Large Scale GAN Training for High Fidelity Natural Image Synthesis [1]

February 19, 2020

[1] "Large Scale GAN Training for High Fidelity Natural Image Synthesis" by Brock, Donahue, and Simonyan

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- Explored a lot of techniques of training GANs
- Proposed a “truncation trick” for better sampling at test-time
- Dramatically improved SotA on ImageNet

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- This gives very high values for KL between $p(y|x)$ and $p(y)$.

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Intuition:

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- It is not obvious why we do that with FD instead of KL/JS/etc

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- Progressive growing was unnecessary.
- A model is trained on 128 to 512 TPU v3 cores

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- This improves quality but decreases diversity.
- Some models are not amenable to truncation because of the distribution shift: during training we see z that comes from different distribution.
- Use orthogonal regularization to alleviate this:

$$R_\beta(W) = \beta \left\| W^\top W \odot (1 - I) \right\|_F^2$$

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How to track instability in Generator[2]

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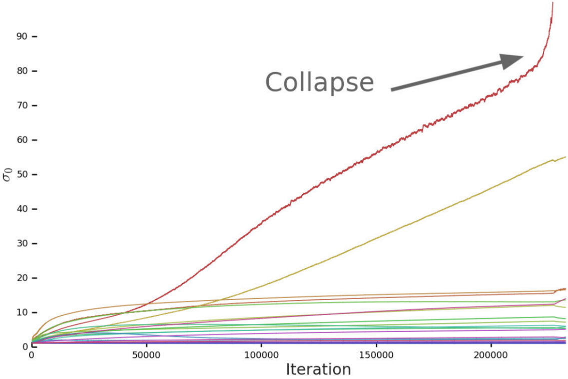
- They tried a lot of tricky ways to regularize them, but it worked only a little and couldn't guarantee stability.
- This means that singular values explosion is a symptom and not the cause.



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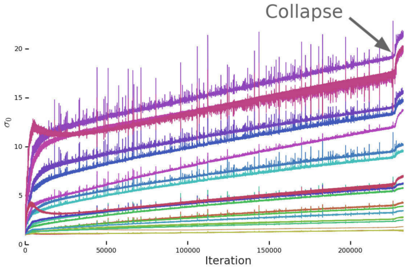
- Singluar values are more noisy and have spikes
- Authors hypothesize that spikes occur because D receives large gradients sometimes
- To alleviate this they use R_1 regularization: it helps it decreases overall performance

$$R_1 := \frac{\gamma}{2}\mathbb{E}_{p_{\mathcal{D}}(x)}\left[\|\nabla D(x)\|_F^2\right] \tag{3}$$



Results

Model	Res.	FID/IS	(min FID) / IS	FID / (valid IS)	FID / (max IS)
SN-GAN	128	$27.62/36.80$	N/A	N/A	N/A
SA-GAN	128	$18.65/52.52$	N/A	N/A	N/A
BigGAN	128	$8.7 \pm .6/98.8 \pm 3$	$7.7 \pm .2/126.5 \pm 0$	$9.6 \pm .4/166.3 \pm 1$	$25 \pm 2/206 \pm 2$
BigGAN	256	$8.7 \pm .1/142.3 \pm 2$	$7.7 \pm .1/178.0 \pm 5$	$9.3 \pm .3/233.1 \pm 1$	$25 \pm 5/291 \pm 4$
BigGAN	512	$8.1/144.2$	$7.6/170.3$	$11.8/241.4$	$27.0/275$
BigGAN-deep	128	$5.7 \pm .3/124.5 \pm 2$	$6.3 \pm .3/148.1 \pm 4$	$7.4 \pm .6/166.5 \pm 1$	$25 \pm 2/253 \pm 11$
BigGAN-deep	256	$6.9 \pm .2/171.4 \pm 2$	$7.0 \pm .1/202.6 \pm 2$	$8.1 \pm .1/232.5 \pm 2$	$27 \pm 8/317 \pm 6$
BigGAN-deep	512	$7.5/152.8$	$7.7/181.4$	$11.5/241.5$	$39.7/298$