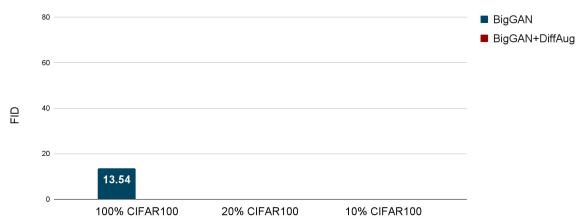


# DigGAN: Discriminator gradlent Gap Regularization for GAN Training with Limited Data

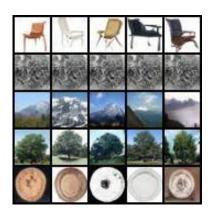
Tiantian Fang, Ruoyu Sun, Alex Schwing

# GAN training with limited data

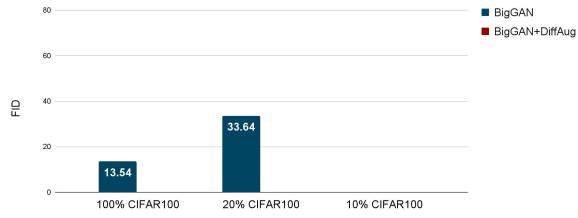




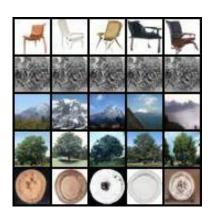
# GAN training with limited data



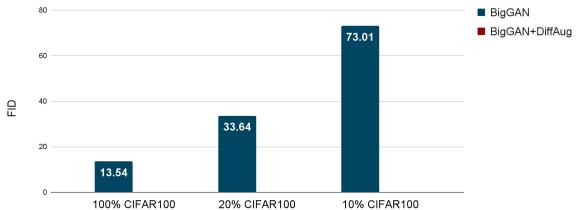




# GAN training with limited data

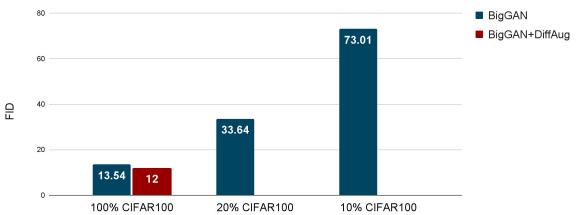






# Data augmentation benefit is limited

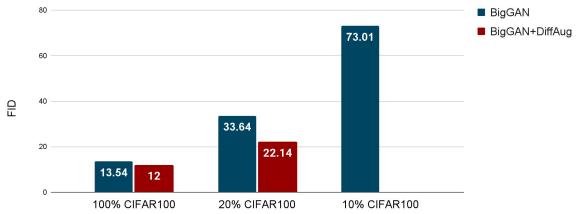




# Data augmentation benefit is limited





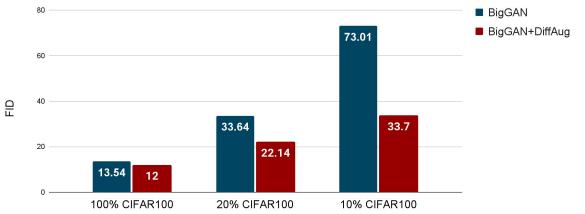


#### Data augmentation benefit is limited







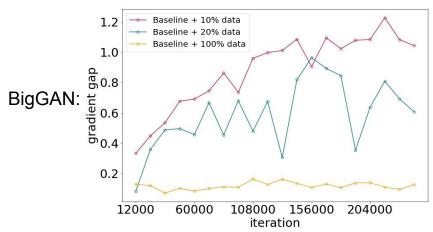


- The norm of the gradient of a discriminator's prediction w.r.t. real images
- The norm of the gradient of a discriminator's prediction w.r.t. generated images

$$R(D, x_R, x_F) = \left( \left\| \frac{\partial D}{\partial x_R} \right\|_2 - \left\| \frac{\partial D}{\partial x_F} \right\|_2 \right)^2$$

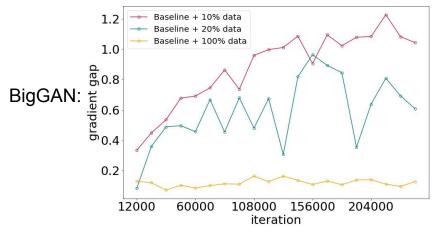
- The norm of the gradient of a discriminator's prediction w.r.t. real images
- The norm of the gradient of a discriminator's prediction w.r.t. generated images

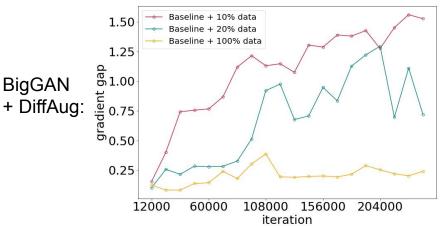
$$R(D, x_R, x_F) = \left( \left\| \frac{\partial D}{\partial x_R} \right\|_2 - \left\| \frac{\partial D}{\partial x_F} \right\|_2 \right)^2$$



- The norm of the gradient of a discriminator's prediction w.r.t. real images
- The norm of the gradient of a discriminator's prediction w.r.t. generated images

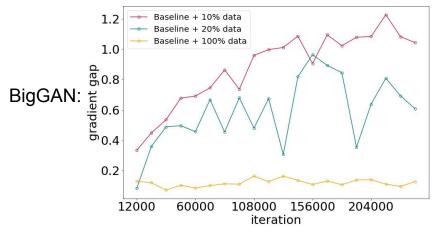
$$R(D, x_R, x_F) = \left( \left\| \frac{\partial D}{\partial x_R} \right\|_2 - \left\| \frac{\partial D}{\partial x_F} \right\|_2 \right)^2$$

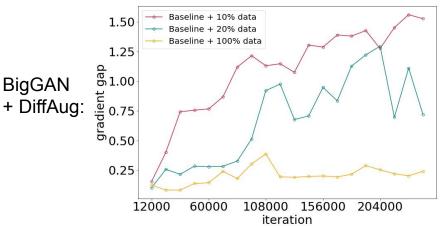


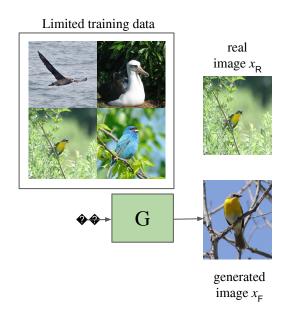


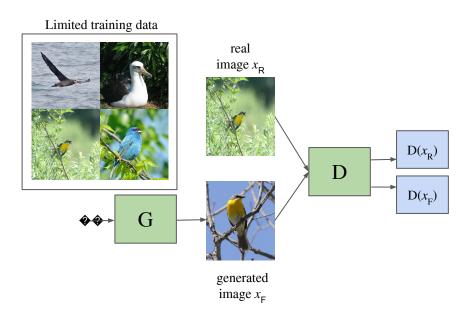
- The norm of the gradient of a discriminator's prediction w.r.t. real images
- The norm of the gradient of a discriminator's prediction w.r.t. generated images

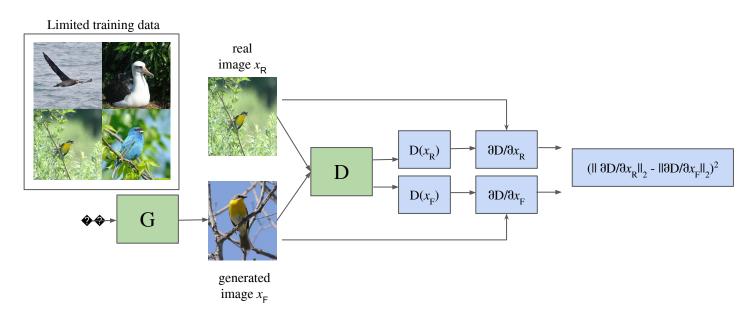
$$R(D, x_R, x_F) = \left( \left\| \frac{\partial D}{\partial x_R} \right\|_2 - \left\| \frac{\partial D}{\partial x_F} \right\|_2 \right)^2$$

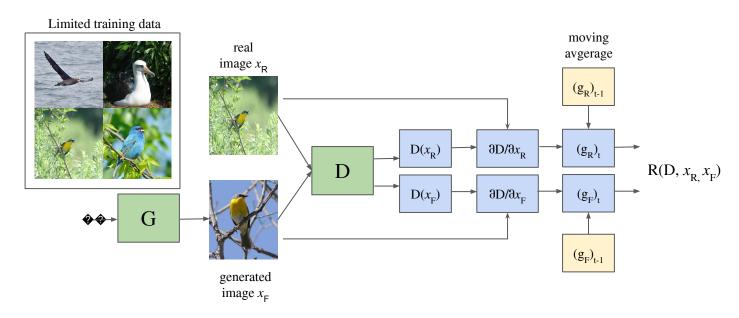












#### Intuition for DigGAN Regularizer and Attractors

Compared to Vanilla GANs, DigGAN shows empirical advantages:

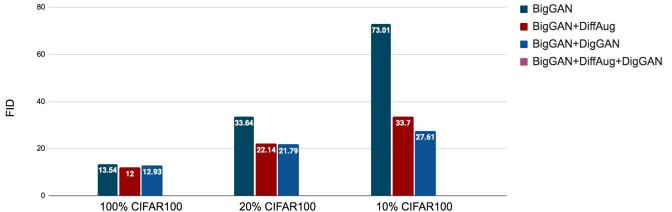
- Avoids getting trapped in bad local attractors
- Escapes from bad local attractors even if starting at local attractors

#### Results: CIFAR-100







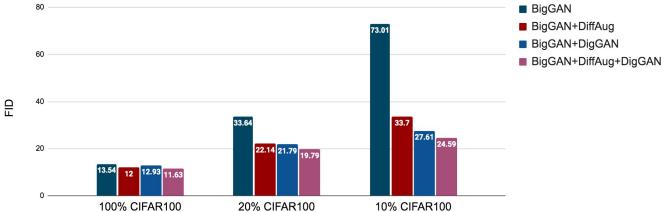


#### Results: CIFAR-100

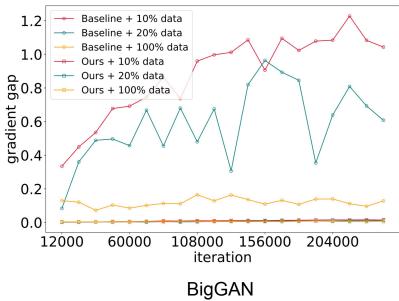








#### Results: CIFAR-100



AN BigGAN + DiffAug

1.25

gradient gap 0.75 0.50

0.25

0.00

12000

Baseline + 10% data

Baseline + 20% data

Ours + 10% data

Ours + 20% data

Ours + 100% data

60000

108000 156000

iteration

204000

Baseline + 100% data

#### Results

	100% Tiny	50% Tiny	10% Tiny	100%	50%
	ImageNet	ImageNet	ImageNet	CUB-200	CUB-200
BigGAN	31.92	43.45	130.77	20.15	48.67
BigGAN+ $R_{LC}$ [51]	28.11	36.11	121.16	40.37	98.38
BigGAN + DigGAN (ours)	<b>17.76</b>	<b>24.63</b>	<b>84.27</b>	<b>14.45</b>	<b>23.20</b>
$\begin{array}{c} \textbf{BigGAN + DiffAug} \\ \textbf{BigGAN+} R_{LC} \text{ [51]+DiffAug} \\ \textbf{BigGAN + DiffAug + DigGAN (ours)} \end{array}$	16.33	24.50	95.40	13.49	24.35
	16.30	23.67	83.76	12.81	23.49
	<b>14.84</b>	<b>22.66</b>	<b>51.18</b>	<b>11.58</b>	<b>21.12</b>

Table 3: Fréchet Inception distance (FID) for BigGAN with Tiny-ImageNet and CUB-200.









100% Tiny-ImageNet

50% Tiny-ImageNet

100% CUB200

50% CUB200

#### Results

	100-shot Obama	100-shot grumpy cat	AnimalFace Dog	AnimalFace Cat
StyleGAN+ADA	49.78	27.34	66.25	41.40
StyleGAN+ADA+DigGAN	<b>41.34</b>	<b>26.75</b>	<b>59.00</b>	<b>37.61</b>

Table 4: Fréchet Inception distance (FID) for StyleGAN2 with ADA on low-shot datasets.

