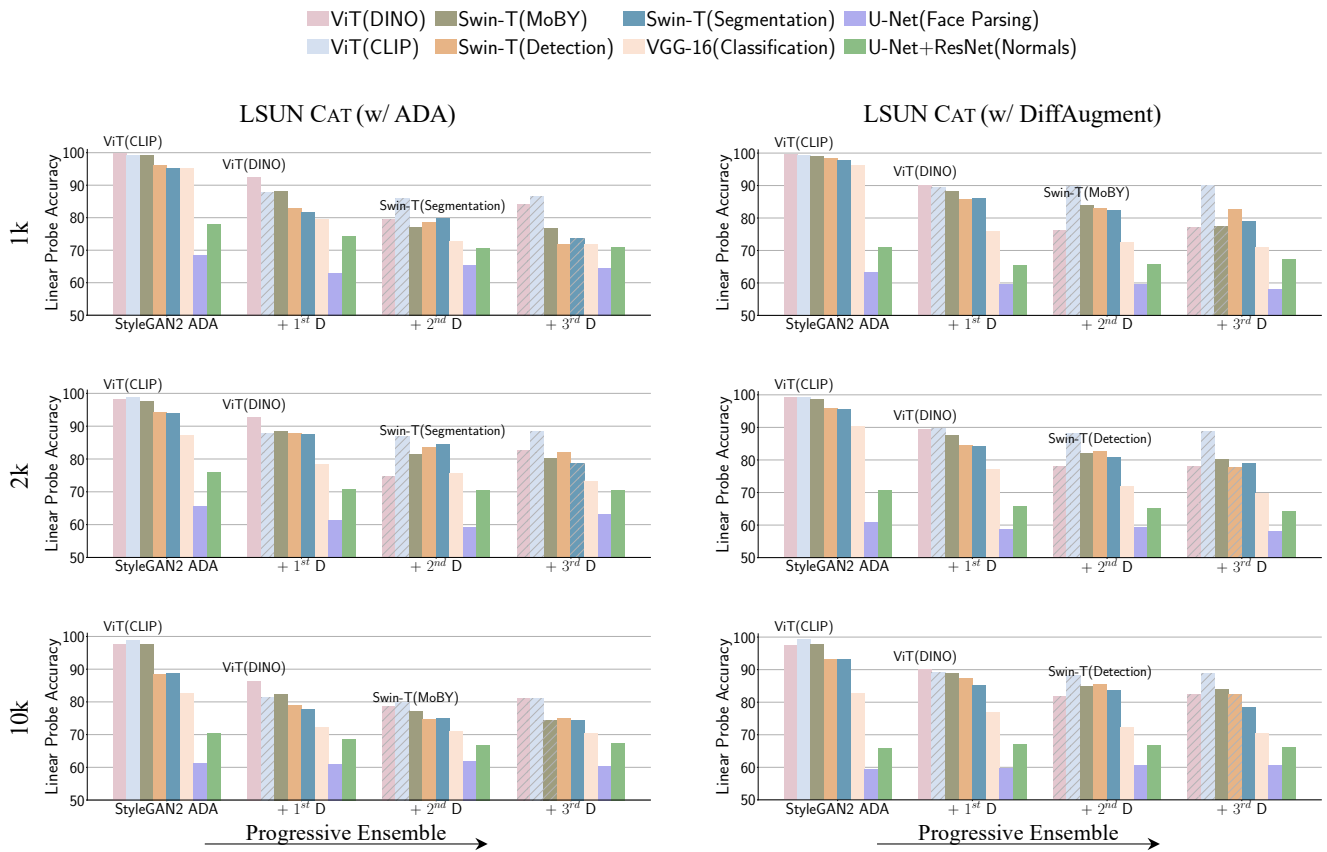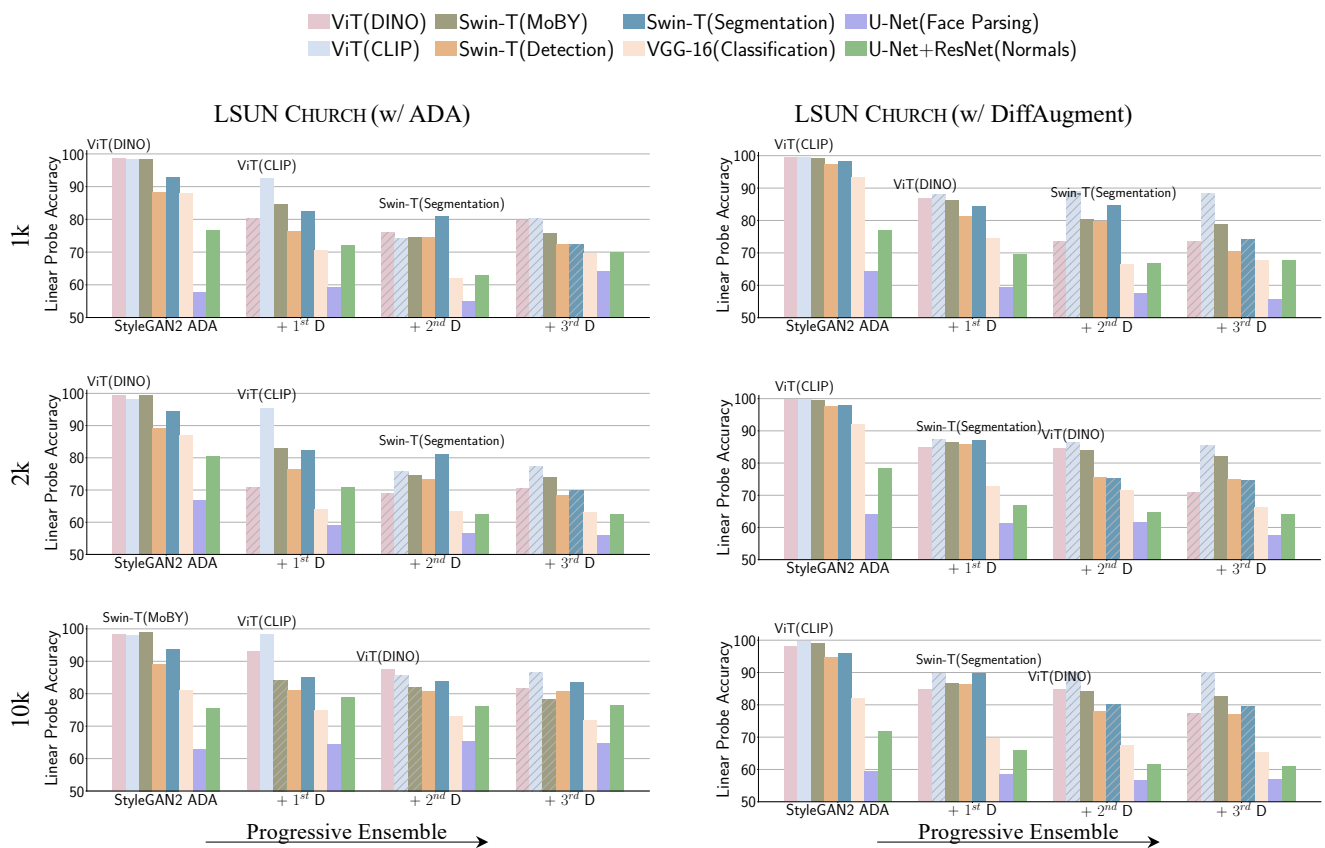
Figure 26. **Linear probe accuracy of off-the-shelf models during our K-progressive ensemble training** on LSUN CAT with different training sample setting for both ADA and DiffAugment. The selected model at each stage is annotated at the top of the bar-plot. As we include more vision-aided discriminators during GAN training, linear probe accuracy of the pretrained models decreases.

Figure 27. **Linear probe accuracy of off-the-shelf models during our K-progressive ensemble training** on LSUN CHURCH with different training sample setting for both ADA and DiffAugment. The selected model at each stage is annotated at the top of the bar-plot. As we include more vision-aided discriminators during GAN training, linear probe accuracy of the pretrained models decreases.
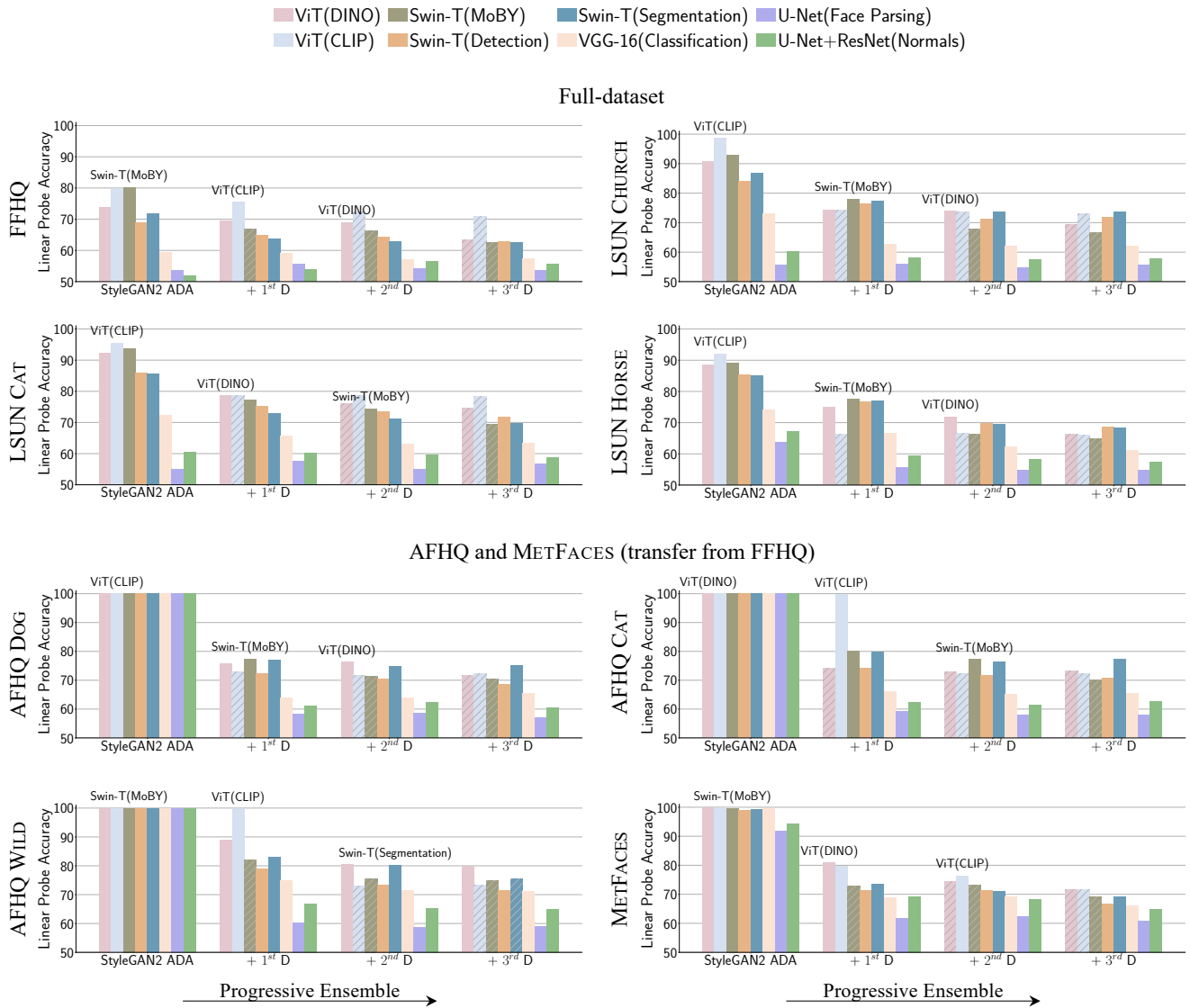
Figure 28. **Linear probe accuracy of off-the-shelf models during our K-progressive ensemble training** on full-dataset of FFHQ, LSUN categories and AFHQ, METFACES (transfer from FFHQ trained generator). In case of transfer from FFHQ, linear probe accuracy is 100% at the start as human faces and AFHQ categories have a significant domain gap. The selected model at each stage is annotated at the top of the bar-plot. As we include more vision-aided discriminators during GAN training, linear probe accuracy of the pretrained models decreases.
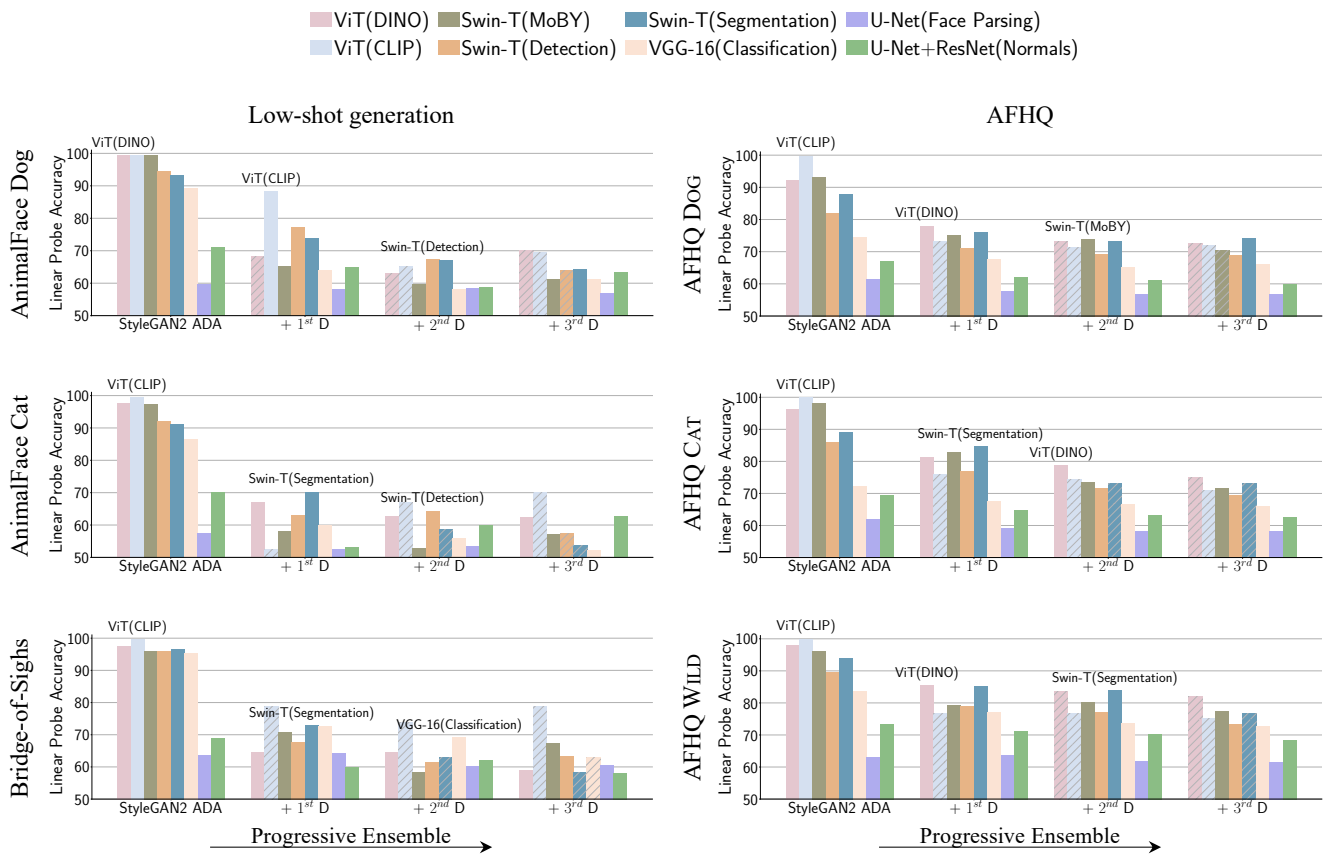
Figure 29. **Linear probe accuracy of off-the-shelf models during our K-progressive ensemble training** on AnimalFace Cat, Dog [82] and 100-shot Bridge-of-Sighs [109] low-shot datasets, and AFHQ categories. The selected model at each stage is annotated at the top of the bar-plot. As we include more vision-aided discriminators during GAN training, linear probe accuracy of the pretrained models decreases.