Progressive Augmentation of GANs (PA-GANs)

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arxiv github

1 Motivation

Generative adversarial network (GAN) [1]:

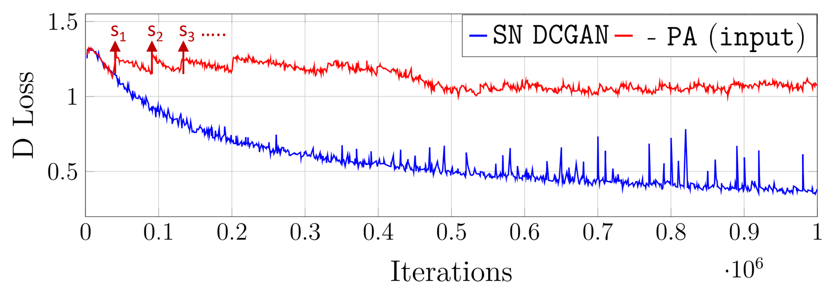
$$\min_G \max_D \mathbb{E}_{\mathbf{x}\sim\mathbb{P}_d}\{\log[D(\mathbf{x})]\} + \mathbb{E}_{\mathbf{x}\sim\mathbb{P}_g}\{\log[1-D(\mathbf{x})]\}$$

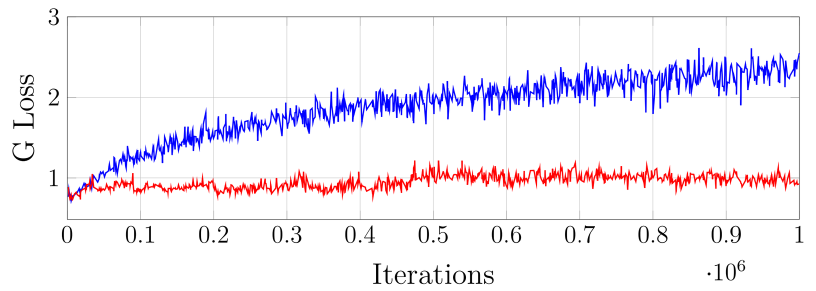
The discriminator (D) tells the samples from the data distribution $\mathbb{P}_d$ and generative model distribution $\mathbb{P}_g$. The generator (G) challenges D by making synthetic samples into data samples, i.e., $\mathbb{P}_g \to \mathbb{P}_d$.

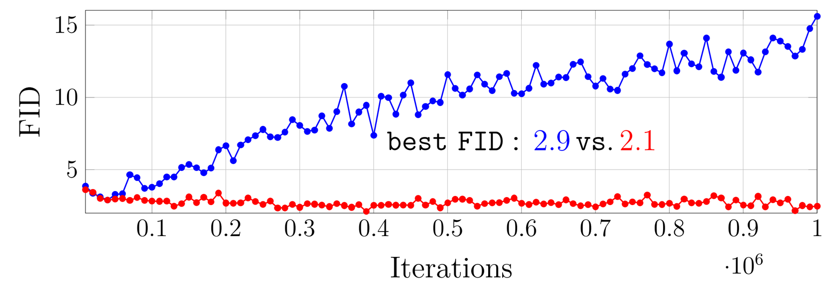
- Sensitive to learning parameters and training schedule;
- Suffers from mode collapse; …

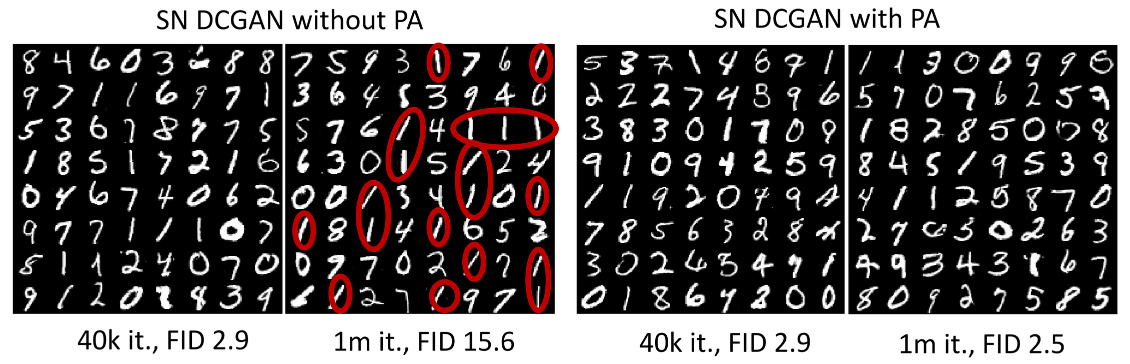
Commonly occurring problem:
Discriminator becomes overconfident, providing a non-informative signal to train the generator.

Our solution:
*Progressive augmentation (**PA**) of discriminator to gradually increase its task difficulty in order to enable continuous learning of generator.*









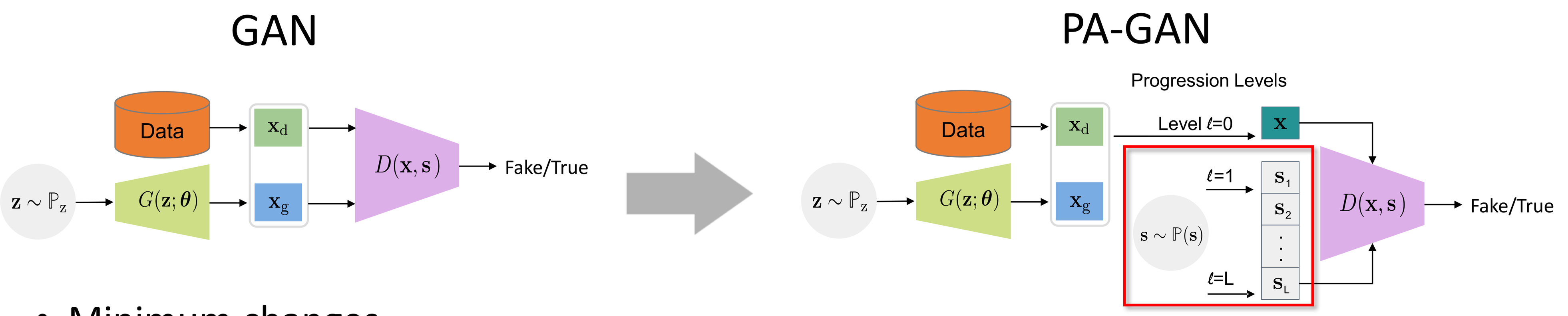
PA prevents mode collapsing to a subset of classes (e.g., digit 1)

- ✓ Novel mechanism to balance the two-player game;
- ✓ Theoretically justified (preserves the original GAN objective);
- ✓ Alleviates (partially) the need for fine hyper-parameter tuning;
- ✓ Improves generated sample diversity.

3 Method

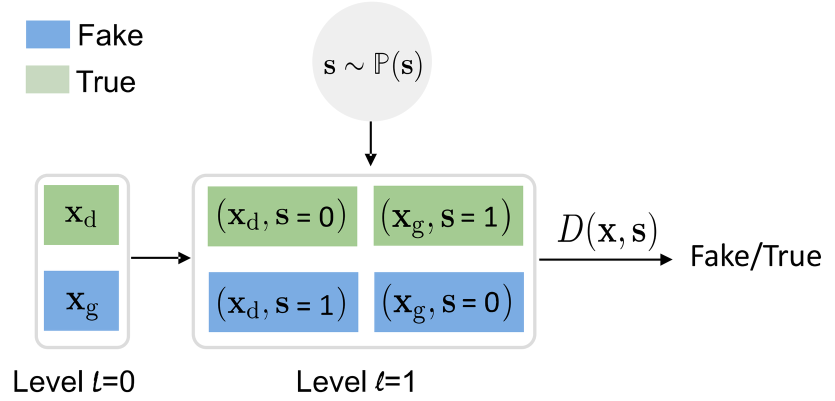
- **Augment** D's input (or its features) ***x*** with random bit ***s*** and cast binary classification of D into ***XOR*** computation between ***x*** and ***s***.
- **Progressively** add more bits ***s***={s_1, …, s_L} to ***x*** in order to gradually complicate D's task during training.

Network Layout



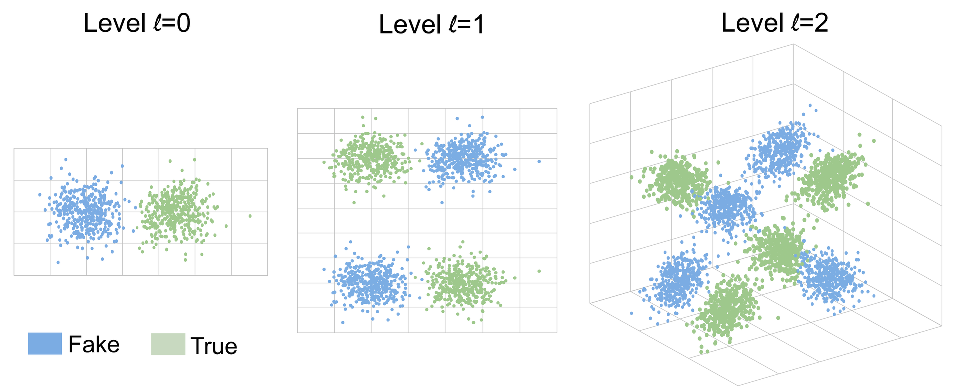
- Minimum changes
- Easy integration

Augmentation principle



- $x_d \sim P_d$ ⇔ 0, $x_g \sim P_g$ ⇔1, and s ∈ {0,1};
- XOR(x, s): 0 (1) ⇔ True(FAKE);
- D preserves the task of estimating the JSD between P_d and P_g under PA.

Progression mechanism



- Automatic scheduling;
- D's task difficulty gradually increases via augmentation progression.

Theorem of PA-GANs: The min-max optimization problem of GANs [1] is equivalent to

$$\min_G \max_D \mathbb{E}_{(\mathbf{x},\mathbf{s}_l)\sim\mathbb{P}}\{\log[D(\mathbf{x},\mathbf{s}_l)]\} + \mathbb{E}_{(\mathbf{x},\mathbf{s}_l)\sim\mathbb{Q}}\{\log[1-D(\mathbf{x},\mathbf{s}_l)]\} \quad \forall l \in \{1,2,\ldots,L\}$$

$$\mathbb{P} \triangleq \begin{cases}\prod_l \mathbb{P}_s(s_l)\mathbb{P}_d(\mathbf{x}) & \text{if } \mathrm{XOR}(\mathbf{s}_l)=0\\ \prod_l \mathbb{P}_s(s_l)\mathbb{P}_g(\mathbf{x}) & \text{if } \mathrm{XOR}(\mathbf{s}_l)=1\end{cases} \quad \mathbb{Q} \triangleq \begin{cases}\prod_l \mathbb{P}_s(s_l)\mathbb{P}_d(\mathbf{x}) & \text{if } \mathrm{XOR}(\mathbf{s}_l)=1\\ \prod_l \mathbb{P}_s(s_l)\mathbb{P}_g(\mathbf{x}) & \text{if } \mathrm{XOR}(\mathbf{s}_l)=0\end{cases} \quad \mathbb{P}_s(s_l)=0.5 \; s_l \in \{0,1\}$$

4 Experiments

Performance across different architectures and datasets

Method	PA	F-MNIST	CIFAR10	CELEBA-HQ	T-ImageNet	$\overline{\Delta\text{PA}}$
SN DCGAN [2]	✗	10.6	26.0	24.3	-	4.2
	input	**6.2**	**22.2**	20.8	-	
	feat	**6.2**	22.6	**18.8**	-	
SA GAN (sBN) [3]	✗	-	18.8	17.8	47.6	2.6
	input	-	**16.1**	**15.4**	44.8	
	feat	-	16.3	15.8	**44.7**	

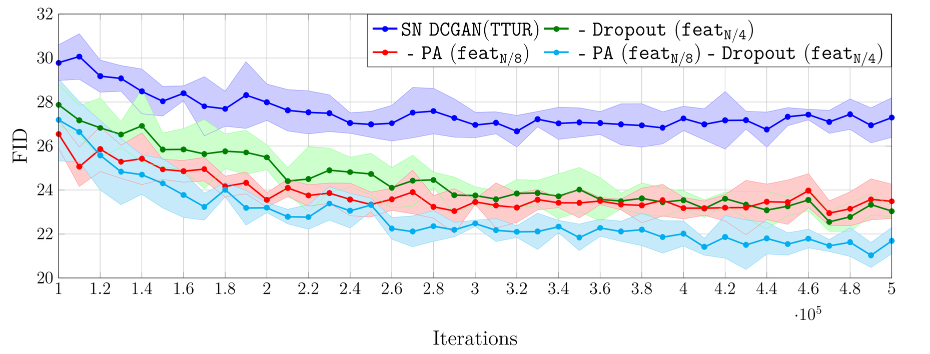
PA achieves ~3 FID point improvement.

lr_g \ lr_d	PA ($\text{feat}_{N/8}$)	10^{-4}	2×10^{-4}	4×10^{-4}	10^{-3}	$\overline{\Delta\text{PA}}$
10^{-4}	✗	27.0	25.8	*25.3*	27.0	3.5
	✓	23.3	**22.2**	22.6	22.9	
2×10^{-4}	✗	26.7	<u>26.0</u>	26.2	27.2	3.1
	✓	24.8	<u>22.6</u>	22.3	24.0	
4×10^{-4}	✗	28.7	26.1	26.3	28.2	3.6
	✓	24.7	23.3	22.9	24.2	
10^{-3}	✗	28.5	27.0	26.4	27.4	2.9
	✓	25.7	23.6	23.4	25.0	

Insensitive to hyper-parameter settings.

Comparison with other regularization techniques

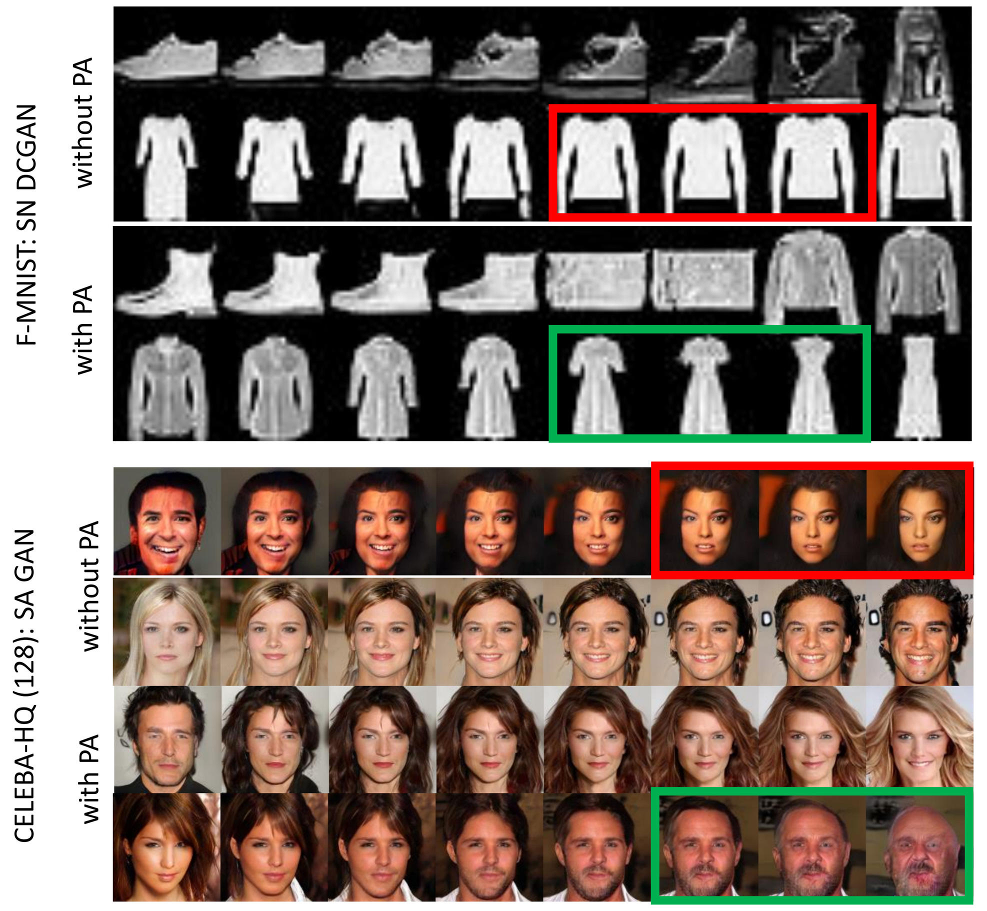
Method	PA	GAN	-Label smooth. [4]	-GP [5]	-GP$_{\text{zero-cent}}$ [6]	-Dropout [7]	-SS [8]	$\overline{\Delta\text{PA}}$
SN DCGAN [2]	✗	26.0	25.8	26.7	26.5	22.1	–	
	input	22.2	23.1	21.8	22.3	21.9	–	3.0
	feat	22.6	22.3	22.7	23.0	**20.6**	–	3.1
SA GAN (sBN) [3]	✗	18.8	–	17.8	17.8	16.2	15.7	
	input	16.1	–	15.8	16.1	15.5	**14.7**	1.3
	feat	16.3	–	16.1	15.9	15.6	14.9	1.3
	$\overline{\Delta\text{PA}}$	3.1	3.1	3.2	2.8	0.8	0.9	2.3



Consistent and complementary performance gain.

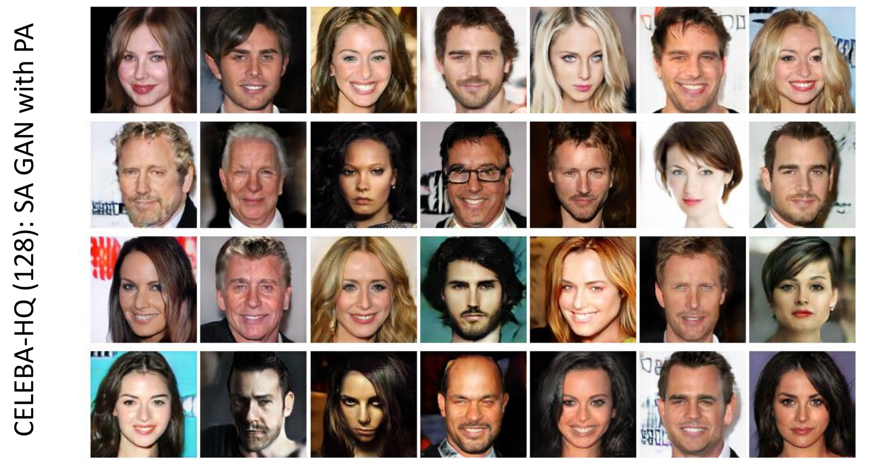
Qualitative results

- Images generated via latent space interpolation



No close-by images look alike.
PA improves sample variation.

- Randomly sampled images



High-fidelity human face synthesis.

5 References

[1] Goodfellow, et al.: Generative adversarial nets, NIPS 2014
[2] Miyato, et al.: Spectral normalization for generative adversarial networks, ICLR 2018
[3] Zhang, et al.: Self-attention generative adversarial networks, ICML 2019
[4] Salimens, et al.: Improved techniques for training GANs, NIPS 2016
[5] Gulrajani, et al.: Improved training of Wasserstein GANs, NIPS 2017
[6] Roth, et al.: Stabilizing training of GANs through regularization, NIPS 2017
[7] Srivastava, et al.: Dropout: a simple way to prevent neural networks from overfitting, JMLR 2014
[8] Chen, et al.: Self-supervised GANs via auxiliary rotation loss, CVPR 2019