Deep Generative Models
Lecture 10

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Evaluation of likelihood-free models

How to evaluate generative models?

Likelihood-based models

- Split data to train/val/test.
- Fit model on the train part.
- Tune hyperparameters on the validation part.
- Evaluate generalization by reporting likelihoods on the test set.

Not all models have tractable likelihoods

- VAE: compare ELBO values.
- GAN: ???

Evaluation of likelihood-free models

Let take some pretrained image classification model to get the conditional label distribution $p(y|\mathbf{x})$ (e.g. ImageNet classifier).

What do we want from samples?

- **Sharpness**

Low sharpness

High sharpness

The conditional distribution $p(y|\mathbf{x})$ should have low entropy (each image $\mathbf{x}$ should have distinctly recognizable object).

- **Diversity**

Low diversity

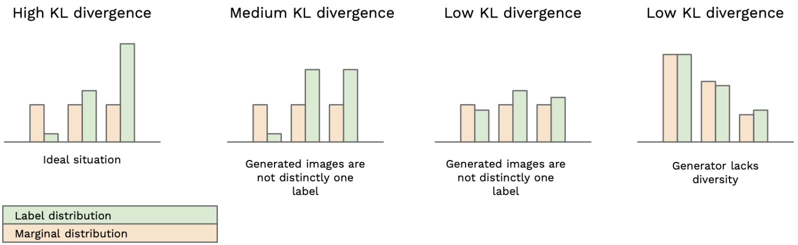
High diversity

The marginal distribution $p(y) = \int p(y|\mathbf{x})p(\mathbf{x})d\mathbf{x}$ should have high entropy (there should be as many classes generated as possible).

Evaluation of likelihood-free models

What do we want from samples?

- **Sharpness.** The conditional distribution $p(y|\mathbf{x})$ should have low entropy (each image $\mathbf{x}$ should have distinctly recognizable object).
- **Diversity.** The marginal distribution $p(y) = \int p(y|\mathbf{x})p(\mathbf{x})d\mathbf{x}$ should have high entropy (there should be as many classes generated as possible).



https://medium.com/octavian-ai/a-simple-explanation-of-the-inception-score-372dff6a8c7a

Evaluation of likelihood-free models

What do we want from samples?

- Sharpness $\Rightarrow$ low $H(y|\mathbf{x}) = -\sum_y \int_{\mathbf{x}} p(y, \mathbf{x}) \log p(y|\mathbf{x}) d\mathbf{x}$.
- Diversity $\Rightarrow$ high $H(y) = -\sum_y p(y) \log p(y)$.

Inception Score

$$
\begin{aligned}
IS &= \exp(H(y) - H(y|\mathbf{x})) \\
&= \exp\left(-\sum_y p(y) \log p(y) + \sum_y \int_{\mathbf{x}} p(y, \mathbf{x}) \log p(y|\mathbf{x}) d\mathbf{x}\right) \\
&= \exp\left(\sum_y \int_{\mathbf{x}} p(y, \mathbf{x}) \log \frac{p(y|\mathbf{x})}{p(y)} d\mathbf{x}\right) \\
&= \exp\left(\mathbb{E}_{\mathbf{x}} \sum_y p(y|\mathbf{x}) \log \frac{p(y|\mathbf{x})}{p(y)}\right) = \exp\left(\mathbb{E}_{\mathbf{x}} KL(p(y|\mathbf{x}) || p(y))\right)
\end{aligned}
$$

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https://arxiv.org/abs/1606.03498

Evaluation of likelihood-free models

Inception Score

$$IS = \exp\left(\mathbb{E}_{\mathbf{x}} KL(p(y|\mathbf{x}) || p(y))\right)$$

IS limitations

- Inception score depends on the quality of the pretrained classifier $p(y|\mathbf{x})$.
- If generator produces images with a different set of labels from the classifier training set, IS will be low.
- If the generator produces one image per class, the IS will be perfect (there is no measure of intra-class diversity).
- IS only require samples from the generator and do not take into account the desired data distribution $\pi(\mathbf{x})$ directly (only implicitly via a classifier).

https://arxiv.org/abs/1801.01973

Evaluation of likelihood-free models

Theorem

If $\pi(\mathbf{x})$ and $p(\mathbf{x}|\boldsymbol{\theta})$ has moment generation functions then

$$\pi(\mathbf{x}) = p(\mathbf{x}|\boldsymbol{\theta}) \Leftrightarrow \mathbb{E}_\pi \mathbf{x}^k = \mathbb{E}_p \mathbf{x}^k, \quad \forall k \geq 1.$$

This is intractable to calculate all moments.

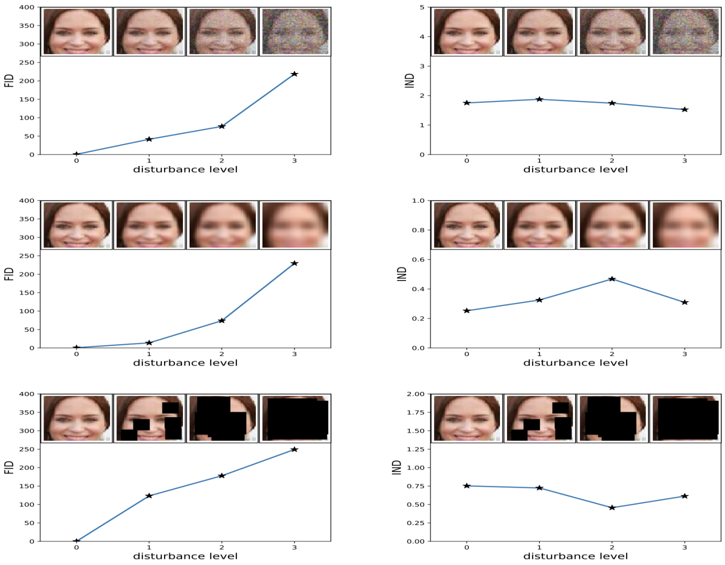
Frechet Inception Distance

$$D^2(\pi, p) = \|\mathbf{m}_\pi - \mathbf{m}_p\|_2^2 + \mathrm{Tr}\left(\mathbf{C}_\pi + \mathbf{C}_p - 2\sqrt{\mathbf{C}_\pi \mathbf{C}_p}\right)$$

- $\mathbf{m}_\pi$, $\mathbf{C}_\pi$ are mean vector and covariance matrix of feature representations for real samples from $\pi(\mathbf{x})$
- $\mathbf{m}_p$, $\mathbf{C}_p$ are mean vector and covariance matrix of feature representations for generated samples from $p(\mathbf{x}|\boldsymbol{\theta})$.
- Representations are outputs of intermediate layer from pretrained classification model.

https://arxiv.org/abs/1706.08500

Evaluation of likelihood-free models



https://arxiv.org/abs/1706.08500

Evaluation of likelihood-free models

Frechet Inception Distance

$$D^2(\pi, p) = \|\mathbf{m}_\pi - \mathbf{m}_p\|_2^2 + \mathrm{Tr}\left(\mathbf{C}_\pi + \mathbf{C}_p - 2\sqrt{\mathbf{C}_\pi \mathbf{C}_p}\right)$$

FID limitations

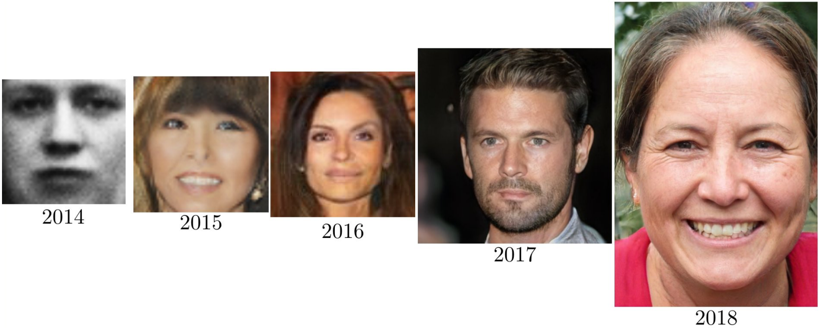
- FID depends on the pretrained classification model.
- FID needs a large samples size for evaluation.
- Calculation of FID is slow.
- FID extimates only two sample moments.

https://arxiv.org/abs/1706.08500

Summary

- Wasserstein GAN uses Kantorovich-Rubinstein duality to estimate Wasserstein distance.
- Gradient Penalty proposes the regularizer to enforce Lipschitzness.
- Spectral normalization is a weight normalization technique to enforce Lipshitzness.
- f-divergence family is a unified framework for divergence minimization.
- Inception Score and Frechet Inception Distance are the common metrics for GAN evaluation.

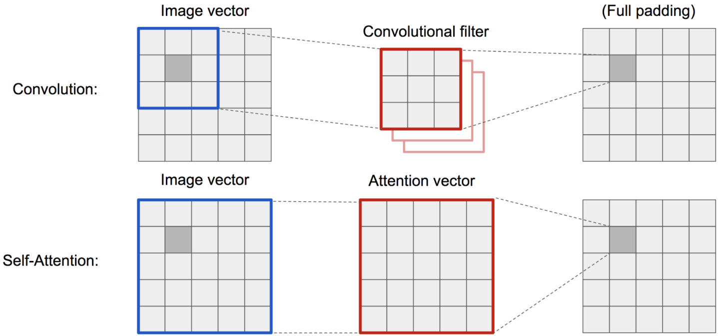
Evolution of GANs



- **Vanilla GAN** https://arxiv.org/abs/1406.2661
- **DCGAN** https://arxiv.org/abs/1511.06434
- **CoGAN** https://arxiv.org/abs/1606.07536
- **ProGAN** https://arxiv.org/abs/1710.10196
- **StyleGAN** https://arxiv.org/abs/1812.04948

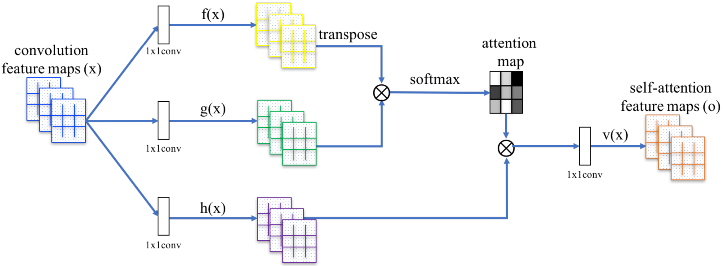
Self-Attention GAN

- Convolutional layers process the information in a local neighborhood.
- Using convolutional layers alone is computationally inefficient for modeling long-range dependencies in images.



https://lilianweng.github.io/lil-log/2018/06/24/attention-attention.html

Self-Attention GAN



- $\mathbf{x}$ – feature vector for one feature location.
- N – number of feature locations.

$$\mathbf{f}(\mathbf{x}) = \mathbf{W}_f(\mathbf{x}), \quad \mathbf{g}(\mathbf{x}) = \mathbf{W}_g(\mathbf{x}), \quad \mathbf{h}(\mathbf{x}) = \mathbf{W}_h(\mathbf{x}), \quad \mathbf{v}(\mathbf{x}) = \mathbf{W}_v(\mathbf{x})$$

$$s_{ij} = \mathbf{f}(\mathbf{x}_i)^T \mathbf{g}(\mathbf{x}_j), \quad a_{ij} = \frac{\exp s_{ij}}{\sum_{i=1}^{N} \exp s_{ij}}, \quad \mathbf{o}_j = \mathbf{v}\left(\sum_{i=1}^{N} a_{ij}\mathbf{h}(\mathbf{x}_i)\right)$$

https://arxiv.org/abs/1805.08318

Self-Attention GAN

Technical Details

- Hinge loss for training.
- Spectral Normalization in both the generator and the discriminator.
- Separate learning rates for the generator and the discriminator.

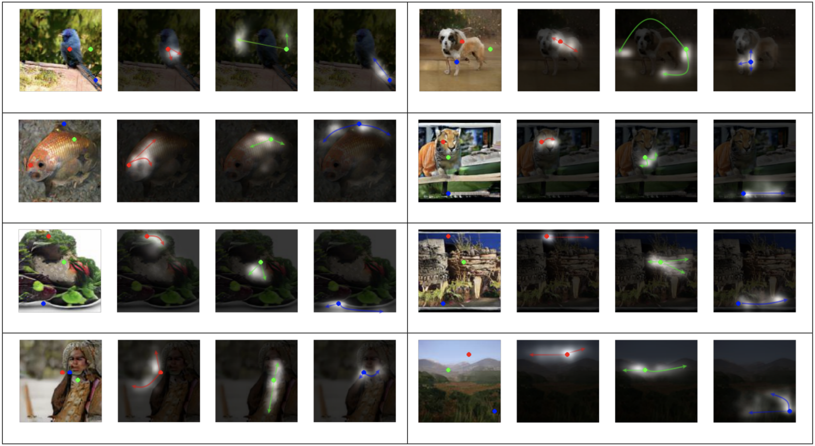
Model	no attention	SAGAN				Residual			
		$feat_8$	$feat_{16}$	$feat_{32}$	$feat_{64}$	$feat_8$	$feat_{16}$	$feat_{32}$	$feat_{64}$
FID	22.96	22.98	22.14	**18.28**	18.65	42.13	22.40	27.33	28.82
IS	42.87	43.15	45.94	51.43	**52.52**	23.17	44.49	38.50	38.96

Model	Inception Score	Intra FID	FID
AC-GAN (Odena et al., 2017)	28.5	260.0	/
SNGAN-projection (Miyato & Koyama, 2018)	36.8	92.4	27.62*
SAGAN	**52.52**	**83.7**	**18.65**

https://arxiv.org/abs/1805.08318

Self-Attention GAN

Visualization of attention maps



https://arxiv.org/abs/1805.08318

BigGAN

Model description

- Self-Attention GAN baseline.
- Class-conditional generator.
- Increasing batch size gives tremendous benefit (allows to cover more modes).
- Increasing model size is helpful (wider helps as much as deeper).
- Hinge loss for training.
- Orthogonal regularization for smoothness the generator output.
- Truncation trick for balancing between diversity and fidelity.

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https://arxiv.org/abs/1809.11096

BigGAN

- **Orthogonal regularization**

$$\|\mathbf{W}^T\mathbf{W} - \mathbf{I}\|^2 \quad \Rightarrow \|\mathbf{W}^T\mathbf{W} - \mathrm{diag}(\mathbf{W}^T\mathbf{W})\|^2$$

- **Truncation trick.** Coordinates of samples $\mathbf{z} \sim \mathcal{N}(0, \mathbf{I})$ which fall outside a predefined range are resampled to fall inside that range.

Batch	Ch.	Param (M)	Shared	Skip-z	Ortho.	Itr $\times 10^3$	FID	IS
256	64	81.5	SA-GAN Baseline			1000	18.65	52.52
512	64	81.5	✗	✗	✗	1000	15.30	58.77($\pm$1.18)
1024	64	81.5	✗	✗	✗	1000	14.88	63.03($\pm$1.42)
2048	64	81.5	✗	✗	✗	732	12.39	76.85($\pm$3.83)
2048	96	173.5	✗	✗	✗	295($\pm$18)	9.54($\pm$0.62)	92.98($\pm$4.27)
2048	96	160.6	✓	✗	✗	185($\pm$11)	9.18($\pm$0.13)	94.94($\pm$1.32)
2048	96	158.3	✓	✓	✗	152($\pm$7)	8.73($\pm$0.45)	98.76($\pm$2.84)
2048	96	158.3	✓	✓	✓	165($\pm$13)	8.51($\pm$0.32)	99.31($\pm$2.10)
2048	64	71.3	✓	✓	✓	371($\pm$7)	10.48($\pm$0.10)	86.90($\pm$0.61)

https://arxiv.org/abs/1809.11096

BigGAN

Samples (512x512)

https://arxiv.org/abs/1809.11096

BigGAN

Interpolations

https://arxiv.org/abs/1809.11096

Progressive Growing GAN

Problems with HR image generation

- Disjoint manifolds $\Rightarrow$ gradient problem.
- Small minibatch $\Rightarrow$ training instability.

Solution

Grow both the generator and discriminator progressively, starting from LR images, and add new layers that introduce higher-resolution details as the training progresses.

- Train GAN which generate 4x4 images (just 2 convolutions for G and D).
- Add upsampling layers to G, downsampling layers to D.
- Train GAN which generate 8x8 images.
- etc.

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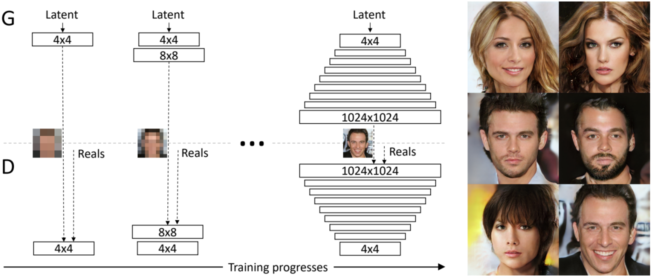
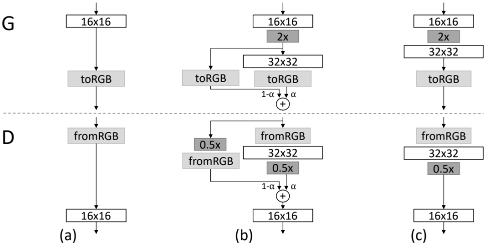
https://arxiv.org/abs/1710.10196

Progressive Growing GAN





https://arxiv.org/abs/1710.10196

Progressive Growing GAN

Samples (1024x1024)

https://arxiv.org/abs/1710.10196

StyleGAN

- Generating of HR images is hard.
- Progressive growing greatly simplifies the task.
- The ability to control specific features of the generated image is very limited.

Face image features

- Coarse (pose, general hair style, face shape). Resolution $4^2 - 8^2$.
- Middle (finer facial features, hair style, eyes open/closed). Resolution $16^2 - 32^2$.
- Fine (color scheme (eye, hair and skin) and micro features). Resolution $64^2 - 1024^2$.

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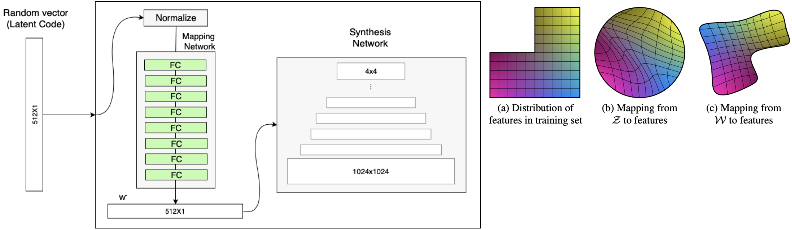
https://arxiv.org/abs/1812.04948

StyleGAN

Step 1: Mapping Network

- Generator input is likely to be **disentangled**. Each component of input vector **z** should be responsible for one generative factor.
- Mapping network $f : \mathcal{Z} \rightarrow \mathcal{W}$ is used to reduce correlations between components of **z**.

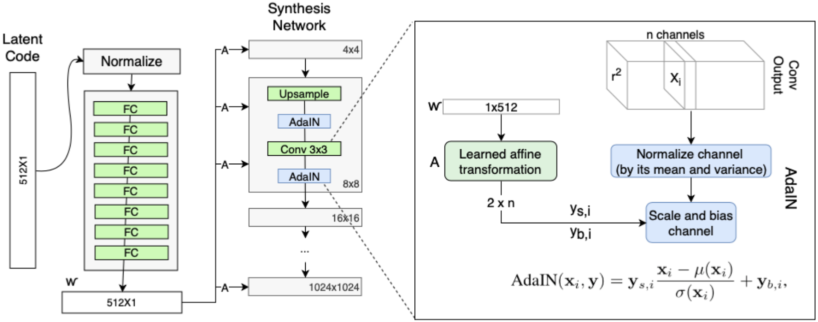


https://arxiv.org/abs/1812.04948

StyleGAN

Step 2: Style modulation

- Adaptive Instance Normalization transfers the **w** vector to the synthesis Network.
- The module is added to each resolution to define the visual expression of the features.



$$\mathrm{AdaIN}(\mathbf{x}_i, \mathbf{y}) = \mathbf{y}_{s,i} \frac{\mathbf{x}_i - \mu(\mathbf{x}_i)}{\sigma(\mathbf{x}_i)} + \mathbf{y}_{b,i},$$

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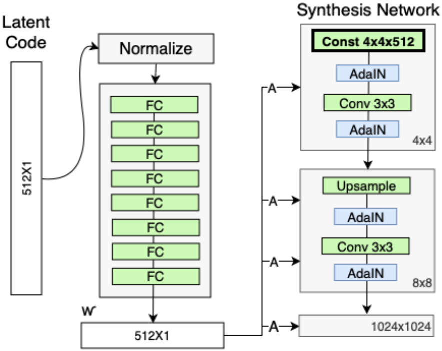
https://arxiv.org/abs/1812.04948

StyleGAN

Step 3: Remove traditional input

Mapping network provides stochasticity to different stages of the synthesis network. Input of the synthesis network is a trainable vector.



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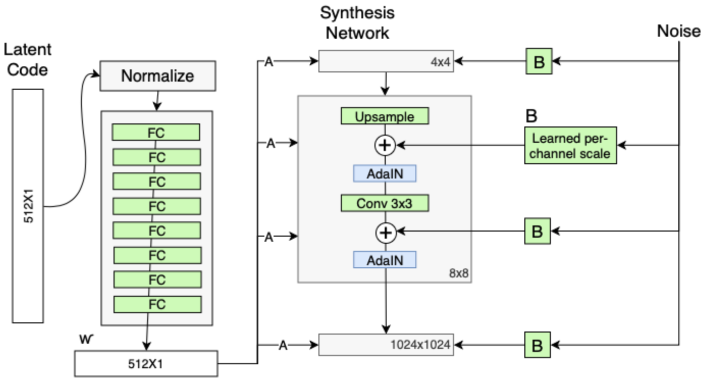
https://arxiv.org/abs/1812.04948

StyleGAN

Step 4: Stochastic variation

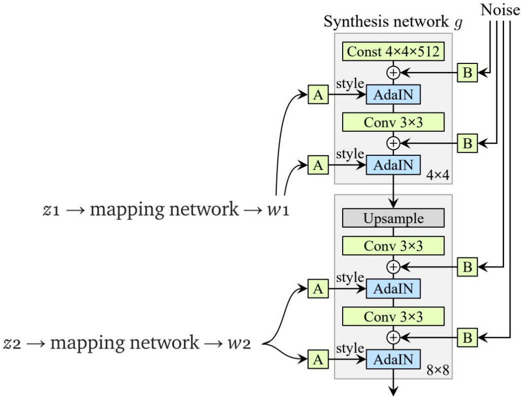
Inject random noise to add small aspects, such as freckles, exact placement of hairs, wrinkles, features which make the image more realistic and increase the variety of outputs.



https://arxiv.org/abs/1812.04948

StyleGAN

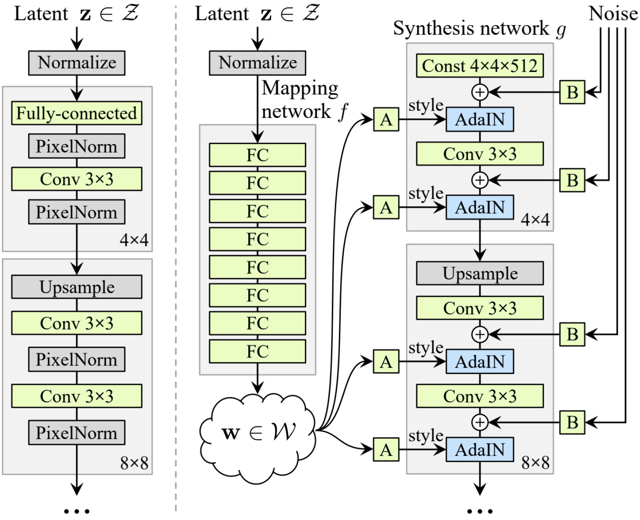
Step 4: Style Mixing



- Makes different levels of synthesis network to be independent.
- Allows to couple diffirent styles.

https://arxiv.org/abs/1812.04948

StyleGAN



(a) Traditional (b) Style-based generator

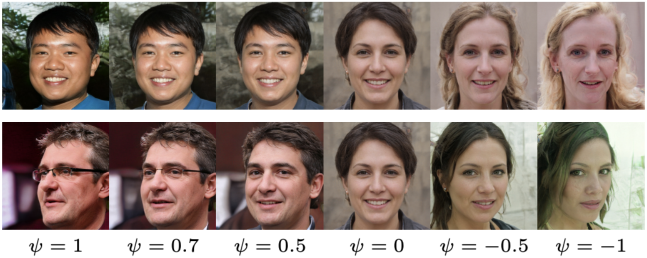
https://arxiv.org/abs/1812.04948

StyleGAN

Truncation trick

$$\mathbf{w}' = \hat{\mathbf{w}} - \psi \cdot (\mathbf{w} - \hat{\mathbf{w}}), \quad \hat{\mathbf{w}} = \mathbb{E}_{\mathbf{z}} p(f(\mathbf{z}))$$

- Constant ψ is a tradeoff between diversity and fidelity.
- $\psi = 0.7$ is used for most of the results.
- Truncation is done only at the low-resolution layers.



https://arxiv.org/abs/1812.04948

StyleGAN

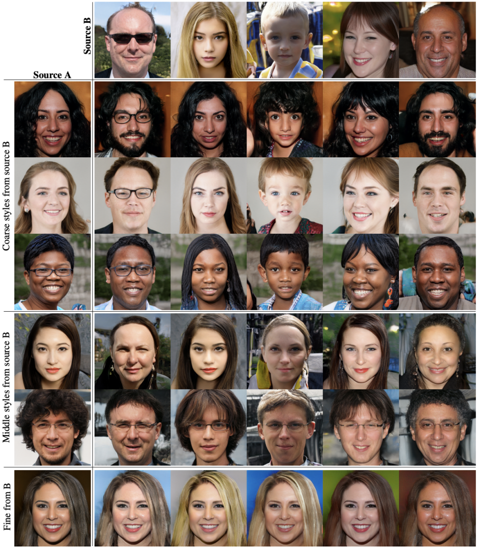
Results

	Method	CelebA-HQ	FFHQ
A	Baseline Progressive GAN [30]	7.79	8.04
B	+ Tuning (incl. bilinear up/down)	6.11	5.25
C	+ Add mapping and styles	5.34	4.85
D	+ Remove traditional input	5.07	4.88
E	+ Add noise inputs	**5.06**	4.42
F	+ Mixing regularization	5.17	**4.40**

Samples (1024x1024)

https://arxiv.org/abs/1812.04948

StyleGAN



https://arxiv.org/abs/1812.04948

References

- A Note on the Inception Score
  https://arxiv.org/abs/1801.01973
  Summary: Inception Score is not an ideal metric.
- GANs Trained by a Two Time-Scale Update Rule Converge to a Local Nash Equilibrium
  https://arxiv.org/abs/1706.08500
  Summary: Frechet inception distance was proposed for GAN evaluation.
- **SAGAN**: Self-Attention Generative Adversarial Networks
  https://arxiv.org/abs/1805.08318
  Summary: Self-attention was proposed for G and D. Hinge loss was used for training. Spectral Normalization was injected not only for D, but also for G.
- **BigGAN**: Large Scale GAN Training for High Fidelity Natural Image Synthesis
  https://arxiv.org/abs/1809.11096
  Summary: SAGAN as a baseline. High-quality image generation. Increasing batch is really helpful (covering more modes). Propose orthogonalization regularization. Use truncation trick for trade-off between sample fidelity and variety.
- **ProGAN**: Progressive Growing of GANs for Improved Quality, Stability, and Variation
  https://arxiv.org/abs/1710.10196
  Summary: The key idea is to grow both the generator and discriminator progressively: starting from a low resolution, we add new layers that model increasingly fine details as training progresses.
- **StyleGAN**: A Style-Based Generator Architecture for Generative Adversarial Networks
  https://arxiv.org/abs/1812.04948
  Summary: Mapping network for disentanglement. ProgressiveGAN as a baseline. AdaIN operation to modulate style. Noise injection for variability. Hierarchical style mixing. Perceptual path length as a measure of disentanglement.