Generative Adversarial Networks (GANs)

Fiseha B. Tesema, PhD

Slide Credit

- Majority of the slide is complied from
  1. Deep Learning for computer vision: University of Michigan, https://web.eecs.umich.edu/~justincj/teaching/eecs498/WI2022/
  2. CS231n: Deep Learning for Computer Vision, Stanford university, https://cs231n.stanford.edu/

Generative Models

- Given training data, generate new samples from same distribution

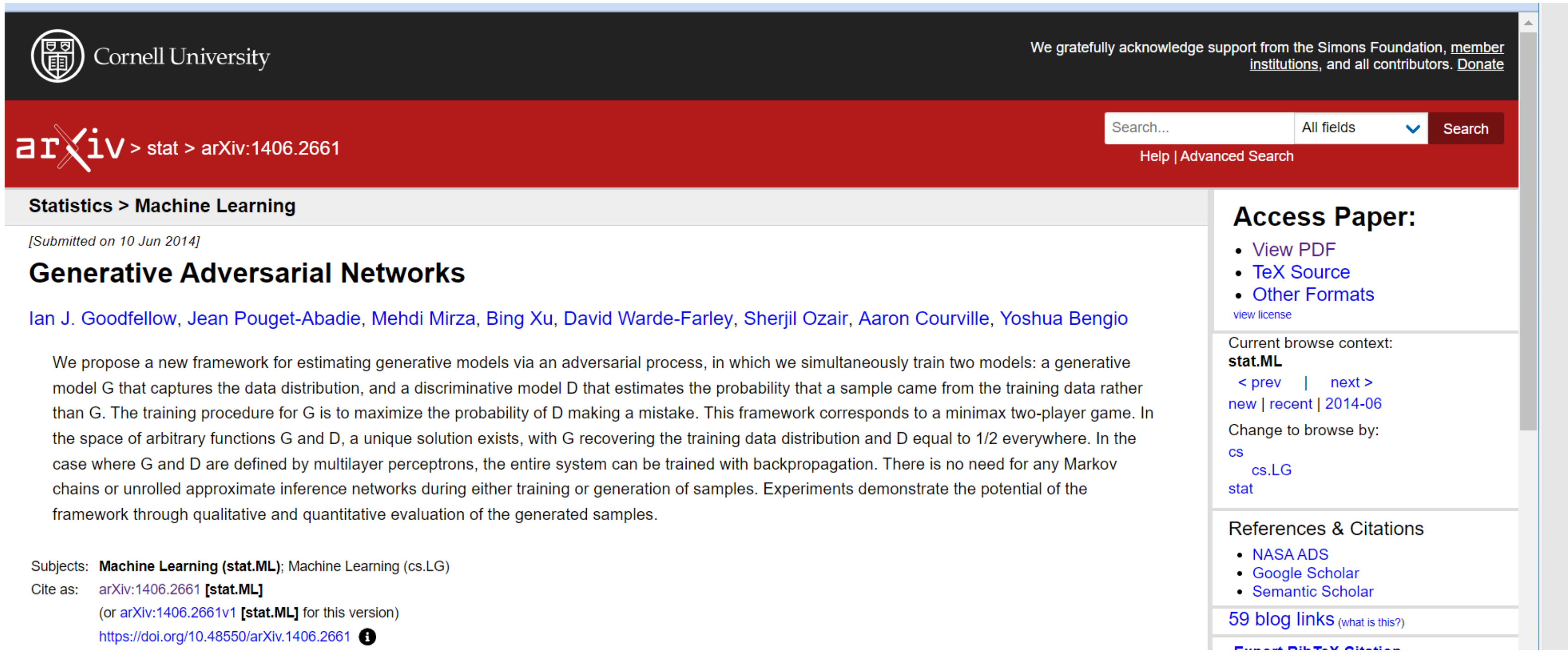
Training data ~ $p_{data}(x)$

Generated samples ~ $p_{model}(x)$

Want to learn $p_{model}(x)$ similar to $p_{data}(x)$

What is a Generative Adversarial Network?

The GAN architecture was first described in the 2014 paper by Ian Goodfellow, et al. titled “Generative Adversarial Networks.”



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arXiv > stat > arXiv:1406.2661

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[Submitted on 10 Jun 2014]

Generative Adversarial Networks

Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, Yoshua Bengio

We propose a new framework for estimating generative models via an adversarial process, in which we simultaneously train two models: a generative model G that captures the data distribution, and a discriminative model D that estimates the probability that a sample came from the training data rather than G. The training procedure for G is to maximize the probability of D making a mistake. This framework corresponds to a minimax two-player game. In the space of arbitrary functions G and D, a unique solution exists, with G recovering the training data distribution and D equal to 1/2 everywhere. In the case where G and D are defined by multilayer perceptrons, the entire system can be trained with backpropagation. There is no need for any Markov chains or unrolled approximate inference networks during either training or generation of samples. Experiments demonstrate the potential of the framework through qualitative and quantitative evaluation of the generated samples.

Subjects: **Machine Learning (stat.ML)**; Machine Learning (cs.LG)

Cite as: arXiv:1406.2661 **[stat.ML]**

(or arXiv:1406.2661v1 **[stat.ML]** for this version)

https://doi.org/10.48550/arXiv.1406.2661

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References & Citations

- NASA ADS
- Google Scholar
- Semantic Scholar

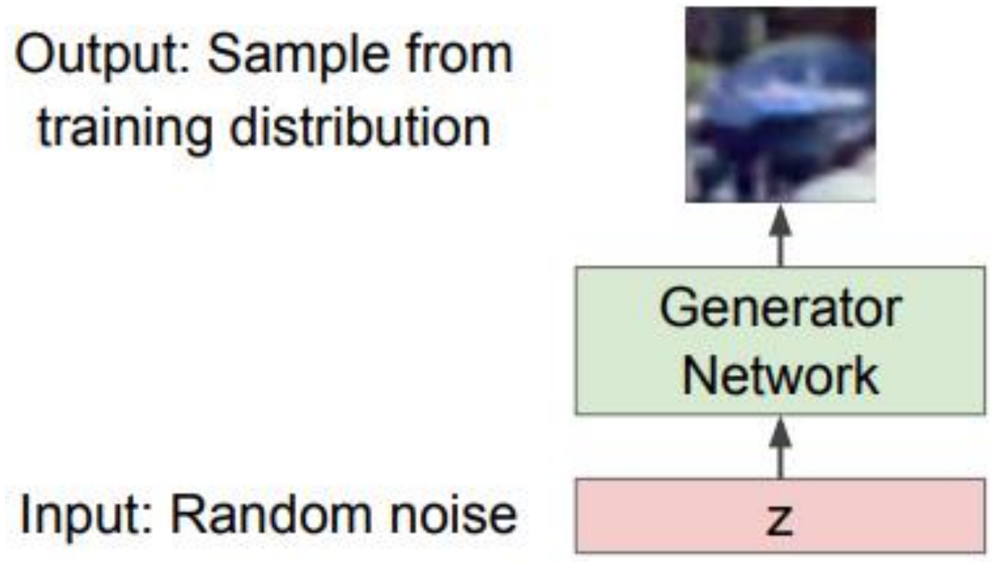
59 blog links (what is this?)

“the most interesting idea in the last 10 years in machine learning”,
Yann LeCun, Chief AI Scientist at Facebook

What is a Generative Adversarial Network?

- GAN for short
  - “Generative” = it generates/produces things
  - “Adversarial” = element of competition
  - “Network” = well, it’s a network

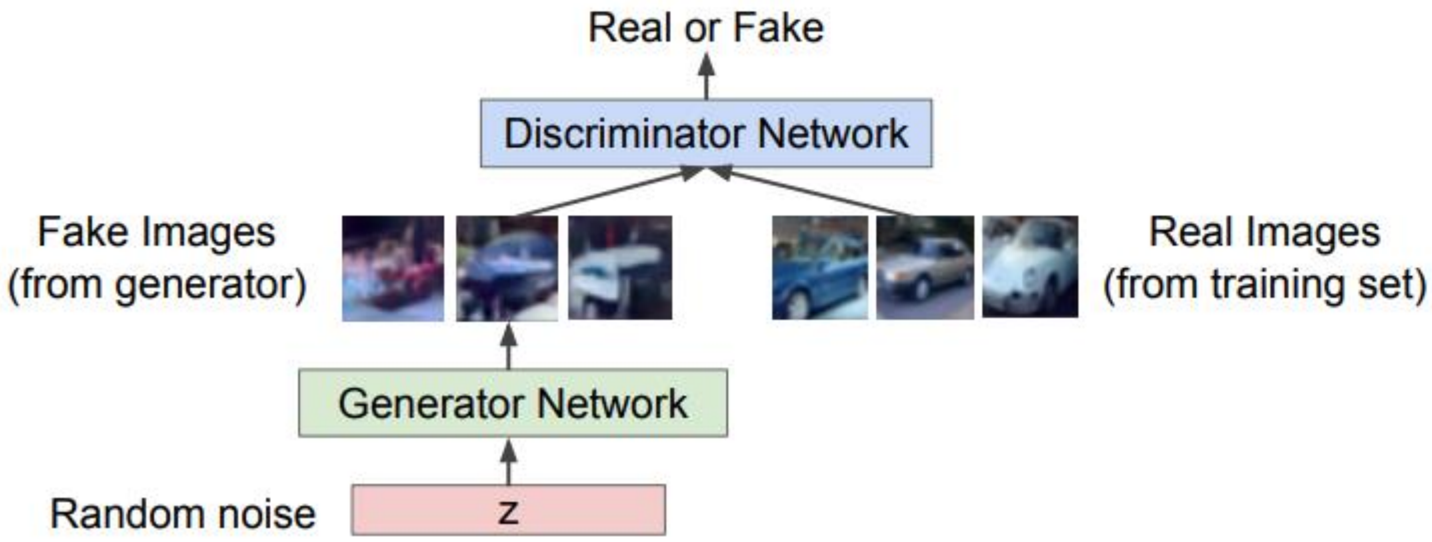
Generative Adversarial Network



From Goodfellow et al, 2014, Generative Adversarial Networks

Training GANs: Two –player game

- **Generator network:** try to fool the discriminator by generating real-looking images
- **Discriminator network:** try to distinguish between real and fake images



Training GANs: Two –player game

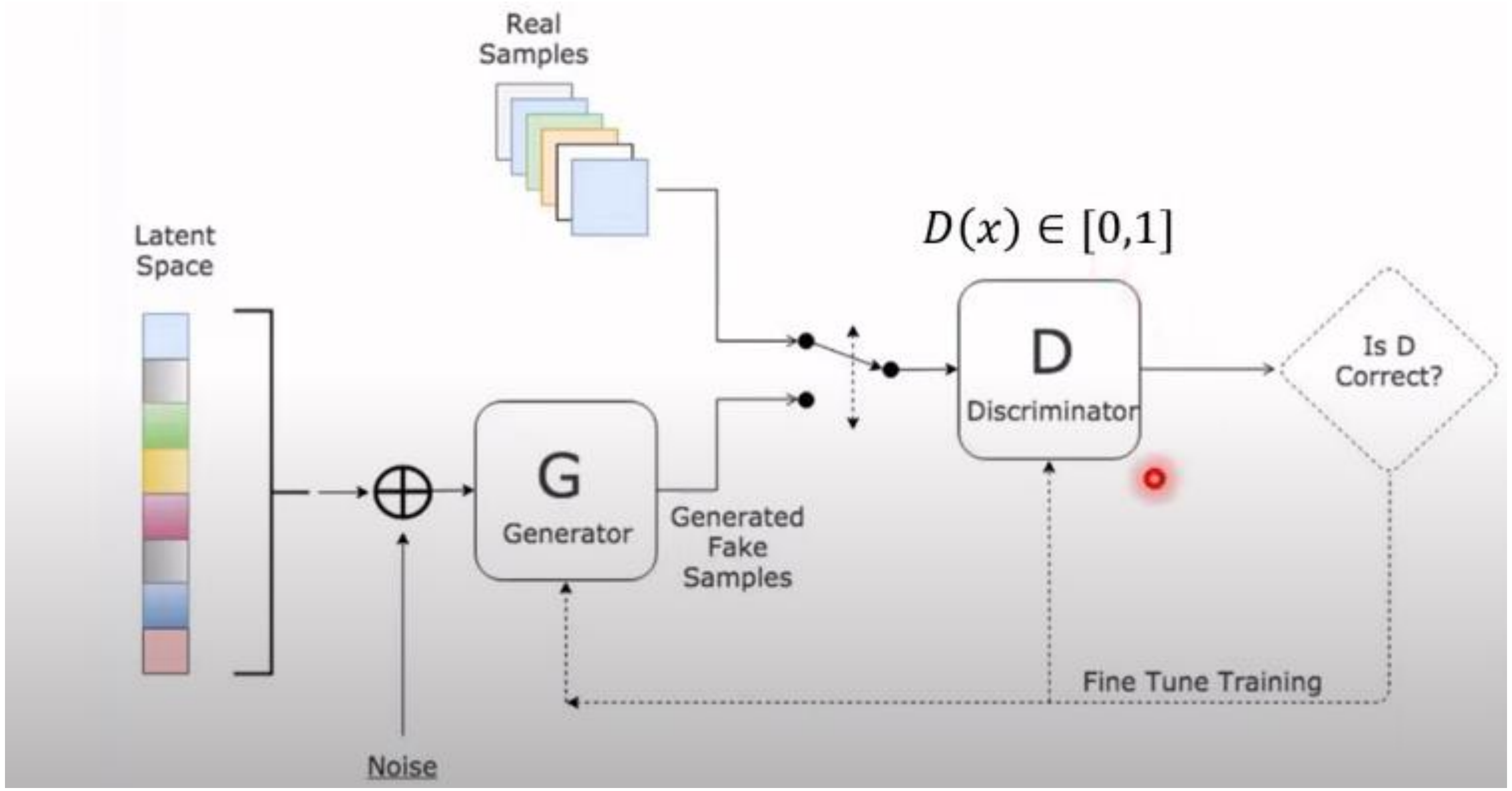


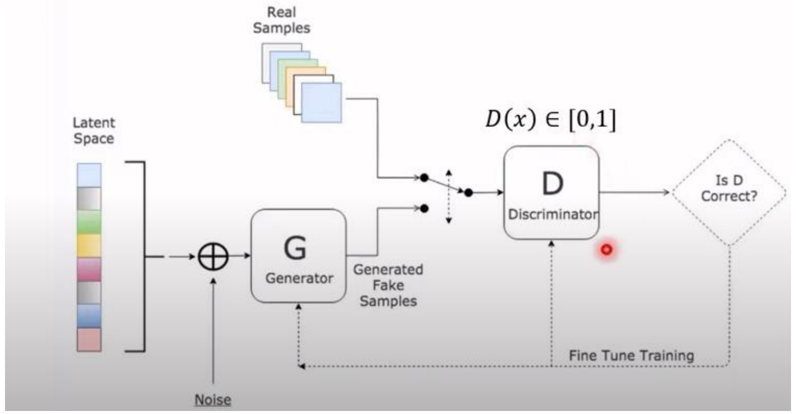
Image source: https://www.youtube.com/watch?v=-UDvuBpcCXw

Training GANs: Two –player game

- **Generator network:** try to fool the discriminator by generating real-looking images
- **Discriminator network:** try to distinguish between real and fake images
- Train Jointly in **minimax game:**
  - Minimax objective function:

Discriminator outputs likelihood in (0,1) of real image

$$\min_{\theta_g}\max_{\theta_d}\left[\mathbb{E}_{x\sim p_{data}}\log \underbrace{D_{\theta_d}(x)}_{\text{Discriminator output for real data x}} + \mathbb{E}_{z\sim p(z)}\log(1-\underbrace{D_{\theta_d}(G_{\theta_g}(z))}_{\text{Discriminator output for generated fake data G(z)}})\right]$$



- Where,
  - D(x) is the discriminator's estimate of the probability that real data instance x is real.
  - Ex is the expected value over all real data instances.
  - G(z) is the generator's output when given noise z.
  - D(G(z)) is the discriminator's estimate of the probability that a fake instance is real.
  - Ez is the expected value over all random inputs to the generator (in effect, the expected value over all generated fake instances G(z)).

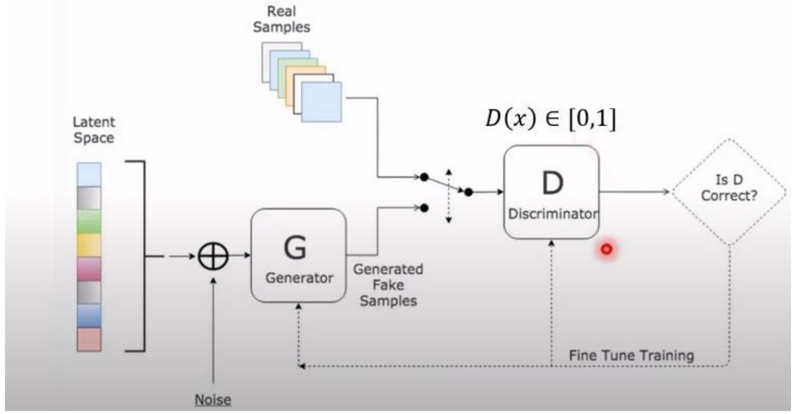
From Goodfellow et al, 2014, Generative Adversarial Networks

Training GANs: Two –player game

- Minimax objective function:

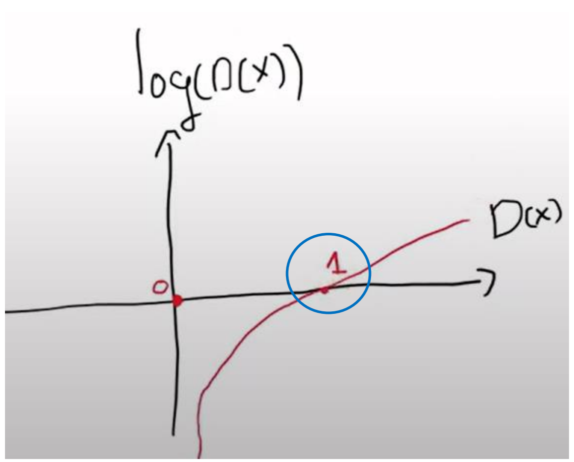
$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

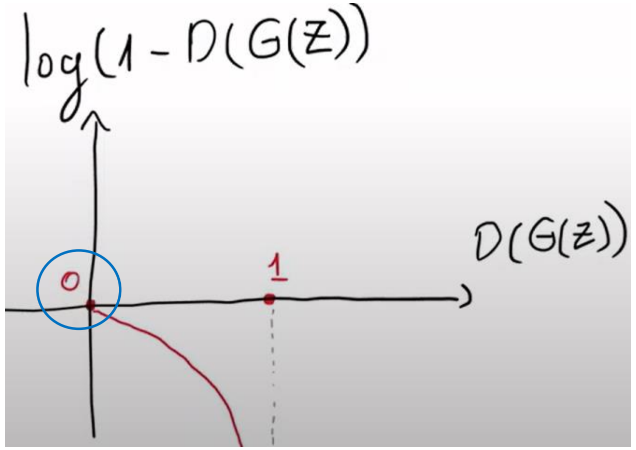
- Alternate between:
  - 1. **Gradient asent** on discriminator



$$\max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \boxed{\log D_{\theta_d}(x)} + \mathbb{E}_{z \sim p(z)} \boxed{\log(1 - D_{\theta_d}(G_{\theta_g}(z)))} \right]$$

- The objective is to predict the real image is 1.
- The max value is when D(x) is 1.
- Thus the objective function needs to be maximized

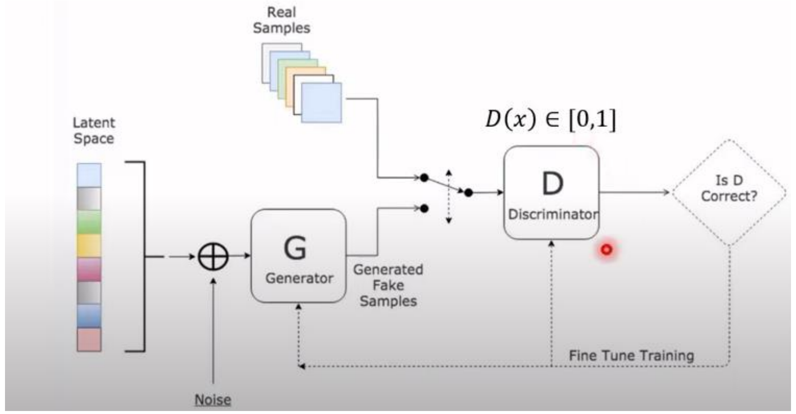




- The objective is to predict the fake image is 0.
- The max value is when D(G(z)) is zero.
- Thus the objective function needs to be maximized to get 0.

From Goodfellow et al, 2014, Generative Adversarial Networks

Training GANs: Two –player game



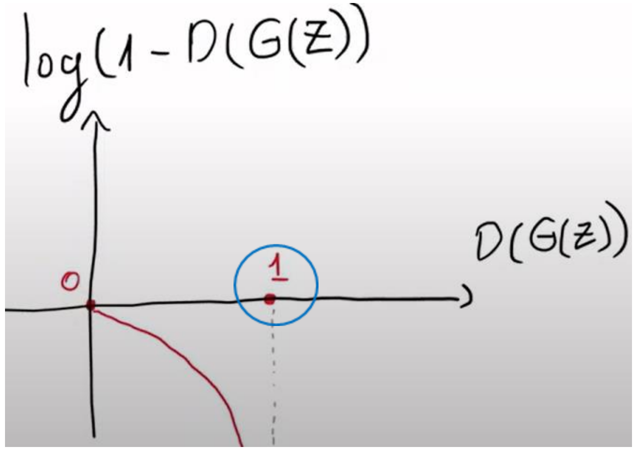
- Minimax objective function:

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

- Alternate between:
  - 1. Gradient desent on generator

$$\min_{\theta_g} \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))$$

- The objective is to predict the fake image is 1.
- The D(G(z)) is become 1 when the objective function is minimized.
- Thus the objective function needs to be minimized.



From Goodfellow et al, 2014, Generative Adversarial Networks

Training GANs: Two –player game

- Minimax objective function:

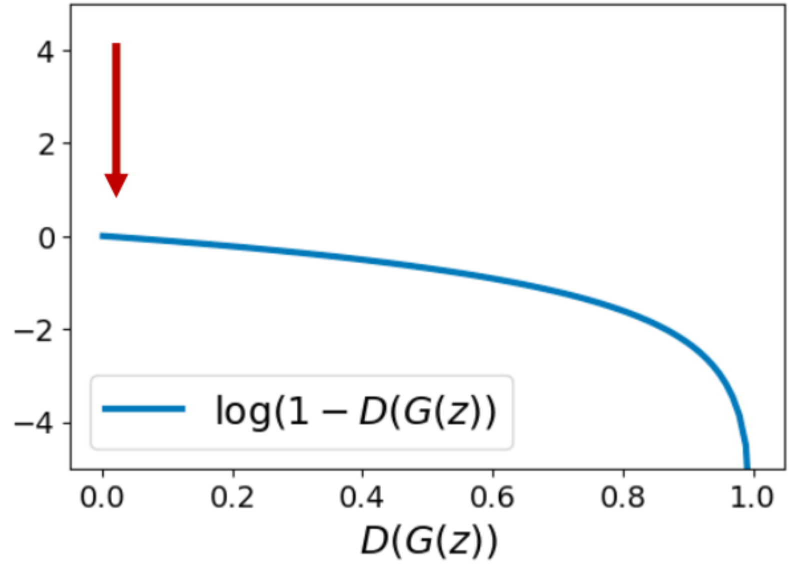
$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x\sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z\sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))\right]$$

- Alternate between:
    - 1. **Gradient asent** on discriminator

$$\max_{\theta_d} \left[\mathbb{E}_{x\sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z\sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))\right]$$

    - 2. **Gradient desent** on generator

$$\min_{\theta_g} \mathbb{E}_{z\sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))$$



At start of training, generator is very bad and discriminator can easily tell apart real/fake, so D(G(z)) close to 0

Problem: Vanishing gradients for G

From Goodfellow et al, 2014, Generative Adversarial Networks

Training GANs: Two –player game

- Minimax objective function:

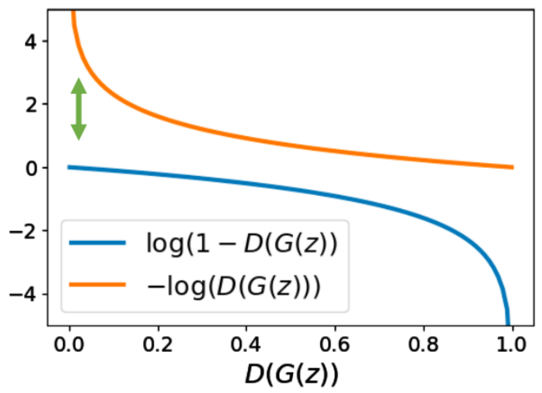
$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x\sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z\sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

- Alternate between:
  - 1. **Gradient asent** on discriminator

$$\max_{\theta_d} \left[\mathbb{E}_{x\sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z\sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

  - 2. **Gradient ascent** on generator, different objective

$$\max_{\theta_g} \mathbb{E}_{z\sim p(z)} \text{-}\log(D_{\theta_d}(G_{\theta_g}(z)))$$



At start of training, generator is very bad and discriminator can easily tell apart real/fake, so D(G(z)) close to 0

Problem: Vanishing gradients for G

Solution: Right now G is trained to minimize log(1-D(G(z)). Instead, train G to maximize –log(D(G(z)).
Then G gets strong gradients at start of training!

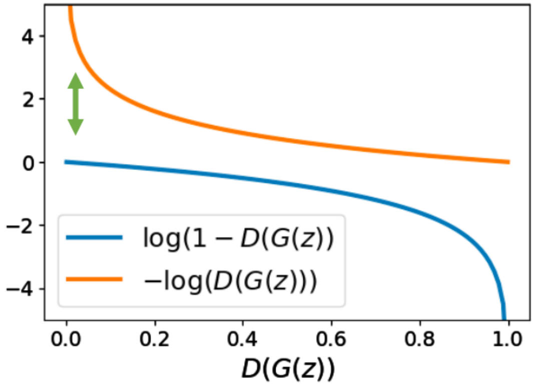
From Goodfellow et al, 2014, Generative Adversarial Networks

Training GANs: Two –player game

Aside: Jointly training two networks is challenging, can be unstable. Choosing objectives with better loss landscapes helps training, is an active area of research.

- Minimax objective function:

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x\sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z\sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))\right]$$



- Alternate between:
  - 1. **Gradient asent** on discriminator

$$\max_{\theta_d} \left[\mathbb{E}_{x\sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z\sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))\right]$$

  - 2. Gradient ascent on generator, different objective

$$\max_{\theta_g} \mathbb{E}_{z\sim p(z)} \text{-}\log(D_{\theta_d}(G_{\theta_g}(z)))$$

At start of training, generator is very bad and discriminator can easily tell apart real/fake, so D(G(z)) close to 0

Problem: Vanishing gradients for G

Solution: Right now G is trained to minimize log(1-D(G(z)). Instead, train G to maximize –log(D(G(z)).
Then G gets strong gradients at start of training!

From Goodfellow et al, 2014, Generative Adversarial Networks

Training GANs: Two-player game

- Putting it together: GAN training algorithm

for number of training iterations **do**
  for k steps **do**
    • Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
    • Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
    • Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D_{\theta_d}(x^{(i)}) + \log(1 - D_{\theta_d}(G_{\theta_g}(z^{(i)}))) \right]$$

  end for
  • Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  • Update the generator by ascending its stochastic gradient (improved objective):

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} -\log(D_{\theta_d}(G_{\theta_g}(z^{(i)})))$$

end for

From Goodfellow et al, 2014, Generative Adversarial Networks

Training GANs: Two-player game

- Putting it together: GAN training algorithm

for number of training iterations **do**

  for k steps **do**

  - Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \dots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  - Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \dots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
  - Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D_{\theta_d}(x^{(i)}) + \log(1 - D_{\theta_d}(G_{\theta_g}(z^{(i)}))) \right]$$

  end for

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \dots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Update the generator by ascending its stochastic gradient (improved objective):

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log(D_{\theta_d}(G_{\theta_g}(z^{(i)})))$$

end for

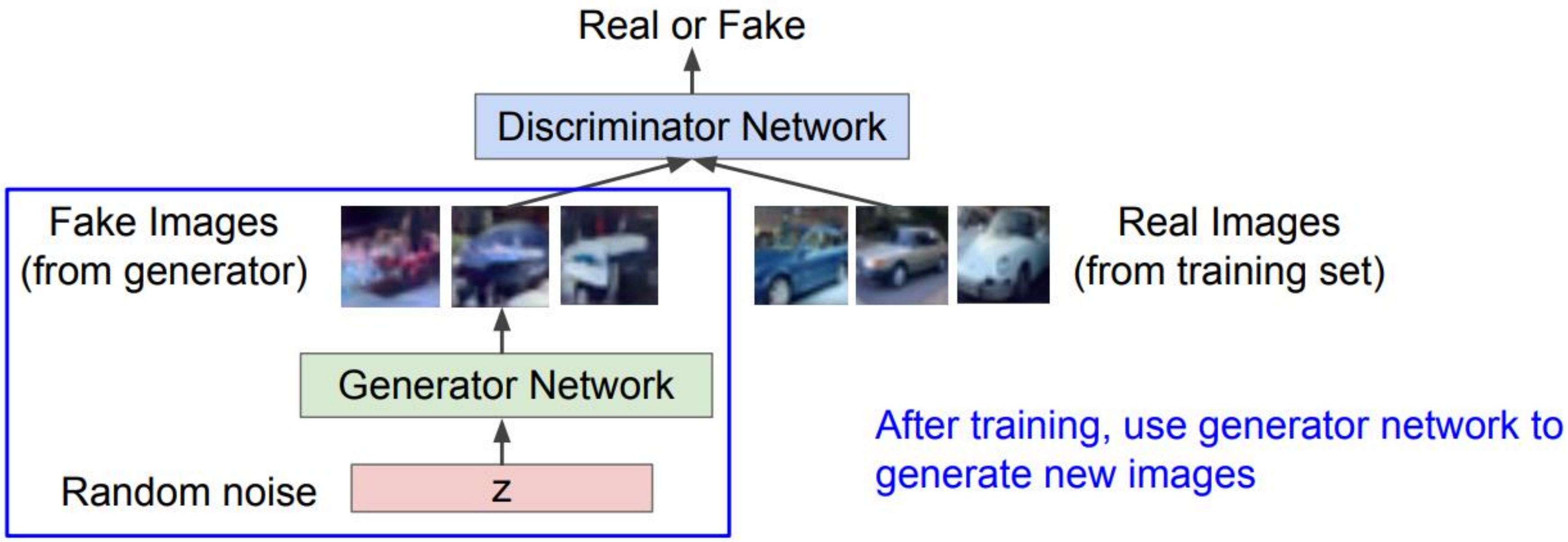
Some find k=1 more stable, others use k > 1, no best rule.

Recent work (e.g. Wasserstein GAN) alleviates this problem, better stability!

From Goodfellow et al, 2014, Generative Adversarial Networks

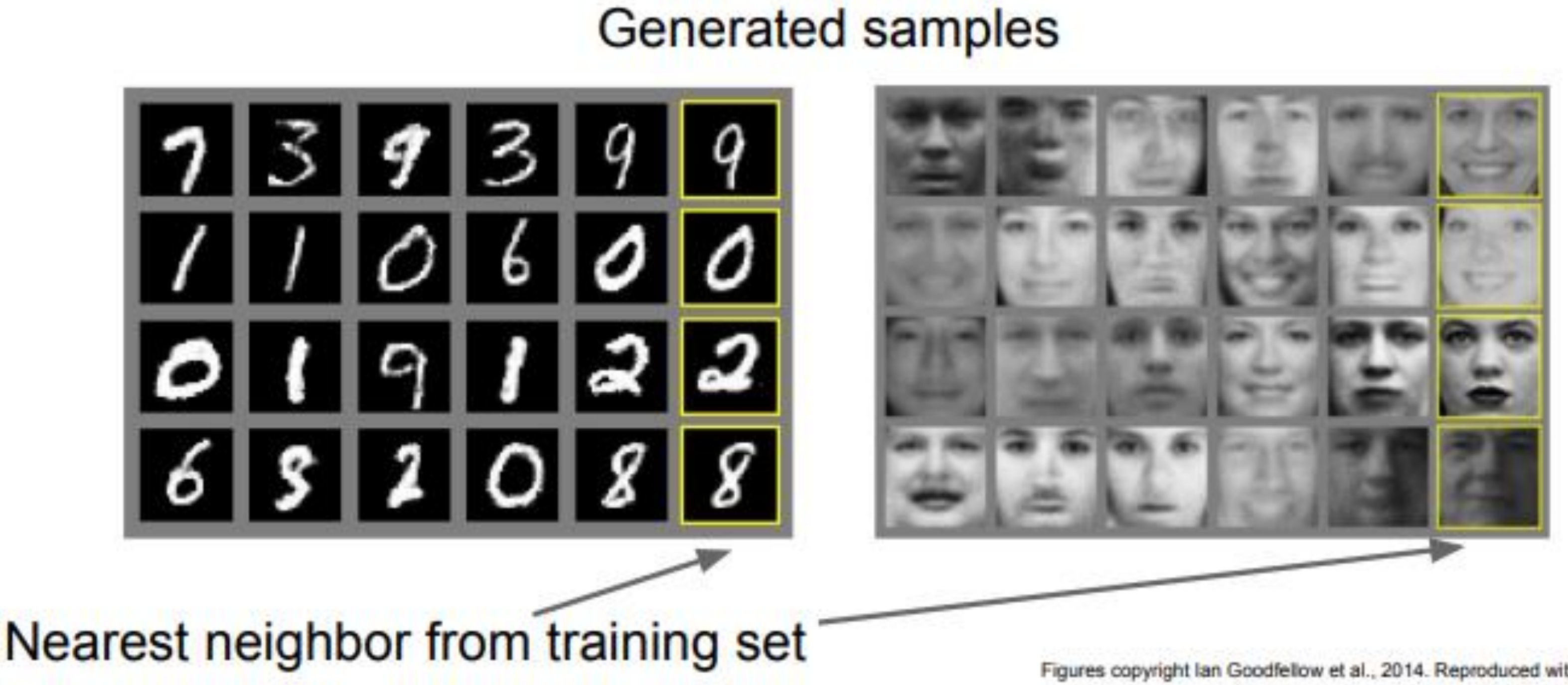
Training GANs: Two-player game

- **Generator network:** try to fool the discriminator by generating real-looking images
- **Discriminator network**: try to distinguish between real and fake images



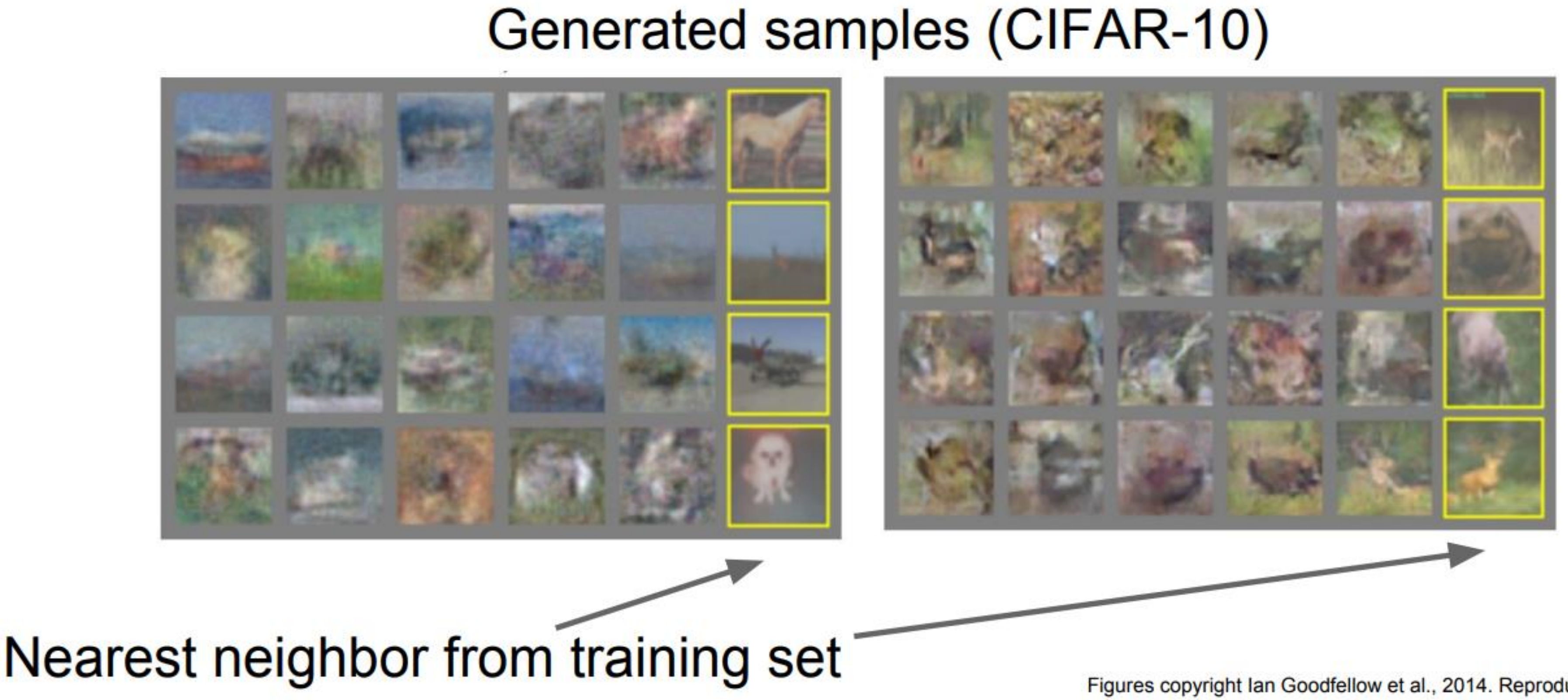
Generative Adversarial Nets

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014



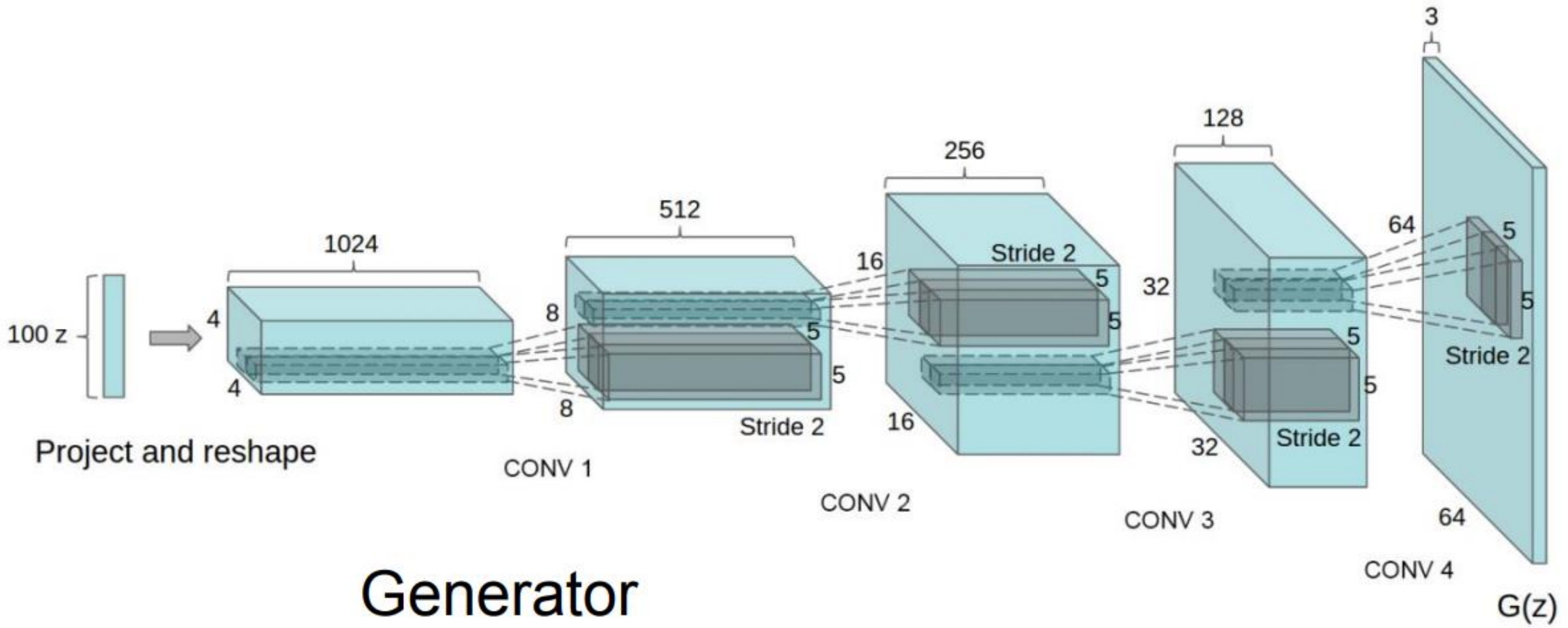
Generative Adversarial Nets

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014



Generative Adversarial Nets: Deep Convolutional (DC)-GAN

- Generator is an upsampling network with fractionally-strided convolutions
  Discriminator is a convolutional network.



Radford et al, “Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks”, ICLR 2016

Generative Adversarial Nets: DC-GAN

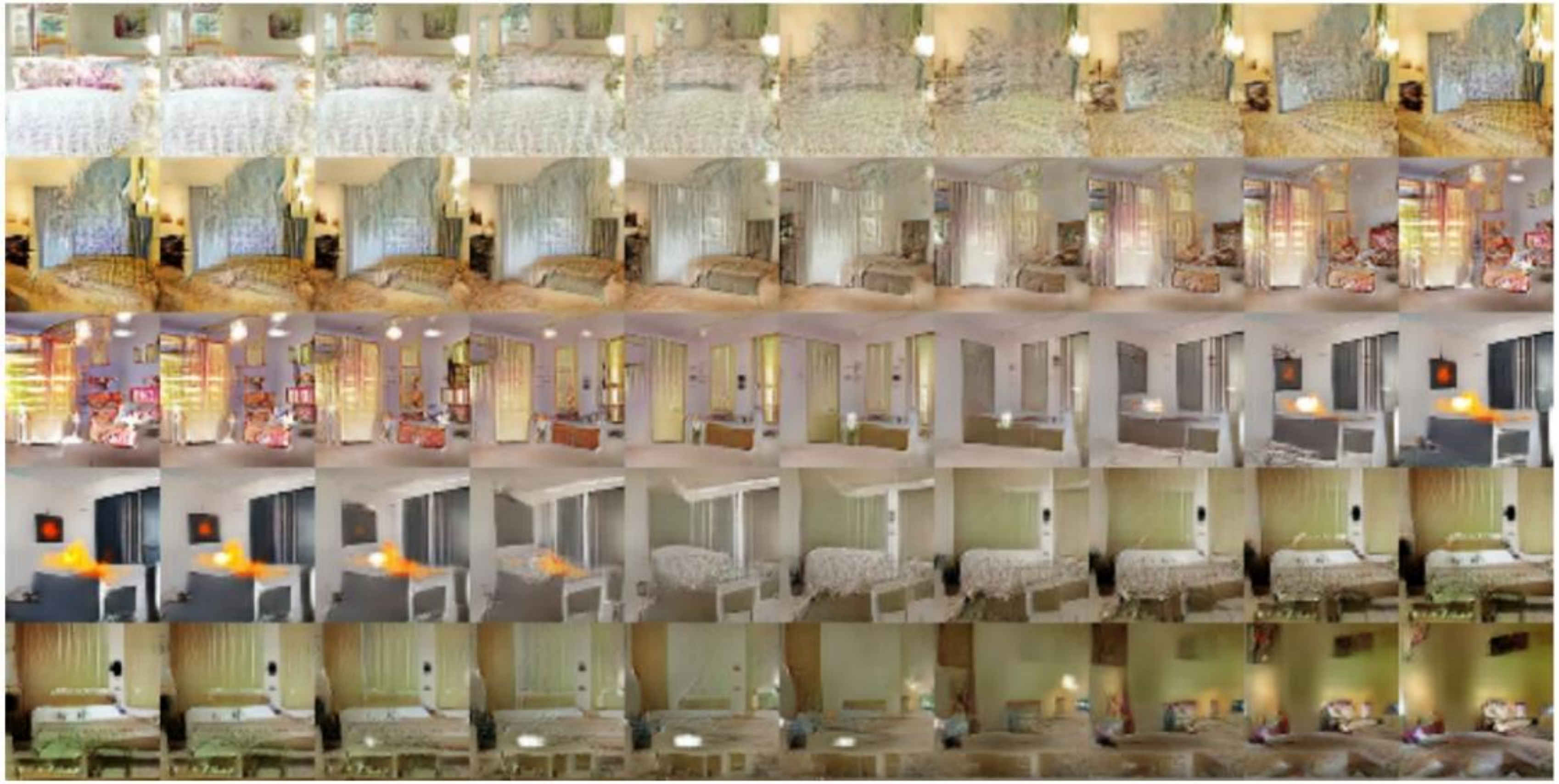
Samples from the model look amazing!

Radford et al, ICLR 2016

Radford et al, “Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks”, ICLR 2016

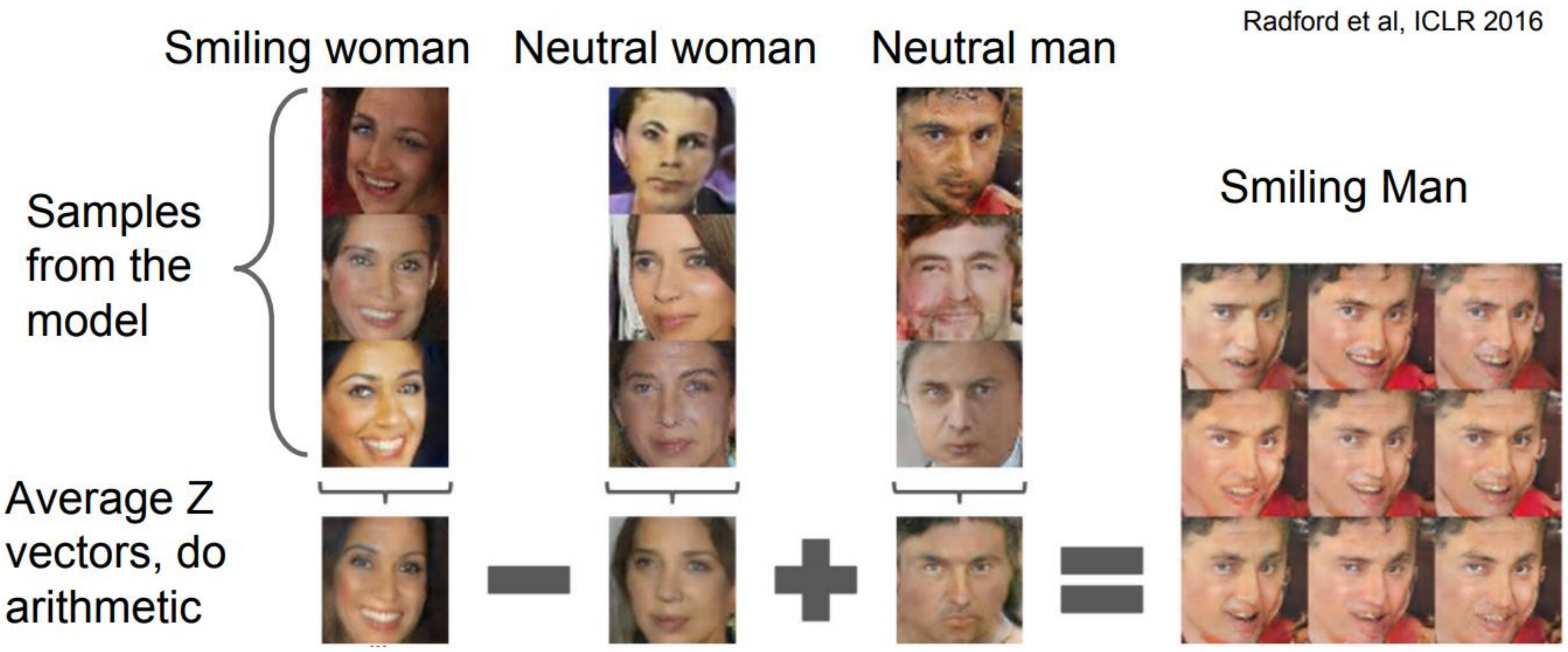
Generative Adversarial Nets: Interpolation

Interpolating between points in latent z space.



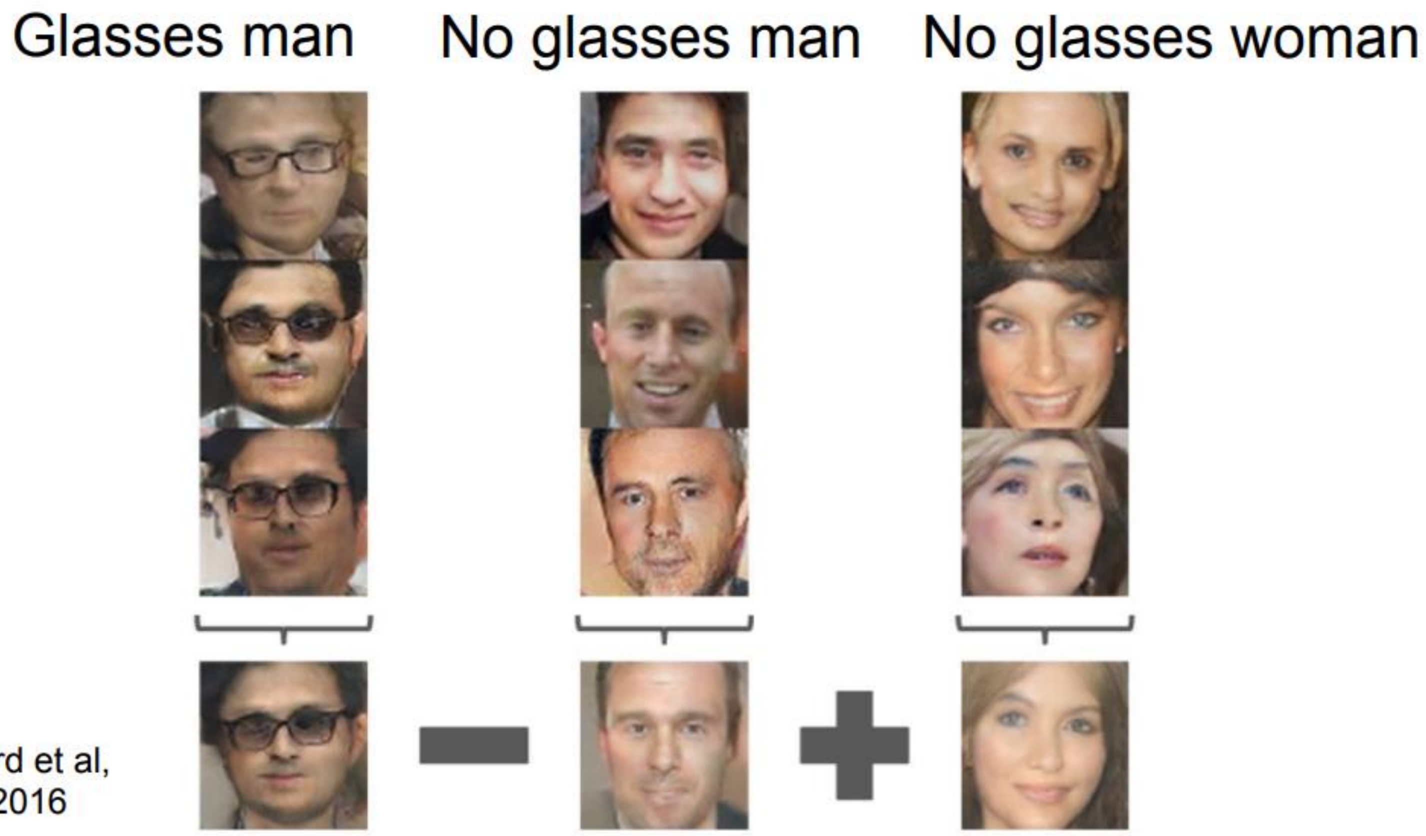
Radford et al, “Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks”, ICLR 2016

Generative Adversarial Nets: Interpretable Vector Math



$$z_{\text{smiling\_man}} = \text{avg}(z_{\text{smiling\_women}}) - \text{avg}(z_{\text{neutral\_women}}) + \text{avg}(z_{\text{neutral\_men}})$$

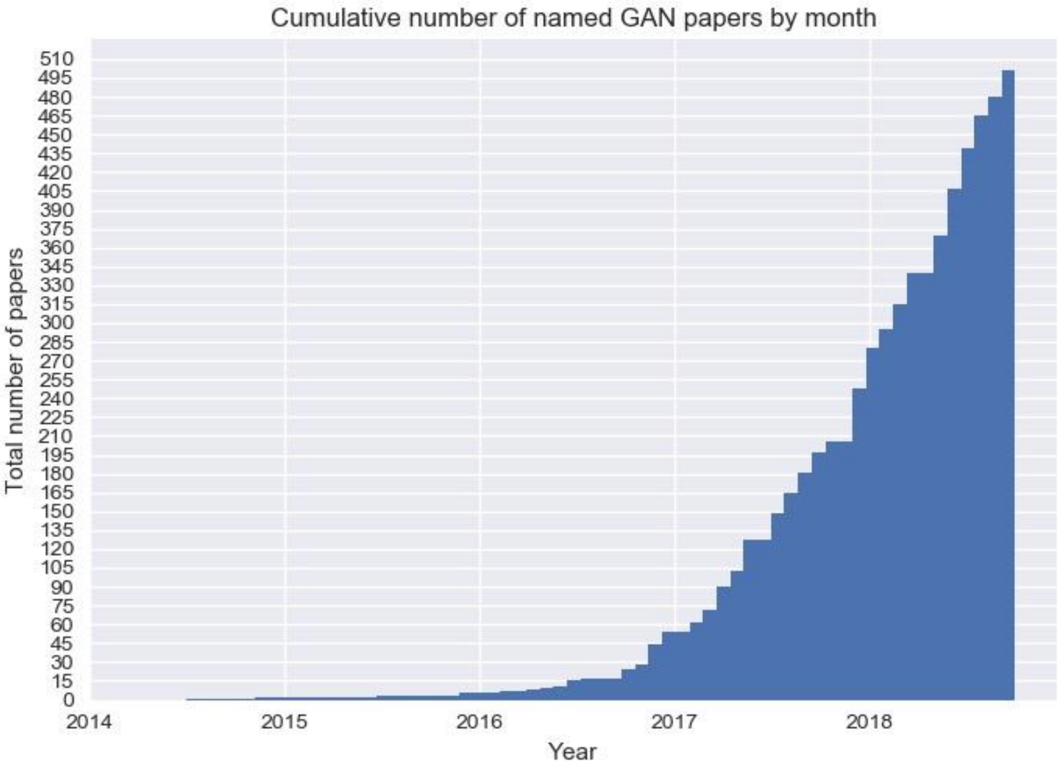
Generative Adversarial Nets: Interpretable Vector Math



Radford et al,
ICLR 2016

Generative Adversarial Nets: Interpretable Vector Math

2017 to present: Explosion of GANs

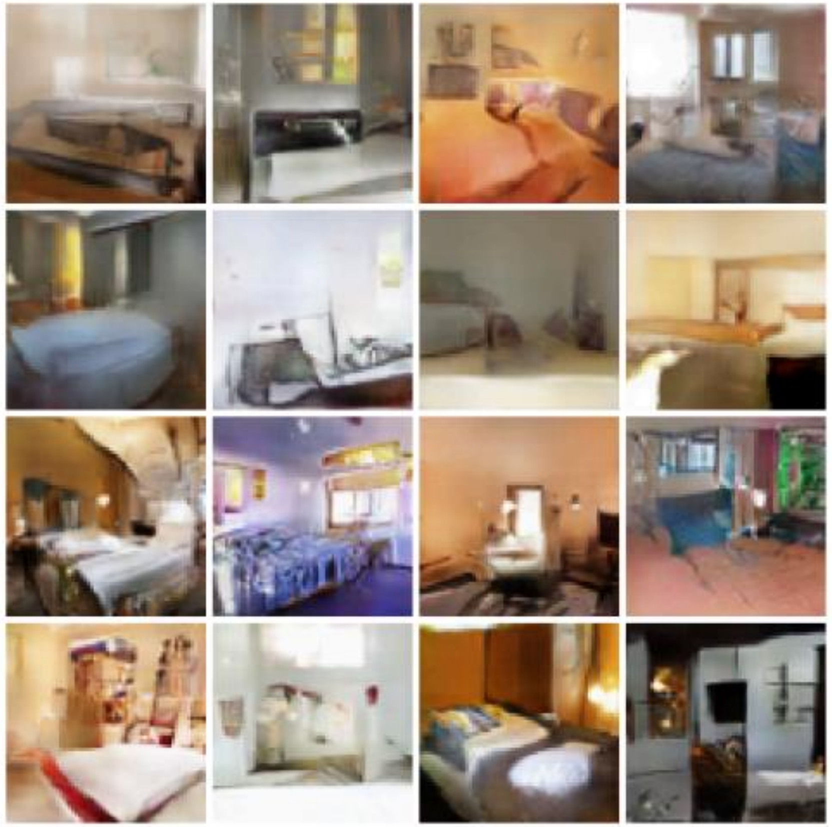


https://github.com/hindupuravinash/the-gan-zoo?tab=readme-ov-file

- 3D-ED-GAN - Shape Inpainting using 3D Generative Adversarial Network and Recurrent Convolutional Networks
- 3D-GAN - Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling (github)
- 3D-IWGAN - Improved Adversarial Systems for 3D Object Generation and Reconstruction (github)
- 3D-PhysNet - 3D-PhysNet: Learning the Intuitive Physics of Non-Rigid Object Deformations
- 3D-RecGAN - 3D Object Reconstruction from a Single Depth View with Adversarial Learning (github)
- ABC-GAN - ABC-GAN: Adaptive Blur and Control for improved training stability of Generative Adversarial Networks (github)
- ABC-GAN - GANs for LIFE: Generative Adversarial Networks for Likelihood Free Inference
- AC-GAN - Conditional Image Synthesis With Auxiliary Classifier GANs
- acGAN - Face Aging With Conditional Generative Adversarial Networks
- ACGAN - Coverless Information Hiding Based on Generative adversarial networks
- acGAN - On-line Adaptative Curriculum Learning for GANs
- ACtuAL - ACtuAL: Actor-Critic Under Adversarial Learning
- AdaGAN - AdaGAN: Boosting Generative Models
- Adaptive GAN - Customizing an Adversarial Example Generator with Class-Conditional GANs
- AdvEntuRe - AdvEntuRe: Adversarial Training for Textual Entailment with Knowledge-Guided Examples
- AdvGAN - Generating adversarial examples with adversarial networks
- AE-GAN - AE-GAN: adversarial eliminating with GAN
- AE-OT - Latent Space Optimal Transport for Generative Models
- AEGAN - Learning Inverse Mapping by Autoencoder based Generative Adversarial Nets
- AF-DCGAN - AF-DCGAN: Amplitude Feature Deep Convolutional GAN for Fingerprint Construction in Indoor Localization System
- AffGAN - Amortised MAP Inference for Image Super-resolution
- AIM - Generating Informative and Diverse Conversational Responses via Adversarial Information Maximization
- AL-CGAN - Learning to Generate Images of Outdoor Scenes from Attributes and Semantic Layouts
- ALI - Adversarially Learned Inference (github)
- AlignGAN - AlignGAN: Learning to Align Cross-Domain Images with Conditional Generative Adversarial Networks
- AlphaGAN - AlphaGAN: Generative adversarial networks for natural image matting
- AM-GAN - Activation Maximization Generative Adversarial Nets
- AmbientGAN - AmbientGAN: Generative models from lossy measurements (github)
- AMC-GAN - Video Prediction with Appearance and Motion Conditions
- AnoGAN - Unsupervised Anomaly Detection with Generative Adversarial Networks to Guide Marker Discovery
- APD - Adversarial Distillation of Bayesian Neural Network Posteriors
- APE-GAN - APE-GAN: Adversarial Perturbation Elimination with GAN
- ARAE - Adversarially Regularized Autoencoders for Generating Discrete Structures (github)
- ARDA - Adversarial Representation Learning for Domain Adaptation
- ARIGAN - ARIGAN: Synthetic Arabidopsis Plants using Generative Adversarial Network
- ArtGAN - ArtGAN: Artwork Synthesis with Conditional Categorial GANs
- ASDL-GAN - Automatic Steganographic Distortion Learning Using a Generative Adversarial Network
- ATA-GAN - Attention-Aware Generative Adversarial Networks (ATA-GANs)
- Attention-GAN - Attention-GAN for Object Transfiguration in Wild Images
- AttGAN - Arbitrary Facial Attribute Editing: Only Change What You Want (github)
- AttnGAN - AttnGAN: Fine-Grained Text to Image Generation with Attentional Generative Adversarial Networks (github)
- AVID - AVID: Adversarial Visual Irregularity Detection
- B-DCGAN - B-DCGAN:Evaluation of Binarized DCGAN for FPGA
- b-GAN - Generative Adversarial Nets from a Density Ratio Estimation Perspective
- BAGAN - BAGAN: Data Augmentation with Balancing GAN
- Bayesian GAN - Deep and Hierarchical Implicit Models
- Bayesian GAN - Bayesian GAN (github)
- BCGAN - Bayesian Conditional Generative Adverserial Networks
- BCGAN - Bidirectional Conditional Generative Adversarial networks
- BEAM - Boltzmann Encoded Adversarial Machines
- BEGAN - BEGAN: Boundary Equilibrium Generative Adversarial Networks
- BEGAN-CS - Escaping from Collapsing Modes in a Constrained Space
- Bellman GAN - Distributional Multivariate Policy Evaluation and Exploration with the Bellman
- BGAN - Binary Generative Adversarial Networks for Image Retrieval (github)
- Bi-GAN - Autonomously and Simultaneously Refining Deep Neural Network Parameters by a Bi-Generative Adversarial Network Aided Genetic Algorithm
- BicycleGAN - Toward Multimodal Image-to-Image Translation (github)
- BiGAN - Adversarial Feature Learning
- BinGAN - BinGAN: Learning Compact Binary Descriptors with a Regularized GAN
- BourGAN - BourGAN: Generative Networks with Metric Embeddings
- BranchGAN - Branched Generative Adversarial Networks for Multi-Scale Image Manifold Learning
- BRE - Improving GAN Training via Binarized Representation Entropy (BRE) Regularization (github)
- BridgeGAN - Generative Adversarial Frontal View to Bird View Synthesis
- BS-GAN - Boundary-Seeking Generative Adversarial Networks
- BubGAN - BubGAN: Bubble Generative Adversarial Networks for Synthesizing Realistic Bubbly Flow Images
- BWGAN - Banach Wasserstein GAN
- C-GAN - Face Aging with Contextual Generative Adversarial Nets
- C-RNN-GAN - C-RNN-GAN: Continuous recurrent neural networks with adversarial training (github)
- CA-GAN - Composition-aided Sketch-realistic Portrait Generation
- CaloGAN - CaloGAN: Simulating 3D High Energy Particle Showers in Multi-Layer Electromagnetic Calorimeters with Generative Adversarial Networks (github)
- CAN - CAN: Creative Adversarial Networks, Generating Art by Learning About Styles and Deviating from Style Norms
- CapsGAN - CapsGAN: Using Dynamic Routing for Generative Adversarial Networks
- CapsuleGAN - CapsuleGAN: Generative Adversarial Capsule Network
- CatGAN - Unsupervised and Semi-supervised Learning with Categorical Generative Adversarial Networks
- CatGAN - CatGAN: Coupled Adversarial Transfer for Domain Generation
- CausalGAN - CausalGAN: Learning Causal Implicit Generative Models with Adversarial Training
- CC-GAN - Semi-Supervised Learning with Context-Conditional Generative Adversarial Networks (github)
- cd-GAN - Conditional Image-to-Image Translation
- CDcGAN - Simultaneously Color-Depth Super-Resolution with Conditional Generative Adversarial Network
- CE-GAN - Deep Learning for Imbalance Data Classification using Class Expert Generative Adversarial Network
- CFG-GAN - Composite Functional Gradient Learning of Generative Adversarial Models
- CGAN - Conditional Generative Adversarial Nets
- CGAN - Controllable Generative Adversarial Network
- Chekhov GAN - An Online Learning Approach to Generative Adversarial Networks
- ciGAN - Conditional Infilling GANs for Data Augmentation in Mammogram Classification
- CinCGAN - Unsupervised Image Super-Resolution using Cycle-in-Cycle Generative Adversarial Networks
- CipherGAN - Unsupervised Cipher Cracking Using Discrete GANs
- ClusterGAN - ClusterGAN : Latent Space Clustering in Generative Adversarial Networks
- CM-GAN - CM-GANs: Cross-modal Generative Adversarial Networks for Common Representation Learning
- CoAtt-GAN - Are You Talking to Me? Reasoned Visual Dialog Generation through Adversarial Learning
- CoGAN - Coupled Generative Adversarial Networks
- ComboGAN - ComboGAN: Unrestrained Scalability for Image Domain Translation (github)
- ConceptGAN - Learning Compositional Visual Concepts with Mutual Consistency
- Conditional cycleGAN - Conditional CycleGAN for Attribute Guided Face Image Generation
- constrast-GAN - Generative Semantic Manipulation with Contrasting GAN
- Context-RNN-GAN - Contextual RNN-GANs for Abstract Reasoning Diagram Generation
- CorrGAN - Correlated discrete data generation using adversarial training
- Coulomb GAN - Coulomb GANs: Provably Optimal Nash Equilibria via Potential Fields
- Cover-GAN - Generative Steganography with Kerckhoffs' Principle based on Generative Adversarial Networks
- cowboy - Defending Against Adversarial Attacks by Leveraging an Entire GAN
- CR-GAN - CR-GAN: Learning Complete Representations for Multi-view Generation
- Cramèr GAN - The Cramer Distance as a Solution to Biased Wasserstein Gradients
- Cross-GAN - Crossing Generative Adversarial Networks for Cross-View Person Re-identification
- crVAE-GAN - Channel-Recurrent Variational Autoencoders
- CS-GAN - Improving Neural Machine Translation with Conditional Sequence Generative Adversarial Nets
- CSG - Speech-Driven Expressive Talking Lips with Conditional Sequential Generative Adversarial Networks
- CT-GAN - CT-GAN: Conditional Transformation Generative Adversarial Network for Image Attribute Modification
- CVAE-GAN - CVAE-GAN: Fine-Grained Image Generation through Asymmetric Training
- CycleGAN - Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks

GAN Improvements: Improved Loss Functions

Wasserstein GAN (WGAN)



Arjovsky, Chintala, and Bouttou, "Wasserstein GAN", 2017

WGAN with Gradient Penalty (WGAN-GP)

Gulrajani et al, "Improved Training of Wasserstein GANs", NeurIPS 2017

GAN Improvements: Higher Resolution

256 x 256 bedrooms

1024 x 1024 faces

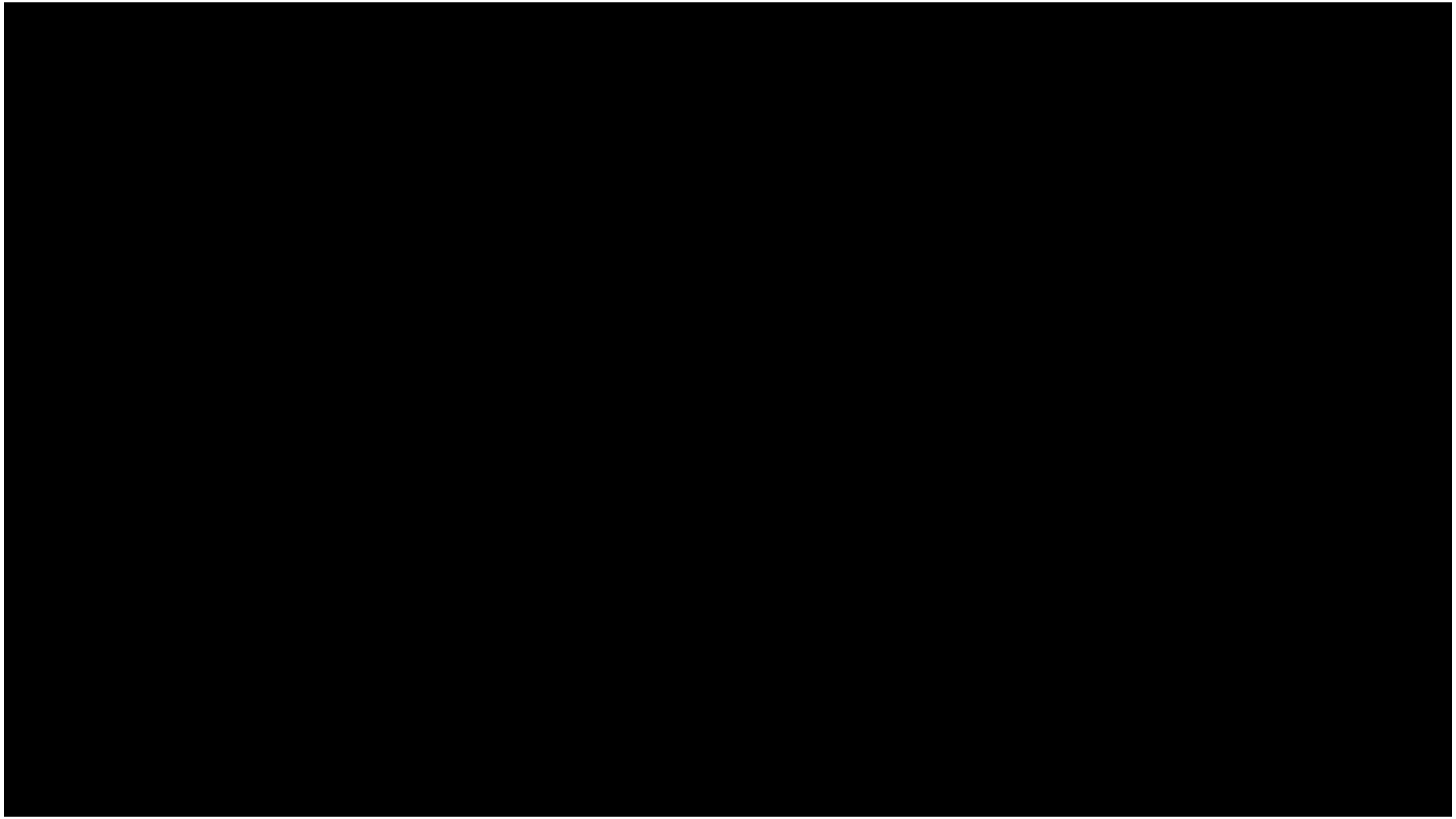
Karras et al, “Progressive Growing of GANs for Improved Quality, Stability, and Variation”, ICLR 2018

GAN Improvements: Higher Resolution

512 x 384 cars

1024 x 1024 faces

Karras et al, “A Style-Based Generator Architecture for Generative Adversarial Networks”, CVPR 2019



- Interpolating the latent space to the high resolution that has been generated by style GAN.

Karras et al, “A Style-Based Generator Architecture for Generative Adversarial Networks”, CVPR 2019

Conditional GANs

- Make generator and discriminator both take label y as an additional input!

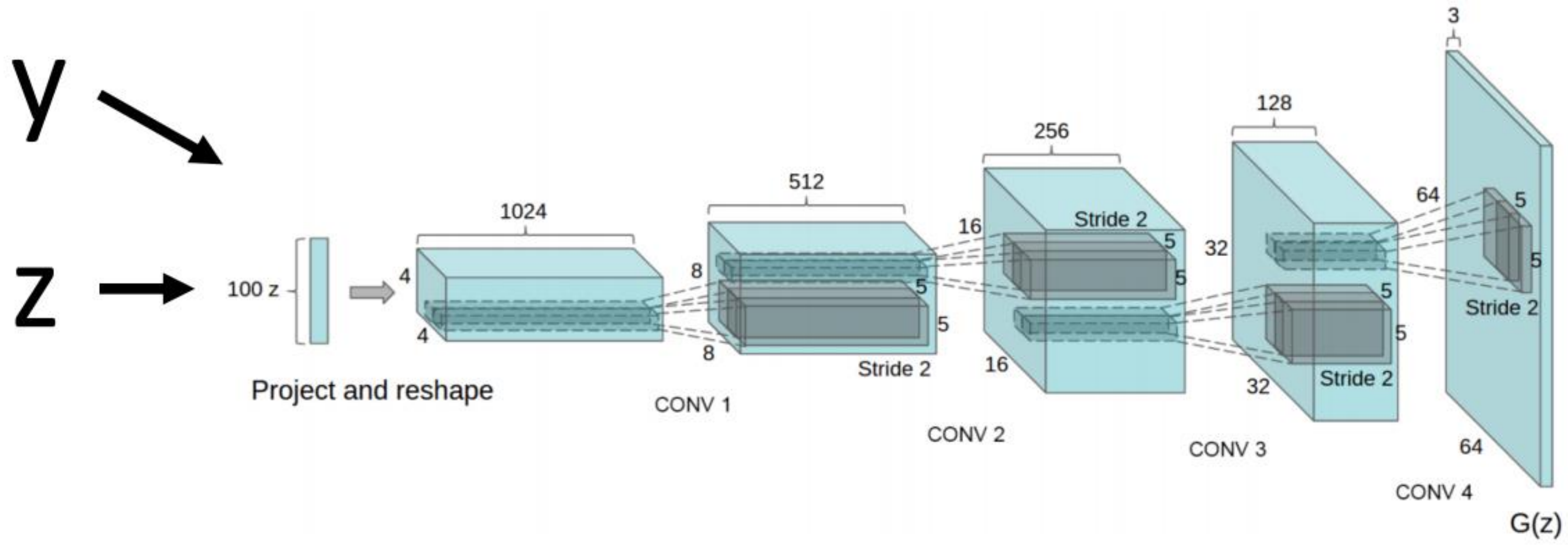


Figure credit: Radford et al, “Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks”, ICLR 2016

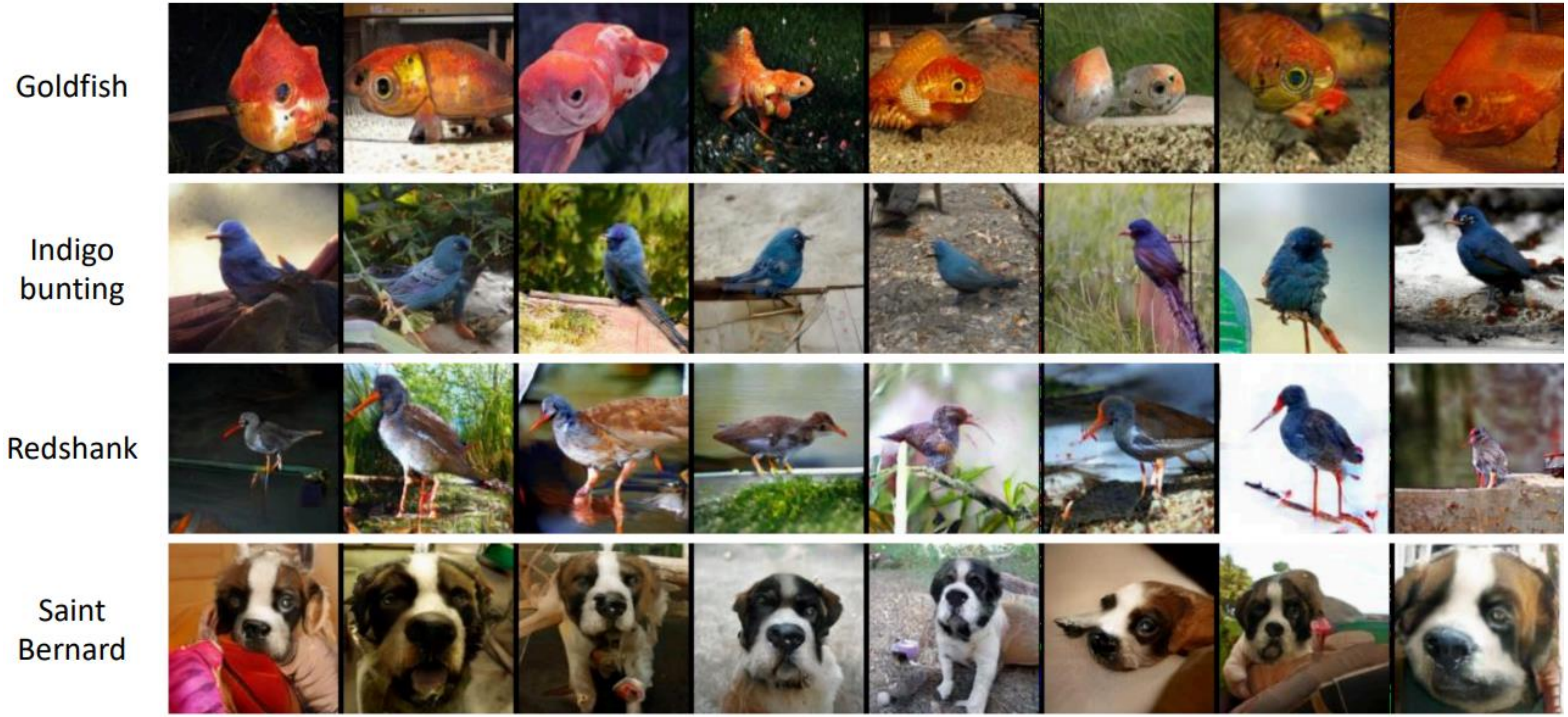
Conditional GANs: Spectral Normalization

128x128 images on ImageNet

- We give the model both random noise and which category want to generate.

Miyato et al, “Spectral Normalization for Generative Adversarial Networks”, ICLR 2018

Conditional GANs: Self-Attention



128x128 images on ImageNet

Zhang et al, "Self-Attention Generative Adversarial Networks", ICML 2019

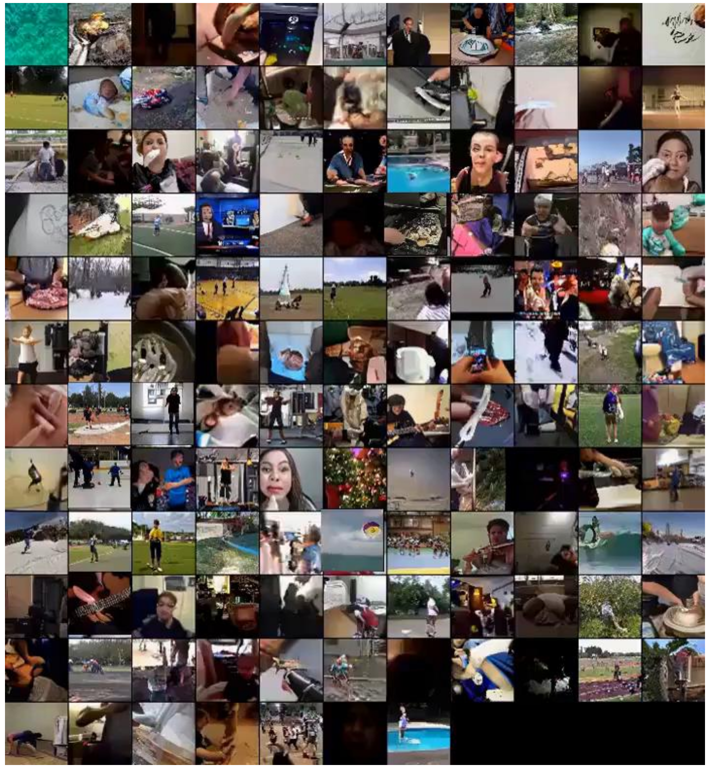
Conditional GANs: BigGAN

512x512 images on ImageNet

Brock et al, “Large Scale GAN Training for High Fidelity Natural Image Synthesis”, ICLR 2019

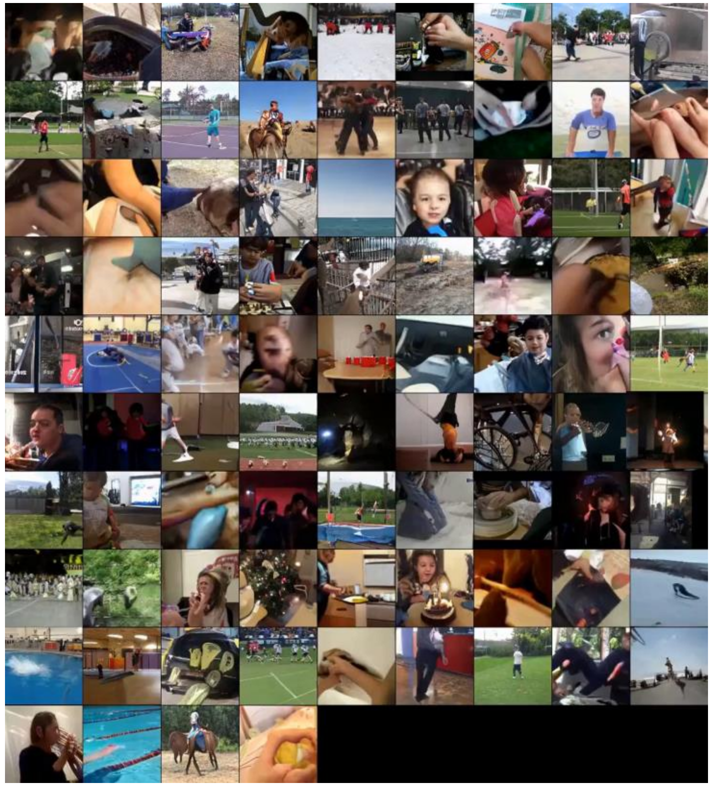
Generating Videos with GANs

Clark et al, "Adversarial Video Generation on Complex Datasets", arXiv 2019



64x64 images, 48 frames

https://drive.google.com/file/d/1FjOQYdUuxPXvS8yeOhXdPQMapUQaklLi/view



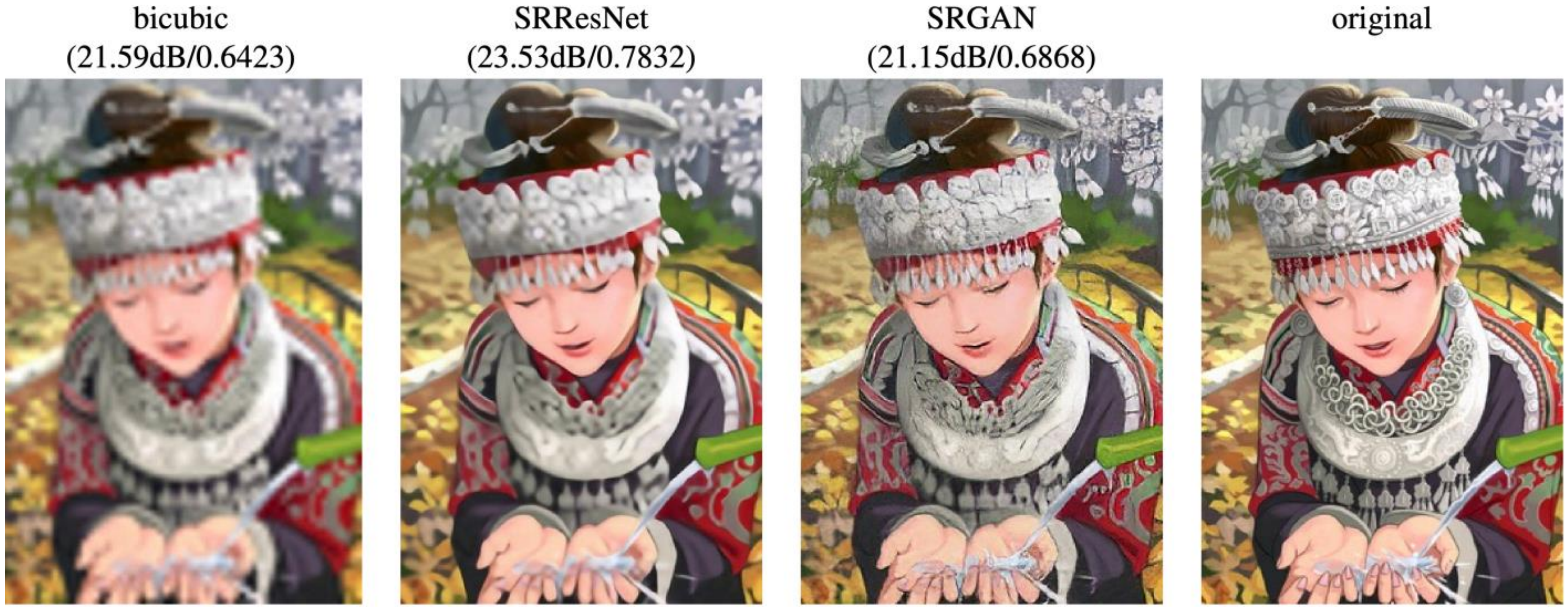
128x128 images, 12 frames

https://drive.google.com/file/d/165Yxuvvu3viOy-39LhhSDGtczbWphj_i/view

Conditioning on more than labels! Text to Image

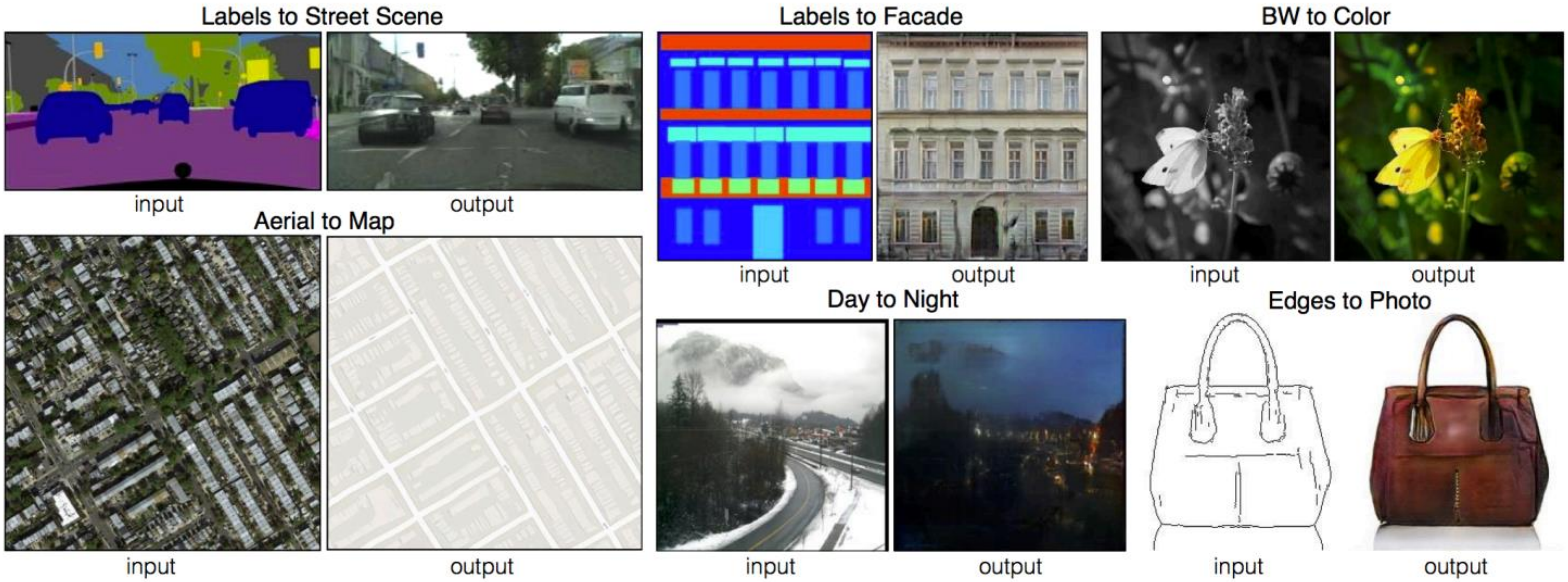
Zhang et al, “StackGAN++: Realistic Image Synthesis with Stacked Generative Adversarial Networks.”, TPAMI 2018
Zhang et al, “StackGAN: Synthesis with Stacked Generative Adversarial Networks.”, ICCV 2017
Reed et al, “Generative Adversarial Text-to-Image Synthesis”, ICML 2016

Image Super-Resolution: Low-Res to High-Res



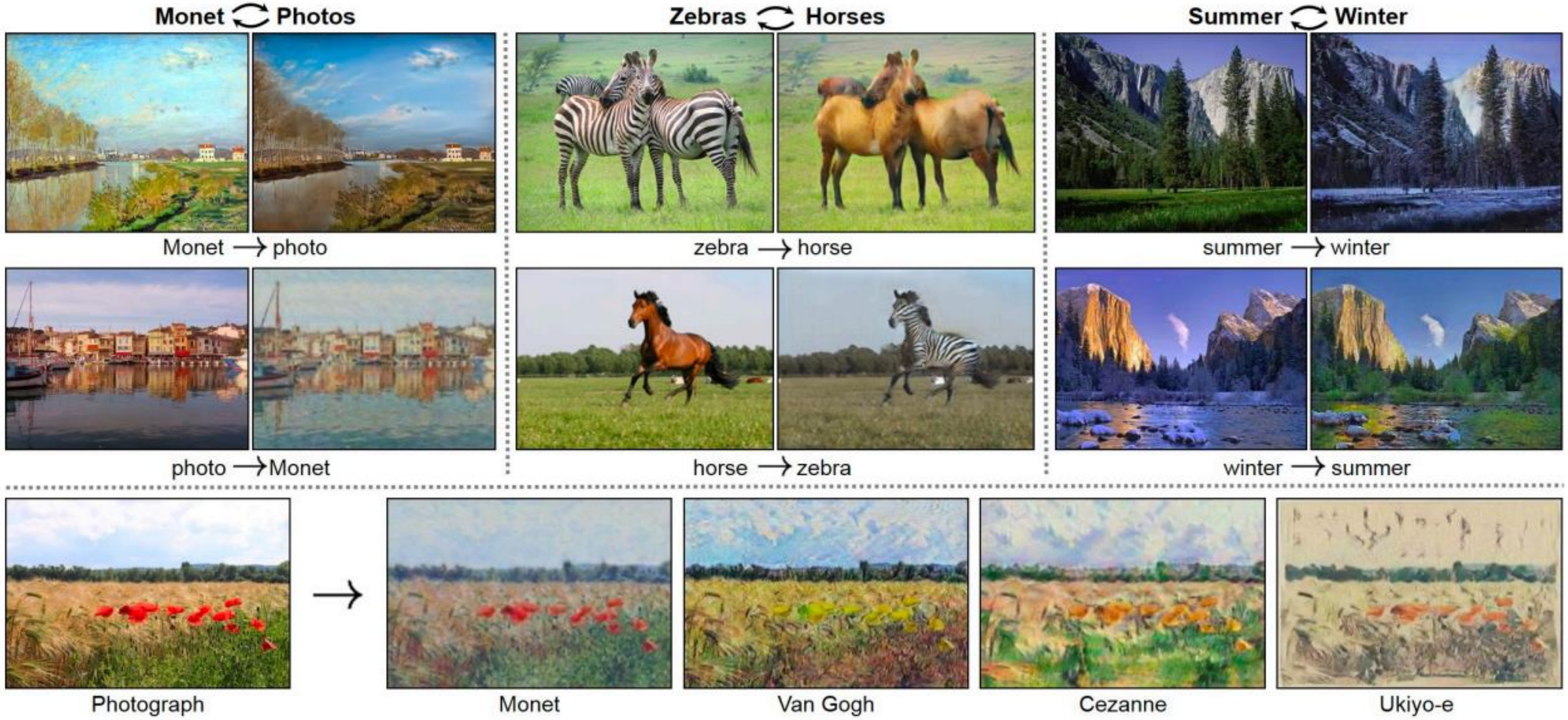
Ledig et al, “Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network”, CVPR 2017

Image-to-Image Translation: Pix2Pix



Isola et al, “Image-to-Image Translation with Conditional Adversarial Nets”, CVPR 2017

Unpaired Image-to-Image Translation: CycleGAN



Zhu et al, "Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks", ICCV 2017

Unpaired Image-to-Image Translation: CycleGAN

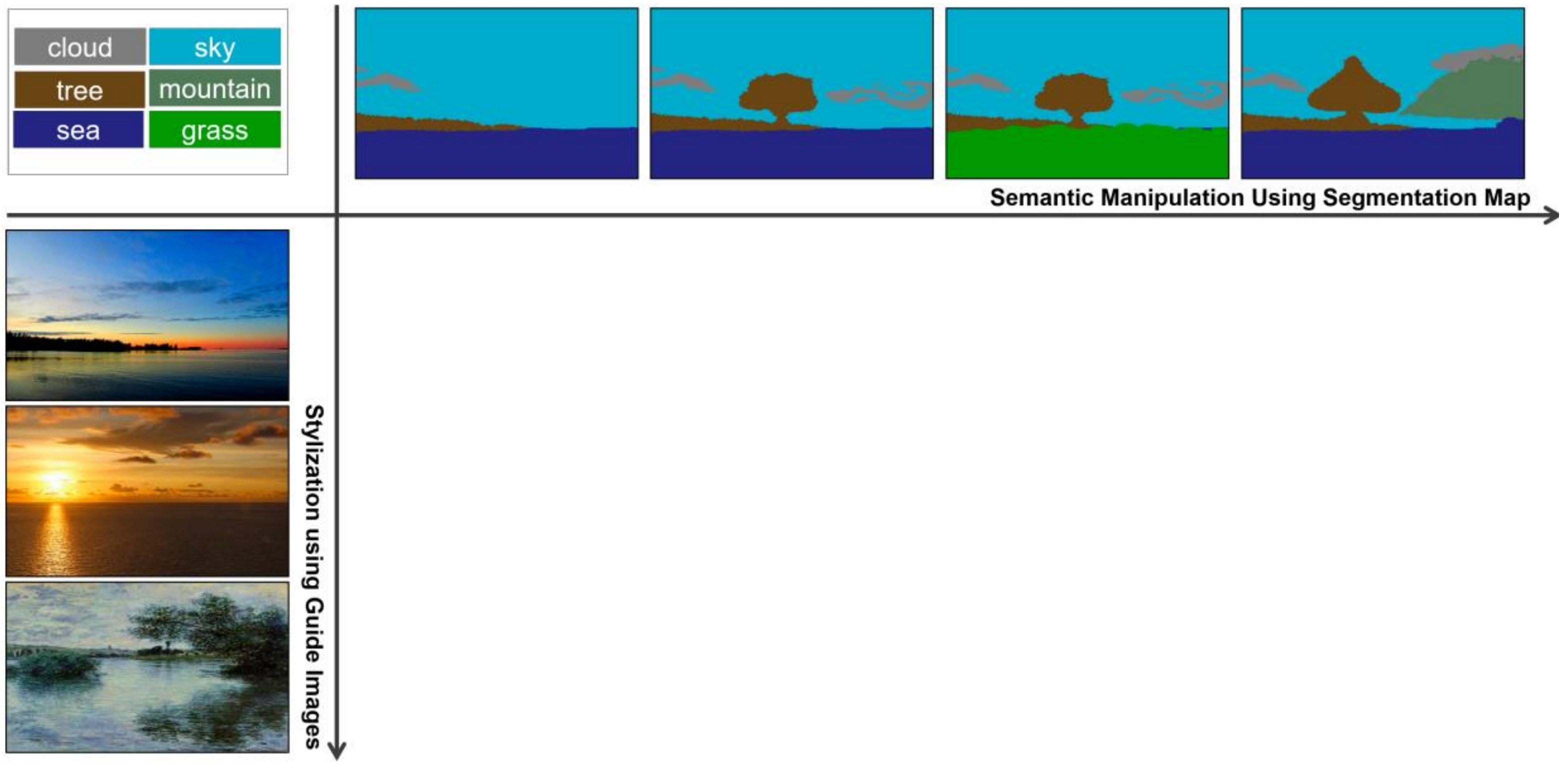
https://www.youtube.com/watch?v=9reHvktowLY

Zhu et al, "Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks", ICCV 2017

Label Map to Image

Input: Label Map

Input:
Style
Image

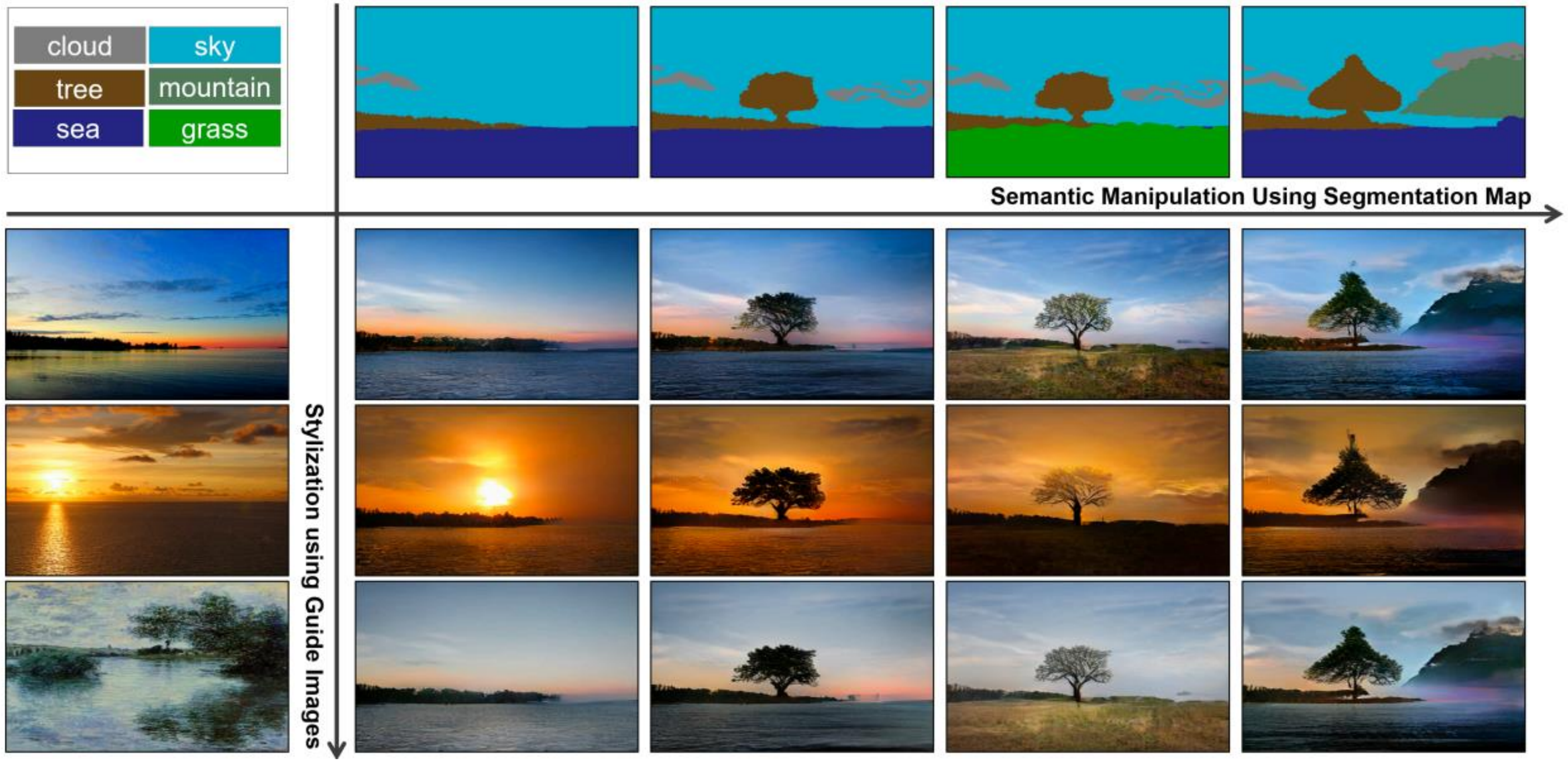


Park et al, “Semantic Image Synthesis with Spatially-Adaptive Normalization”, CVPR 2019

Label Map to Image

Input: Label Map

Input:
Style
Image



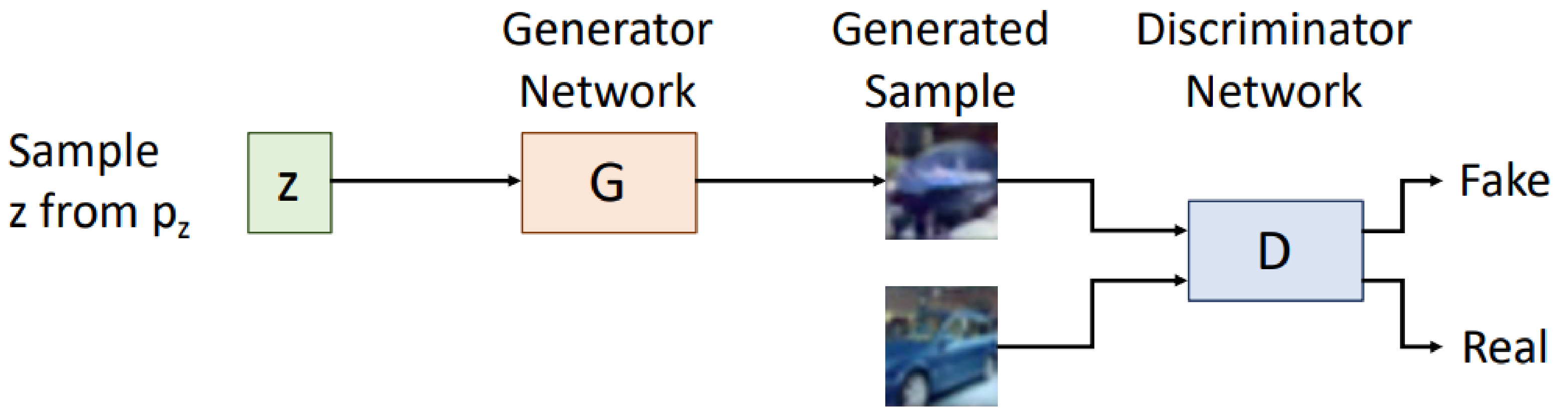
Park et al, "Semantic Image Synthesis with Spatially-Adaptive Normalization", CVPR 2019

GANs: Not just for images! Trajectory Prediction

Gupta, Johnson, Li, Savarese, Alahi, “Social GAN: Socially Acceptable Trajectories with Generative Adversarial Networks”, CVPR 2018

GAN Summary

- Jointly train two networks:
  - **Discriminator**: Classify data as real or fake
  - **Generator**: Generate data that fools the discriminator



- Many applications! Very active area of research!

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- Radford, A., et al. "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks." ICLR, 2016.
- Karras, T., et al. "Progressive Growing of GANs for Improved Quality, Stability, and Variation." ICLR, 2018.
- Karras, T., et al. "A Style-Based Generator Architecture for Generative Adversarial Networks." CVPR, 2019.
- Miyato, T., et al. "Spectral Normalization for Generative Adversarial Networks." ICLR, 2018.
- Zhang, H., et al. "Self-Attention Generative Adversarial Networks." ICML, 2019.
- Brock, A., et al. "Large Scale GAN Training for High Fidelity Natural Image Synthesis." ICLR, 2019.

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- Zhang, H., et al. "StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks." ICCV, 2017.
- Reed, S., et al. "Generative Adversarial Text-to-Image Synthesis." ICML, 2016.
- Ledig, C., et al. "Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network." CVPR, 2017.
- Isola, P., et al. "Image-to-Image Translation with Conditional Adversarial Nets." CVPR, 2017.
- Zhu, J-Y., et al. "Unpaired Image-to-Image Translation Using Cycle-Consistent Adversarial Networks." ICCV, 2017 (listed twice initially; removed duplicate).
- Park, T., et al. "Semantic Image Synthesis with Spatially-Adaptive Normalization." CVPR, 2019.
- Gupta, A., Johnson, J., Li, F-F., Savarese, S., Alahi, A. "Social GAN: Socially Acceptable Trajectories with Generative Adversarial Networks." CVPR, 2018.