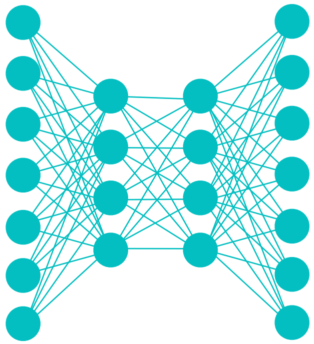
Lecture Notes for

Neural Networks and Machine Learning

BigGAN and StyleGAN



Logistics and Agenda

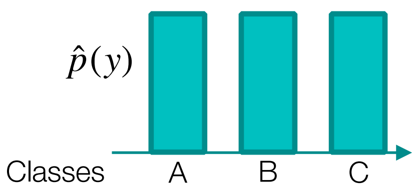
- Logistics
  - **Student Presentation**: None
- Agenda
  - BigGAN
    - Big GAN? or Biggin?
  - Next Time: Stable Diffusion

An Accepted Measure: Inception Score

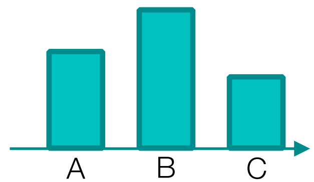
$$\hat{p}(y) = \frac{1}{N}\sum_i p(y\,|\,\mathbf{x}^{(i)}_{fake})$$

marginal

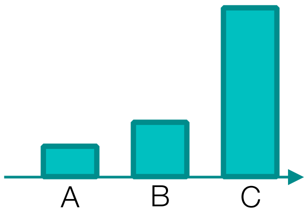
Expected class distribution through a trained CNN, like VGG should be **nearly uniform** in ideal case



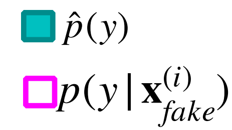
Ideal: Generator has diverse classes



Good: Generator is somewhat diverse



Bad: Generator not diverse

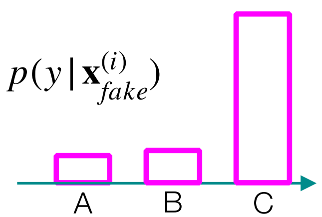


$$IS(G) \approx \exp\left(\frac{1}{N}\sum_i D_{KL}\left(p(y\,|\,\mathbf{x}^{(i)}_{fake})\,\|\,\hat{p}(y)\right)\right)$$

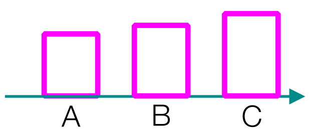
one example generated

typical generation

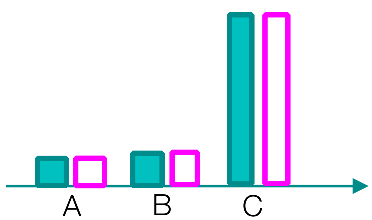
average KL Divergence of marginal of generated images with $\hat{p}$, ideally **differ dramatically**



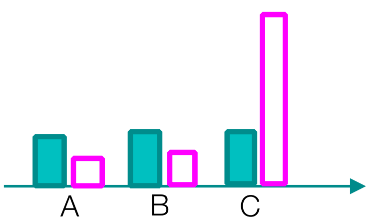
Ideal: Single Example is distinct class



Bad: Single Example is not really distinct



Bad: Distinct because not diverse



Ideal: Diverse and Distinct

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

BigGAN

In a field with 1000's of competing papers,
BigGAN is here to use the most meaningful
Portions of each paper and put them into
One BIG paper.

LARGE SCALE GAN TRAINING FOR HIGH FIDELITY NATURAL IMAGE SYNTHESIS

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BigGAN Overview

- This is an agglomeration of GAN Knowledge from *2013-2020*
- Training is hard, so use heuristics
    - large batches, feature matching
    - use hinge loss (max margin)
- Use attention, conditional classes, spectral normalization, moving average of weights, orthogonal weight initialization, skip connections, orthogonal regularizers
- **Truncation trick:** sample a wide range during training $\sigma = \lambda$, then truncate for evaluation $\sigma = \dfrac{\lambda}{2}$

- Large Scale GAN Training for High Fidelity Natural Image Synthesis, 2018.
- Large Scale GAN Training for High Fidelity Natural Image Synthesis, ICLR 2019. 2019
- Self-Attention Generative Adversarial Networks, 2018.
- A Learned Representation For Artistic Style, 2016.
- Spectral Normalization for Generative Adversarial Networks, 2018.
- Progressive Growing of GANs for Improved Quality, Stability, and Variation, 2017.
- Exact Solutions To The Nonlinear Dynamics Of Learning In Deep Linear Neural Networks, 2013.
- Neural Photo Editing with Introspective Adversarial Networks, 2016.

https://machinelearningmastery.com/a-gentle-introduction-to-the-biggan/

BigGAN Part One: Spectral Normalization

- After updating weights (in critic), use the spectral norm, such that the network satisfies the Lipschitz constraint $\sigma(W) \approx 1$ for each layer
- Which makes the critic a valid Wasserstein estimate, but infinitely easier to compute!

$$\mathbf{W} \leftarrow \frac{\mathbf{W}}{\sigma(\mathbf{W})}$$ ← which is largest singular value of $\mathbf{W}$

Our spectral normalization controls the Lipschitz constant of the discriminator function f by literally constraining the spectral norm of each layer $g : \boldsymbol{h}_{in} \mapsto \boldsymbol{h}_{out}$. By definition, Lipschitz norm $\|g\|_{\text{Lip}}$ is equal to $\sup_{\boldsymbol{h}} \sigma(\nabla g(\boldsymbol{h}))$, where $\sigma(A)$ is the spectral norm of the matrix A (L_2 matrix norm of A)

$$\sigma(A) := \max_{\boldsymbol{h}:\boldsymbol{h}\neq 0} \frac{\|A\boldsymbol{h}\|_2}{\|\boldsymbol{h}\|_2} = \max_{\|\boldsymbol{h}\|_2 \leq 1} \|A\boldsymbol{h}\|_2, \tag{6}$$

which is equivalent to the largest singular value of A.

Paraphrasing from paper:
Most layers in the generator have well-behaved spectra, but without constraints (like in WGAN-GP) a small subset grow throughout training and explode, resulting in a collapse of training. This was solved by monitoring for collapse and loading the best model before the collapse. An attempt was also made to integrate the WGAN-GP constraint in the loss function with BigGAN. While this did make the results more stable, the IS score dropped by 45%.

https://arxiv.org/pdf/1802.05957.pdf Spectral Normalization for Generative Adversarial Networks, 2018.

BigGAN Part One: Spectral Normalization

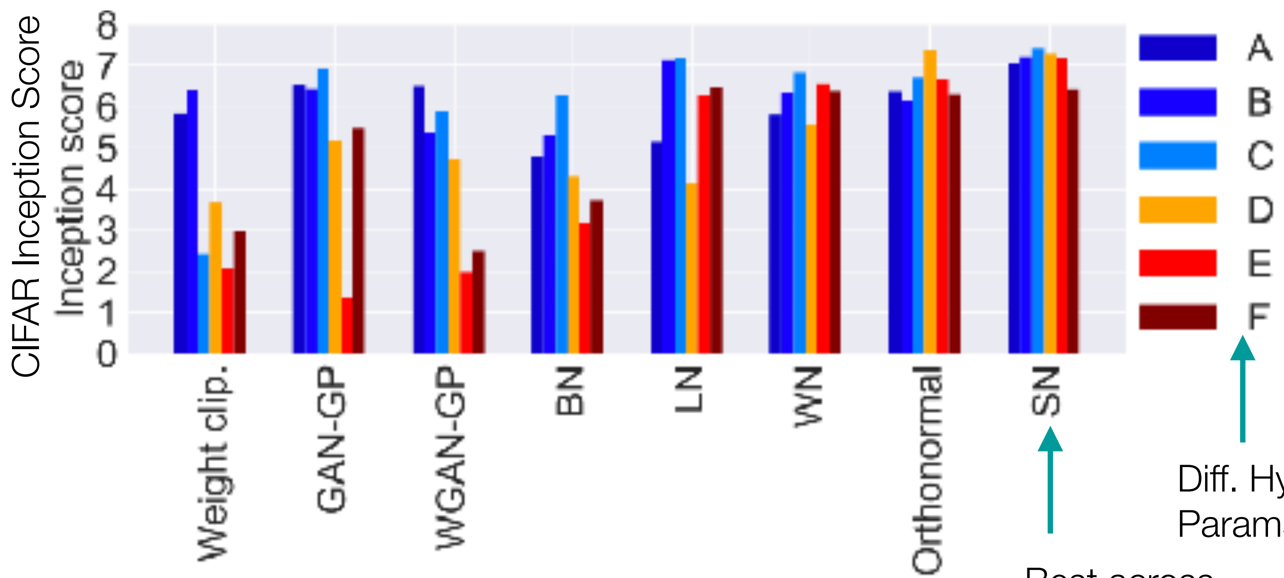
Our *spectral normalization* normalizes the spectral norm of the weight matrix W so that it satisfies the Lipschitz constraint $\sigma(W) = 1$:

$$\bar{W}_{\mathrm{SN}}(W) := W/\sigma(W). \tag{8}$$

$$\frac{\partial \bar{W}_{\mathrm{SN}}(W)}{\partial W_{ij}} = \frac{1}{\sigma(W)} E_{ij} - \frac{1}{\sigma(W)^2} \frac{\partial \sigma(W)}{\partial W_{ij}} W = \frac{1}{\sigma(W)} E_{ij} - \frac{[\boldsymbol{u}_1 \boldsymbol{v}_1^{\mathrm{T}}]_{ij}}{\sigma(W)^2} W \tag{9}$$

$$= \frac{1}{\sigma(W)} \left(E_{ij} - [\boldsymbol{u}_1 \boldsymbol{v}_1^{\mathrm{T}}]_{ij} \bar{W}_{\mathrm{SN}} \right), \tag{10}$$

And we can back propagate through the calculation!



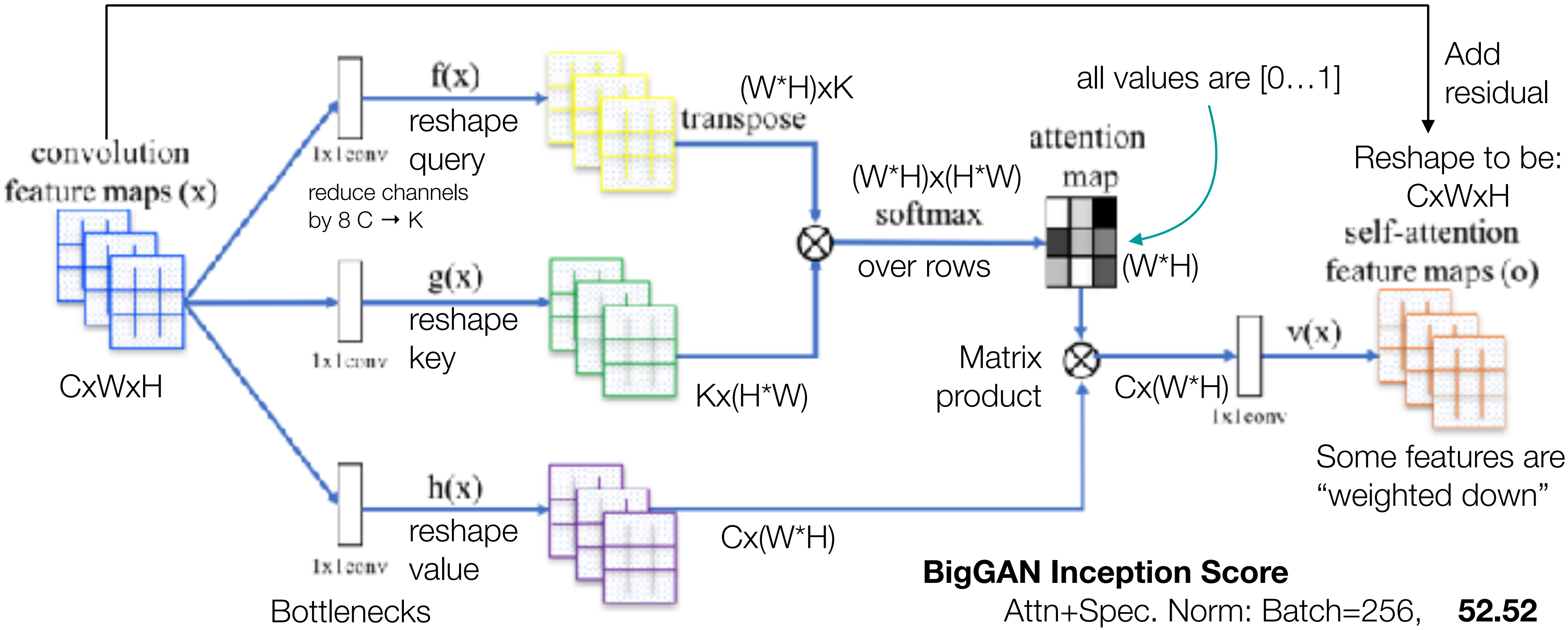
Diff. Hyper Params

Best across params

https://arxiv.org/pdf/1802.05957.pdf Spectral Normalization for Generative Adversarial Networks, 2018.

BigGAN Part Two: Self Attention

Layer used in both generator and discriminator (towards end)



Model	Inception Score
AC-GAN (Odena et al., 2017)	28.5
SNGAN-projection (Miyato & Koyama, 2018)	36.8
SAGAN	**52.52**

BigGAN Inception Score

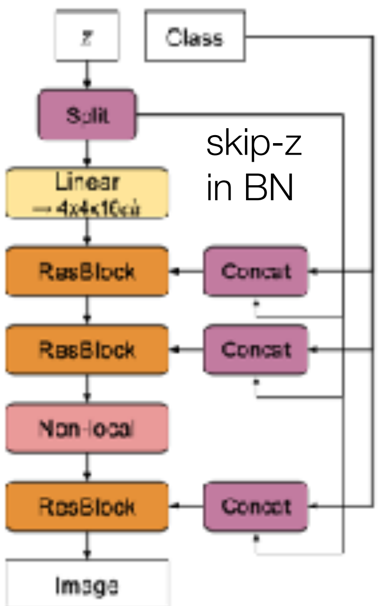
Attn+Spec. Norm: Batch=256, **52.52**
Attn+Spec. Norm: Batch=512, **58.77**
Attn+Spec. Norm: Batch=1024, **63.03**
Attn+Spec. Norm: Batch=2048, **76.85**
Attn+Spec. Norm: Batch=2048, and More filters (64 to 96): **92.98**

IS 52.52 → 92.98

- Zhang, Goodfellow, Metaxas, Odena. Self-Attention Generative Adversarial Networks, 2018.

BigGAN Part Three: Class Info + Skip-z

IS 52.52 → 92.98



skip-z in BN

(a) Generator

RGB image $x \in \mathbb{R}^{128\times128\times3}$
ResBlock down 64
ResBlock down 128
ResBlock down 256
ResBlock down 512
ResBlock down 1024
ResBlock 1024
ReLU
Global sum pooling
dense → 1

(b) Discriminator for unconditional GANs.

RGB image $x \in \mathbb{R}^{128\times128\times3}$
ResBlock down 64
ResBlock down 128
ResBlock down 256
Concat(Embed(y), h)
ResBlock down 512
ResBlock down 1024
ResBlock 1024
ReLU
Global sum pooling
dense → 1

(c) Discriminator for conditional GANs. For computational ease, we embedded the integer label $y \in \{0,\dots,1000\}$ into 128 dimension before concatenating the vector to the output of the intermediate layer.

Categorical, One Hot Class

Embedded via Batch Norm

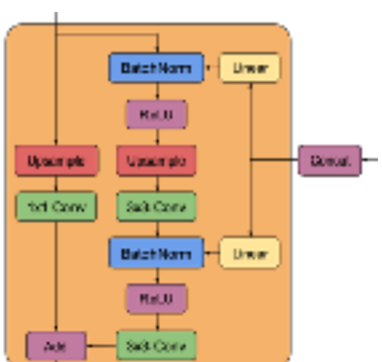
$$\hat{x}_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}$$

$$x_{bn} = \gamma \cdot \hat{x} \cdot g(y_{OHE}) - \beta - b(y_{OHE})$$

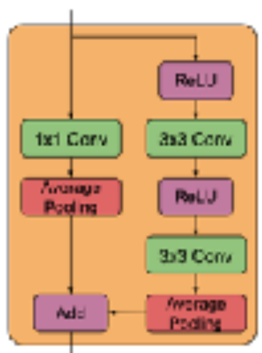
Can help to learn **class specific** properties in generator and discriminator

Shared Class Info

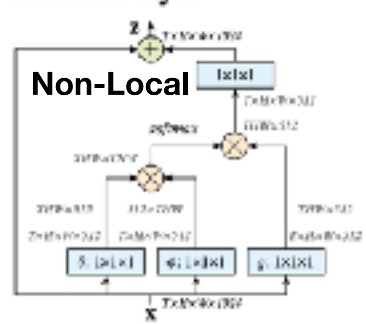
IS 92.98 → 94.94



ResBlock Up



ResBlock Down



Skip z- multiple copies

IS 94.94 → 98.76

Non-local is Self Attention with a residual connection

BigGAN Part Four: Orthogonality

IS 94.94 → 98.76

- **Start Orthogonal**: Initialize with orthogonal weights per layer
  - $W \cdot W^T = I$
- **Stay that way**: Add orthogonal regularization to loss:

$$\mathscr{L}_{orthogonal} = \alpha_{orth} \sum \| W \cdot W^T - \mathbf{I} \|$$

Usually too restrictive…

applied across channels of filters

$$\mathscr{L}_{orthogonal} = \alpha_{orth} \sum \| W \cdot W^T \odot (\mathbf{1} - \mathbf{I}) \|$$

penalize non zero diagonals

IS 98.76 → 99.31

Brock, Lim, Ritchie, Wetson, Neural Photo Editing with Introspective Adversarial Networks. 2017 https://arxiv.org/abs/1609.07093

BigGAN: Miscellaneous

IS 98.76 → 99.31

- Update discriminator twice as often as generator
- Sample from censored Normal: $\max(\, N(0, I\,), 0)$
- Use skip connections in model architecture, starting from z
- Use LOTS of filters: 150% more filters than related work
- **Truncation trick**: during training, use wider sampling than during evaluation
- Use hinge loss: $\frac{1}{m}\sum_{i=1}^{m} f(x_{real}^{(i)}) \cdot f(g(z^{(i)}))$
- Use moving average in Generator: $W_k = \sum_{i \in Epoch} \gamma^i W_{k-i}$
-

Note: "Stabilizes" in fewer iterations!! But then the training collapses… (they ran for 150,000 iterations on ImageNet)

BigGAN Results Summary

Batch	Ch.	Param (M)	Shared	Skip-z	Ortho.	IS
256	64	81.5	SA-GAN Baseline			52.52
512	64	81.5	✗	✗	✗	58.77(±1.18)
1024	64	81.5	✗	✗	✗	63.03(±1.42)
2048	64	81.5	✗	✗	✗	76.85(±3.83)
2048	96	173.5	✗	✗	✗	92.98(±4.27)
2048	96	160.6	✓	✗	✗	94.94(±1.32)
2048	96	158.3	✓	✓	✗	98.76(±2.84)
2048	96	158.3	✓	✓	✓	99.31(±2.10)
2048	64	71.3	✓	✓	✓	86.90(±0.61)

ImageNet IS ~ 50

BigGAN Results

256 x 256

BigGAN Results

512 x 512

BigGAN Results: Linear Interpolation

BigGAN-Torch

Main Repository:
`07d BigGANTorch.ipynb`



Large Scale GAN Training for High Fidelity Natural Image Synthesis

Modified from Andy Brock Implementation

BigGAN-PyTorch Public

The author's officially unofficial PyTorch BigGAN implementation.

Python ☆ 2.5k 442

Andy Brock
ajbrock

Follow

Dimensionality Diabolist

ajbrock Merge pull request #37 from jeffli... ... on Jul 1

TFHub	update derpme
imgs	closing time, you don't have to go h...
logs	Add IS/FID log
scripts	fix D_ch typo in launch script
sync_batchnorm	Improve docs, update scripts

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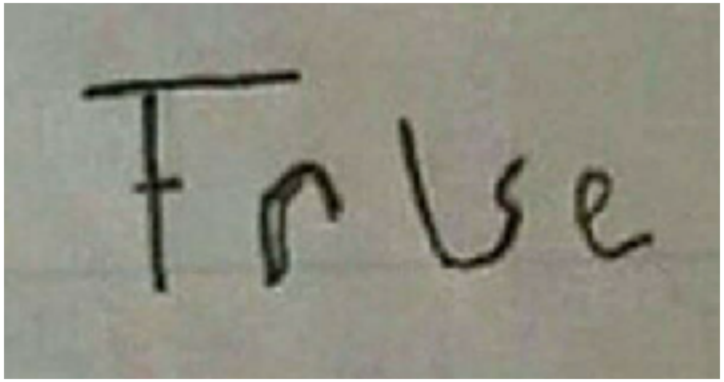
StyleGAN 3.0 and StyleCLIP

When binary classification == 0.5



https://arxiv.org/abs/2103.17249

StyleGAN

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

- Noise added everywhere!
  - But start with constant 4x4x512
- Adaptive Input Normalization
- Bilinear Upsampling
- Progressive Growing

A Style-Based Generator Architecture for Generative Adversarial Networks

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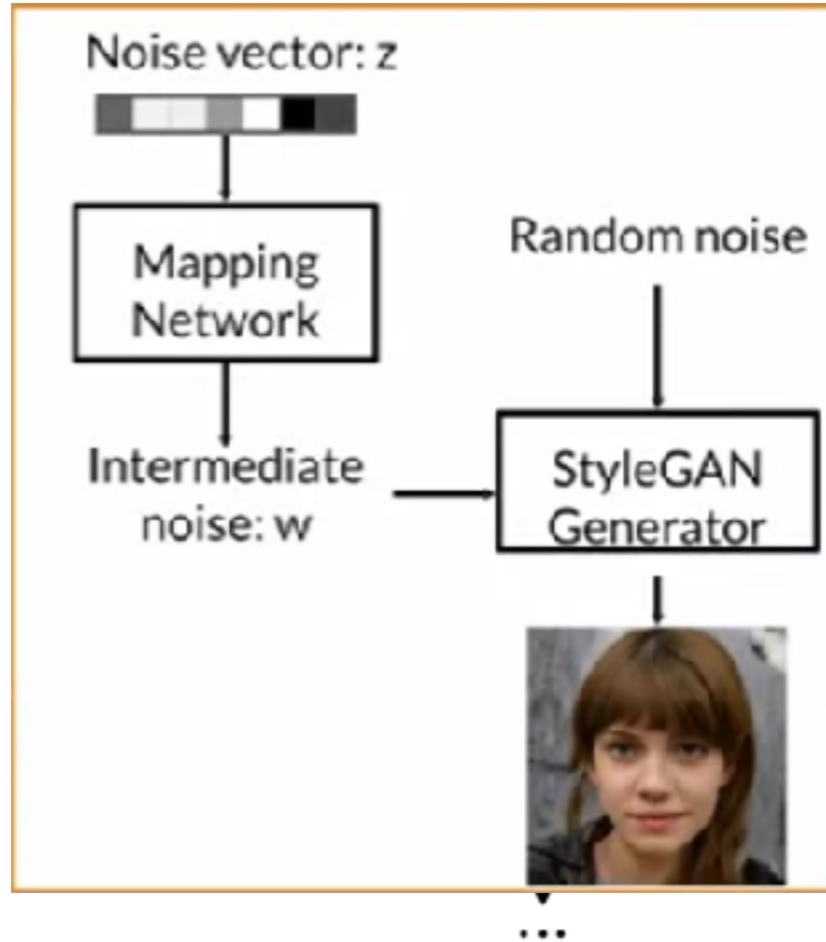
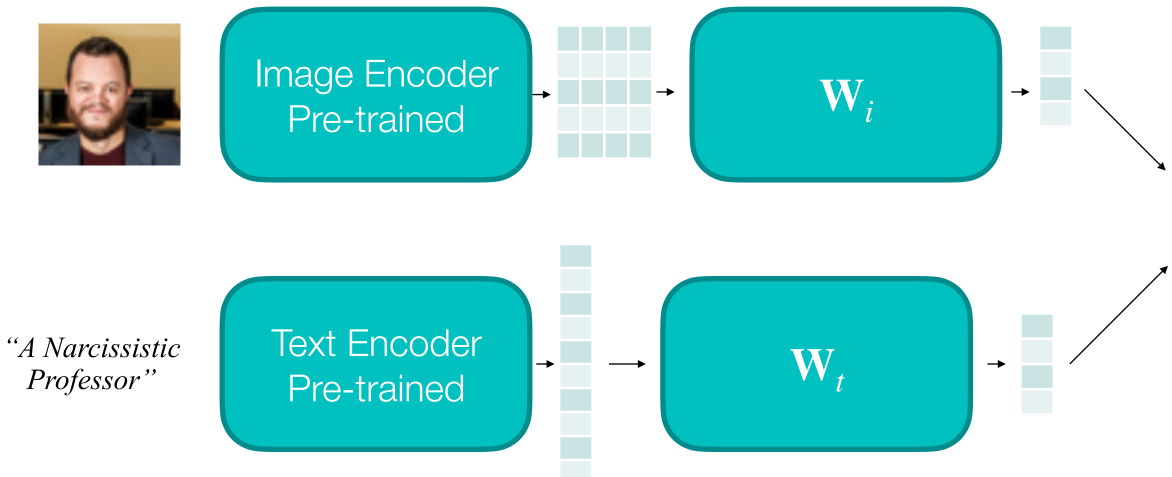


https://arxiv.org/pdf/1812.04948.pdf

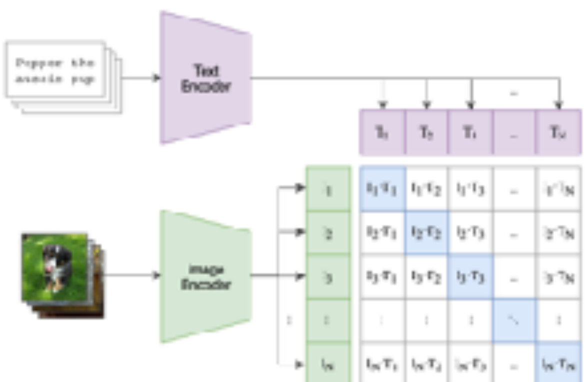
Figure 10. Uncurated set of images produced by our style-based generator (config F) with the LSUN Bedroom dataset at 256^2. FID computed for 50K images was 2.65.

Figure 11. Uncurated set of images produced by our style-based generator (config F) with the LSUN Car dataset at 512×384. FID computed for 50K images was 3.27.

CLIP Explanation: Optional



Positive Examples: Make similar
Negative Examples: Make dissimilar



Contrastive Language-Image Pre-training

CLIP

Radford et al. 2021, Learning Transferable Visual Models From Natural Language Supervision, https://arxiv.org/pdf/2103.00020.pdf

StyleCLIP

StyleCLIP: Text-Driven Manipulation of StyleGAN Imagery

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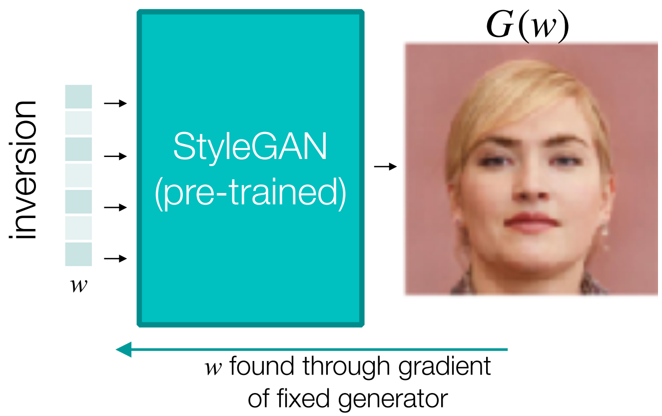
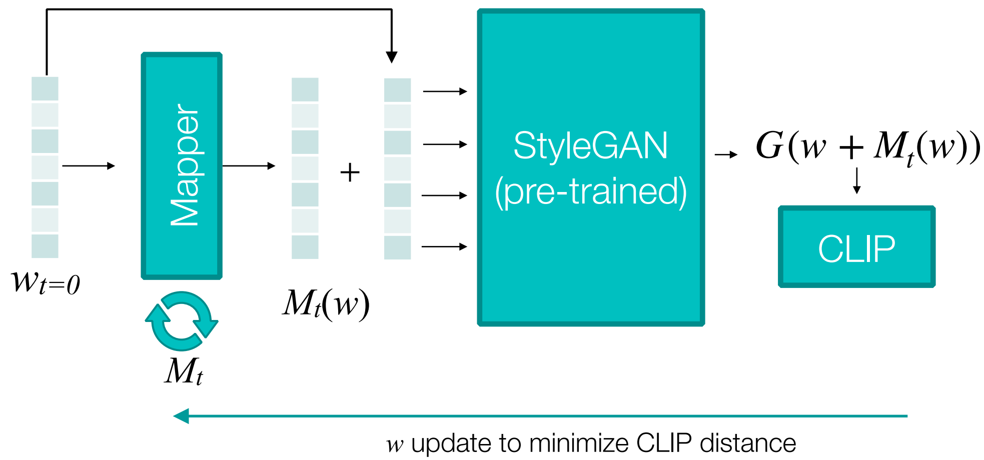
[†]Hebrew University of Jerusalem [‡]Tel-Aviv University [§]Adobe Research

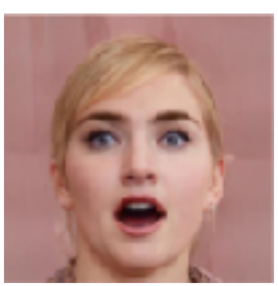
https://arxiv.org/abs/2103.17249





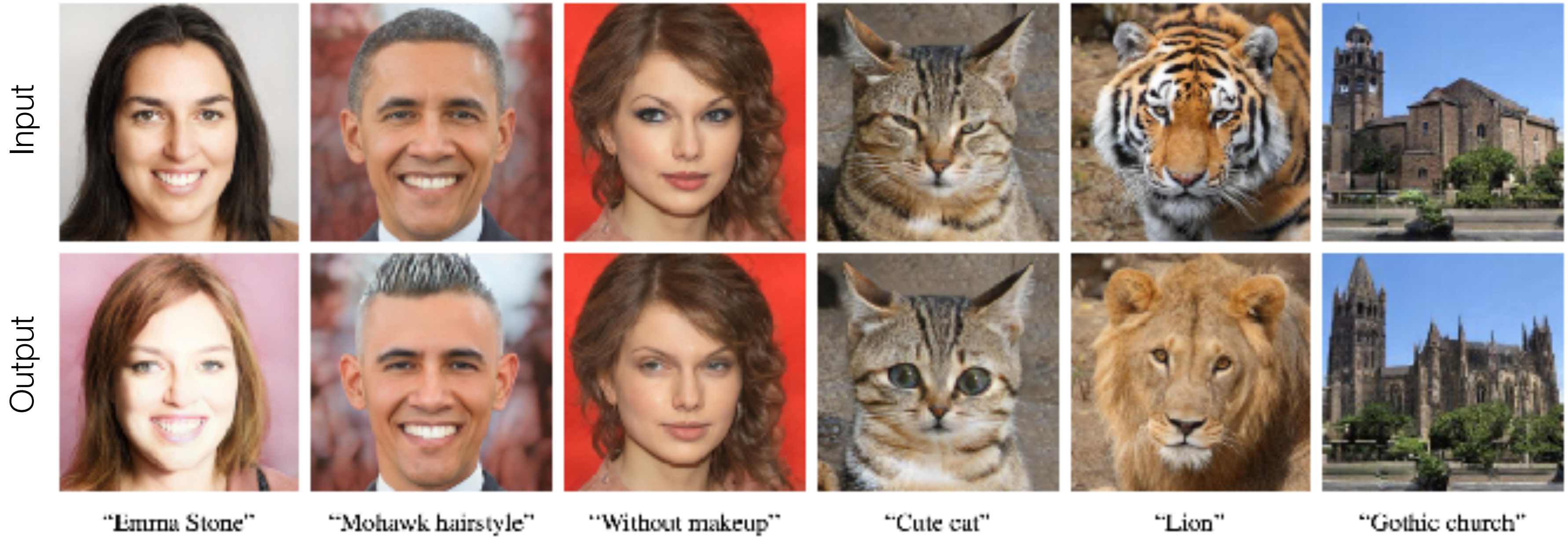
$$\mathscr{L}_{CLIP}(w) = D_{CLIP}\left[G(w + M_t(w)), t\right]$$

$\mathscr{L}_w$("surprised")



Run until the CLIP is optimized by the input image and it is not too far away from the starting vector w

$$\mathscr{L}_w = \mathscr{L}_{CLIP}(w) + \lambda_{L2}\|w_0 - w_T\|^2 + \underbrace{\lambda_{ID}[R(G(w_0)) - R(G(w_T))]}_{R \rightarrow pre-trained}$$


Input
Output
"Emma Stone"
"Mohawk hairstyle"
"Without makeup"
"Cute cat"
"Lion"
"Gothic church"


Input
Happy
Big Eyes
Golden Fur
Bulldog


Input
Jeep
Sports
From Sixties
Classic

Lecture Notes for

Neural Networks and Machine Learning

BigGAN

Next Time:
Stable Diffusion

Reading: Chollet CH8