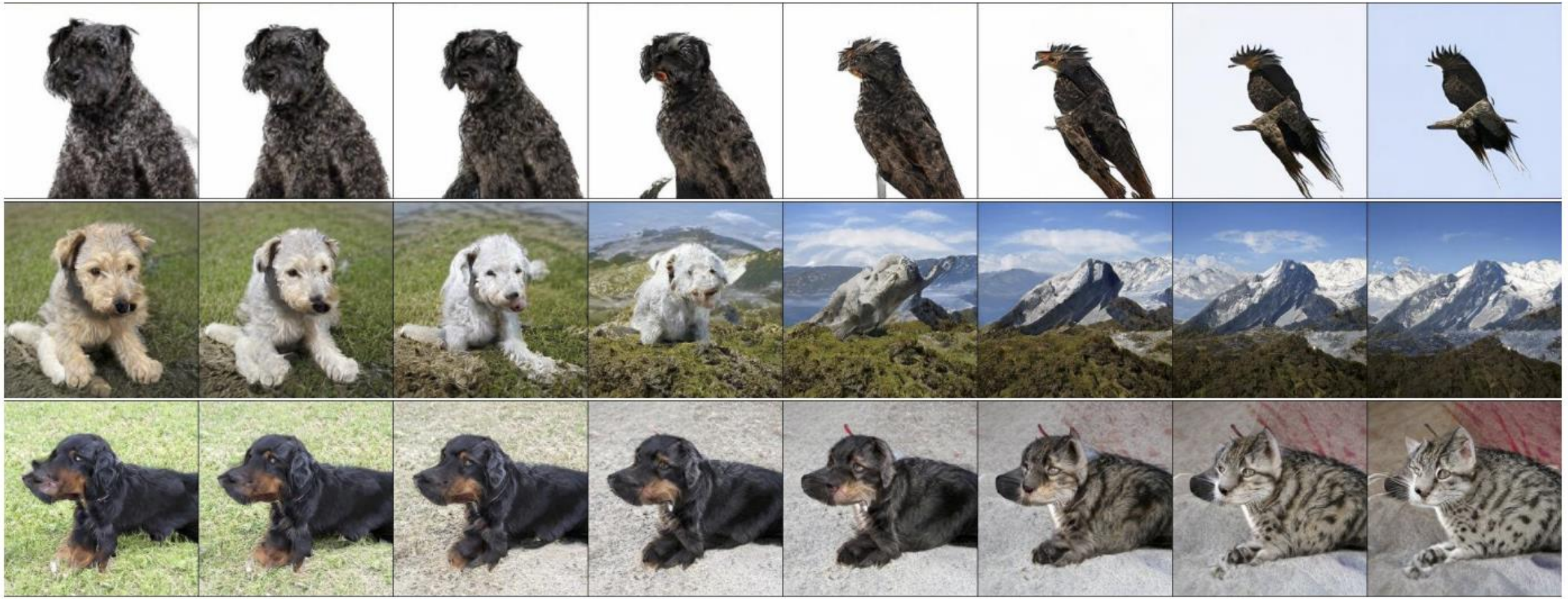
Generative adversarial networks



BigGAN (2018)

Outline

- Unsupervised Learning
- Generative tasks
- Original GAN formulations
  - NSGAN
  - DCGAN
- Other popular formulations
  - WGAN, WGAN-GP
  - LSGAN
- State-of-the-art architectures
  - Progressive GAN, StyleGAN
- Evaluating GANs
- Visualizing and controlling GANs

Supervised vs Unsupervised Learning

Supervised Learning

Data: (x, y)
x is data, y is label

Goal: Learn a function to map x -> y

Examples: Classification,
regression, object detection,
semantic segmentation,
image captioning, etc.

Credit: cs231n,

Supervised vs Unsupervised Learning

Supervised Learning

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Examples: Classification, regression, object detection, semantic segmentation, image captioning, etc.

→ **Cat**

Classification

Supervised vs Unsupervised Learning

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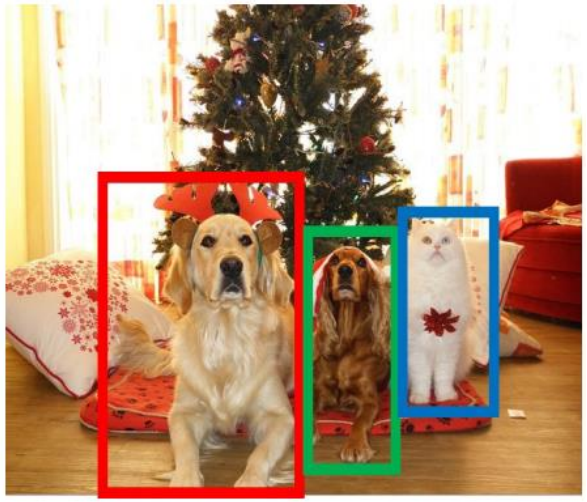

DOG, DOG, CAT

Object Detection

Credit: cs231n, Stanford

Supervised vs Unsupervised Learning

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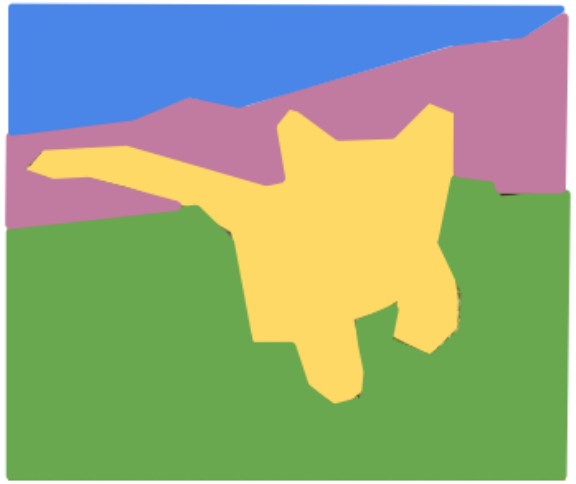

GRASS, CAT, TREE, SKY

Semantic Segmentation

Credit: cs231n, Stanford

Supervised vs Unsupervised Learning

Supervised Learning

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Examples: Classification, regression, object detection, semantic segmentation, image captioning, etc.

A cat sitting on a suitcase on the floor

Image Captioning

Supervised vs Unsupervised Learning

Unsupervised Learning

Data: x
Just data, no labels!

Goal: Learn some underlying hidden structure of the data

Examples: Clustering, dimensionality reduction, feature learning, density estimation, etc.

Credit: cs231n, Stanford

Supervised vs Unsupervised Learning

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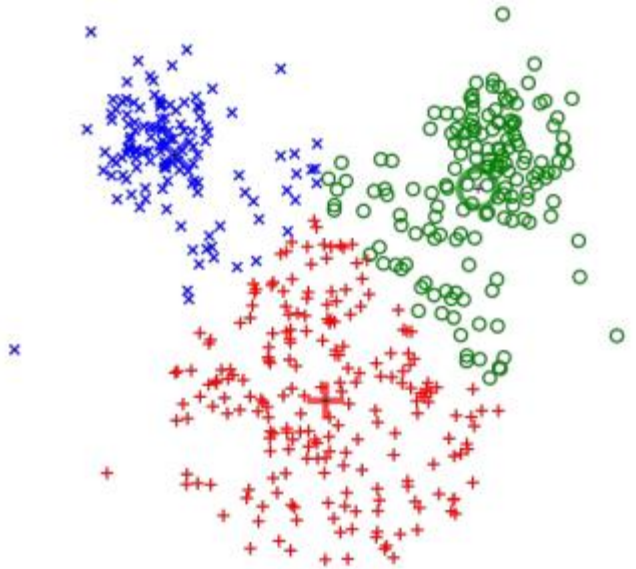

K-Means Clustering

Credit: cs231n, Stanford

Supervised vs Unsupervised Learning

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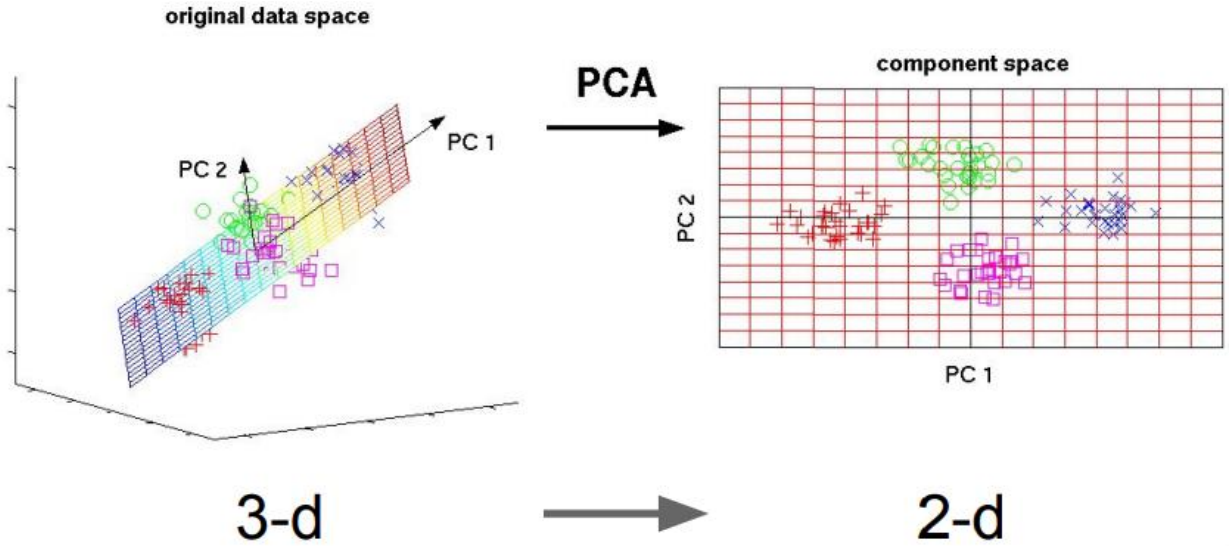

(Principal Component Analysis)
Dimensionality Reduction

Credit: cs231n, Stanford

Supervised vs Unsupervised Learning

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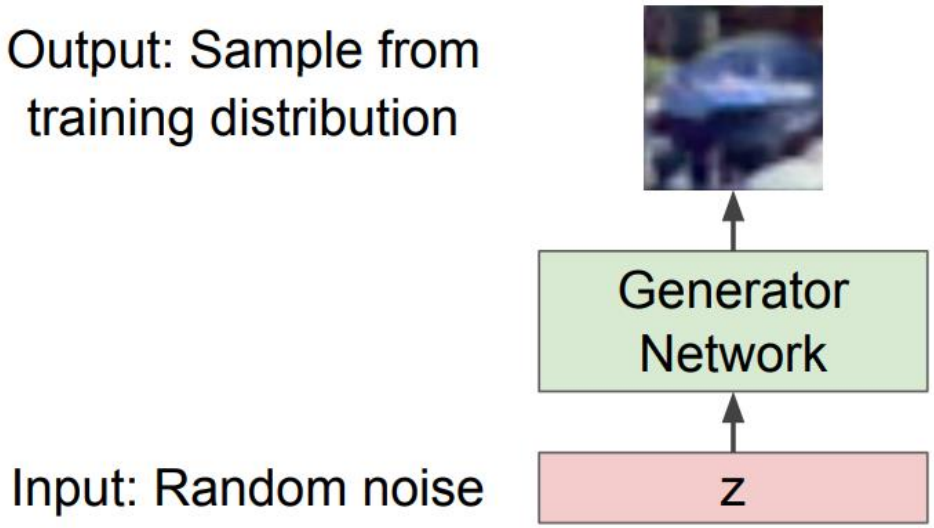
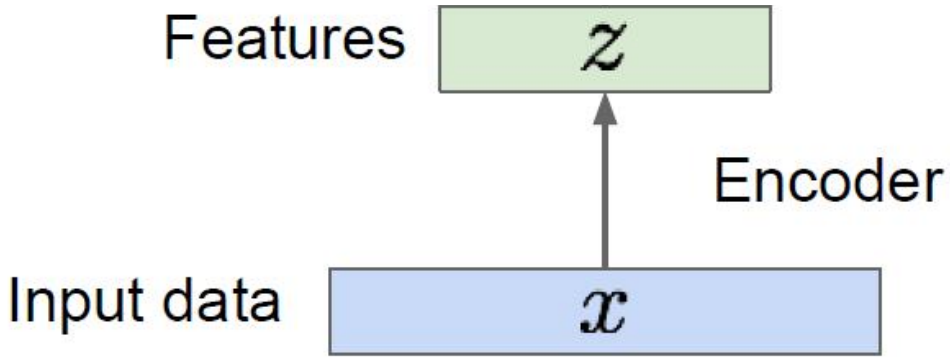


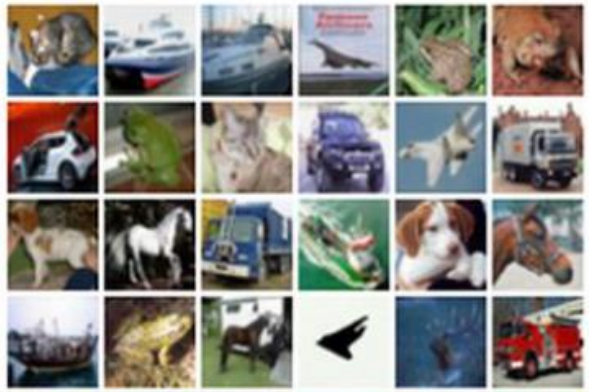
Generative Advarsarial Networks (Distribution learning)

Credit: cs231n, Stanford

Autoencoders

Unsupervised approach for learning a lower-dimensional feature representation from unlabeled training data



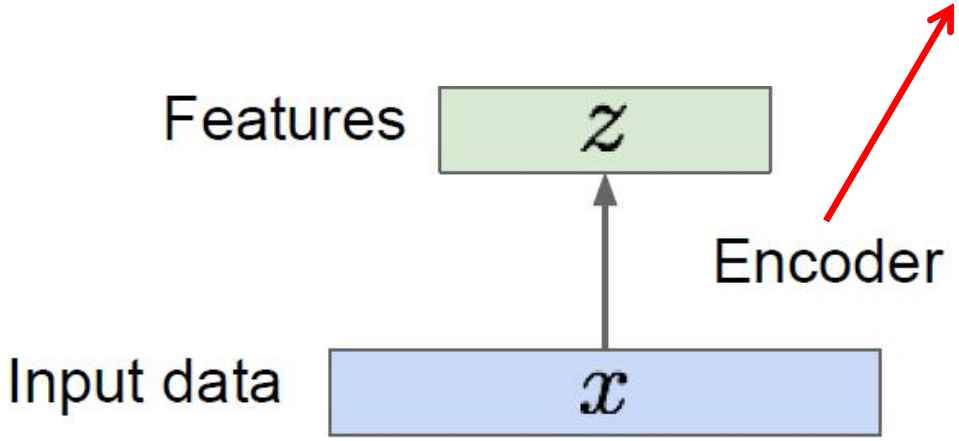


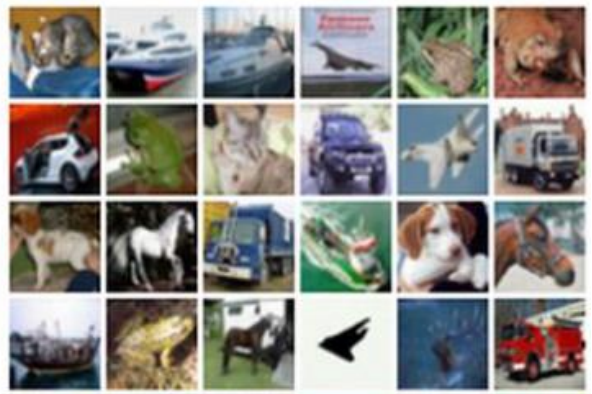
Credit: cs231n, Stanford

Autoencoders

Unsupervised approach for learning a lower-dimensional feature representation from unlabeled training data

Originally: Linear + nonlinearity (sigmoid)
Later: Deep, fully-connected
Later: ReLU CNN





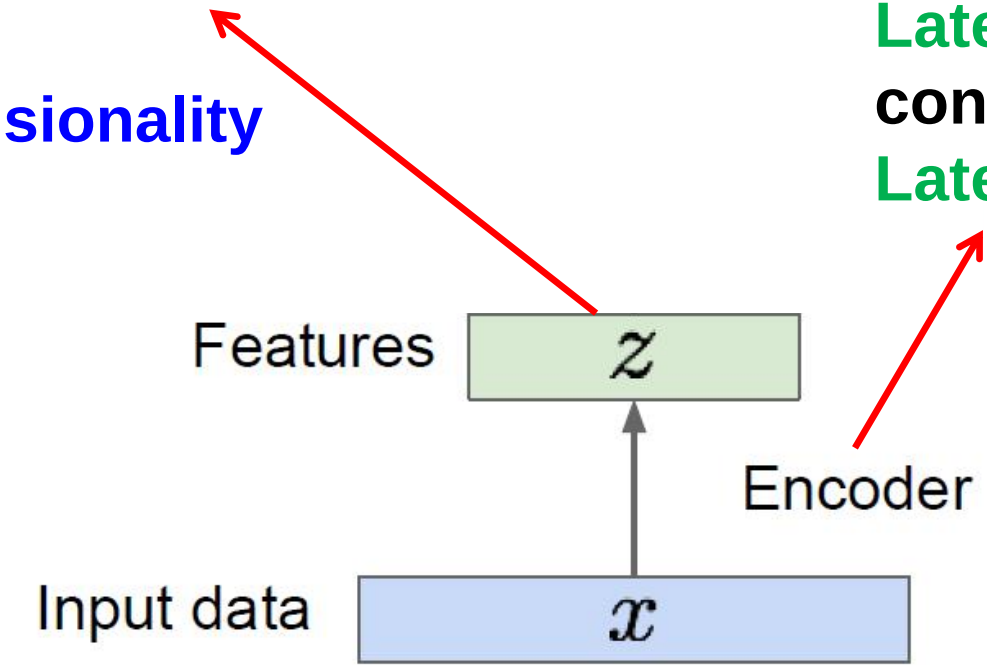
Credit: cs231n, Stanford

Autoencoders

Unsupervised approach for learning a lower-dimensional feature representation from unlabeled training data

Z usually smaller than X (Dimensionality Reduction)

Q: Why dimensionality reduction?



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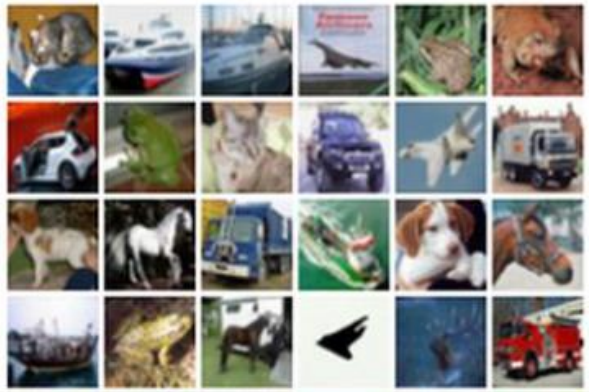

Credit: cs231n, Stanford

Autoencoders

Unsupervised approach for learning a lower-dimensional feature representation from unlabeled training data

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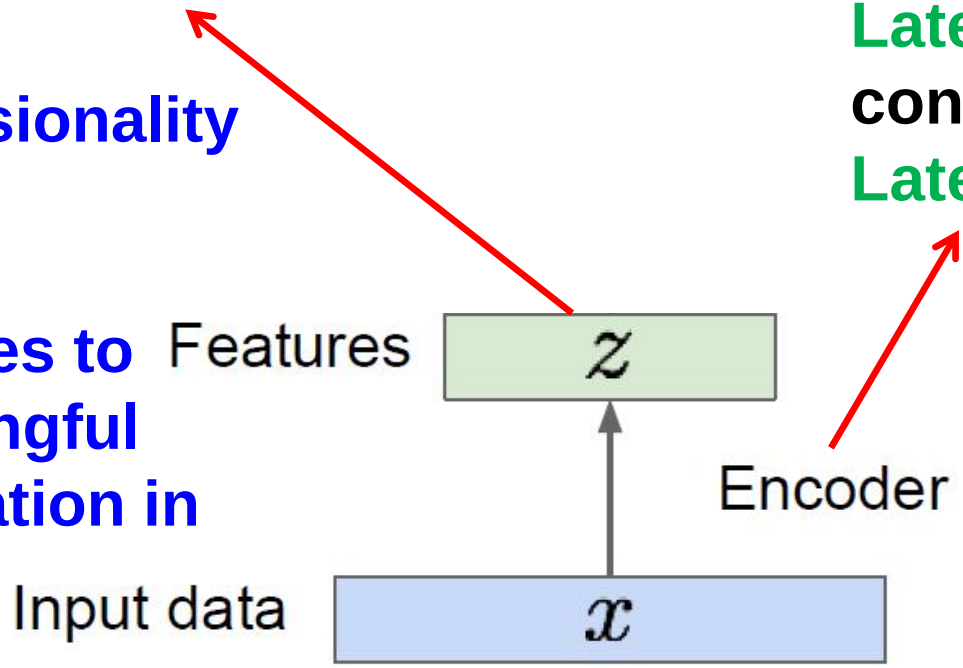
Q: Why dimensionality reduction?

A: Want features to capture meaningful factors of variation in data



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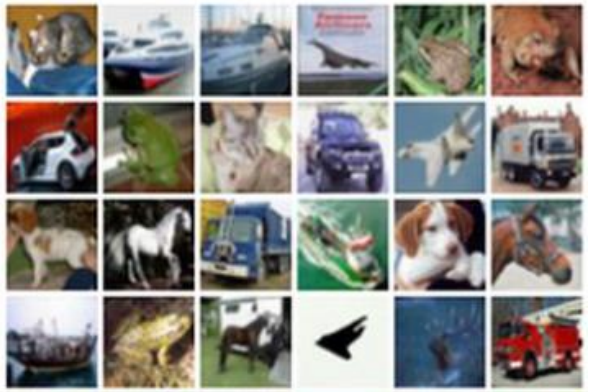
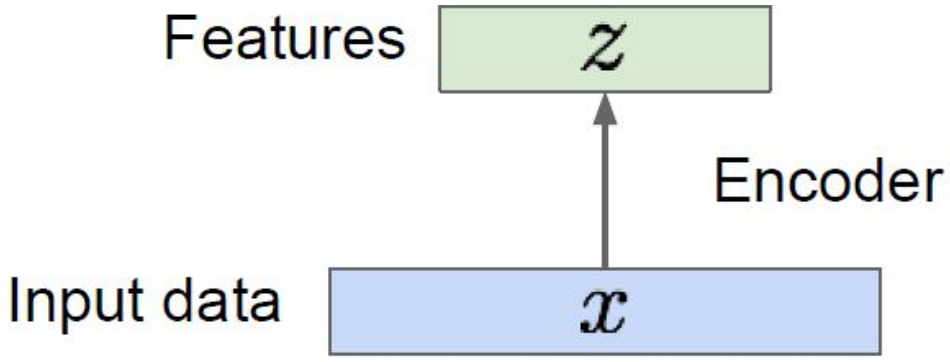


Credit: cs231n, Stanford

Autoencoders

How to learn this feature representation?

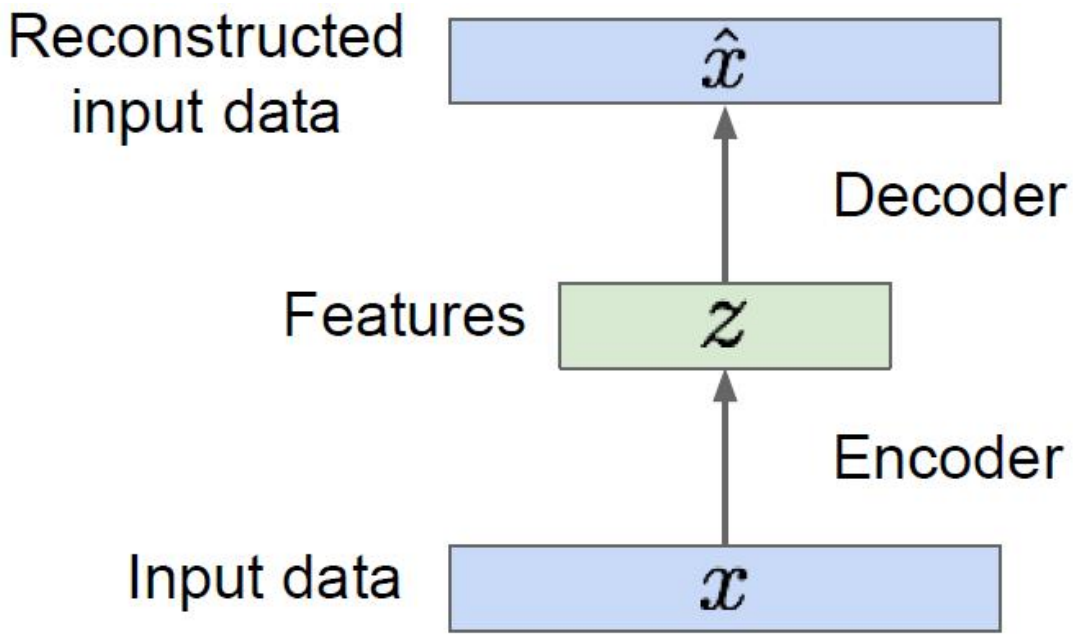


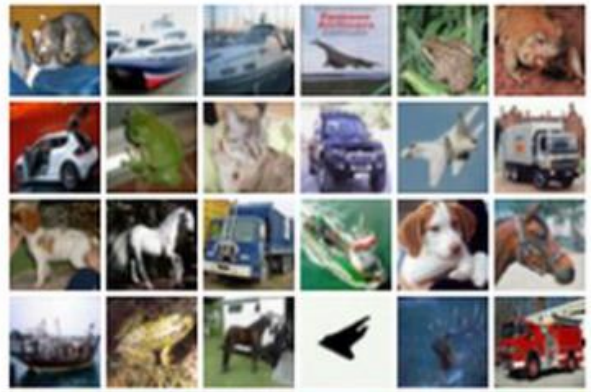
Credit: cs231n, Stanford

Autoencoders

How to learn this feature representation?

Train such that features can be used to reconstruct original data “Autoencoding” - encoding itself





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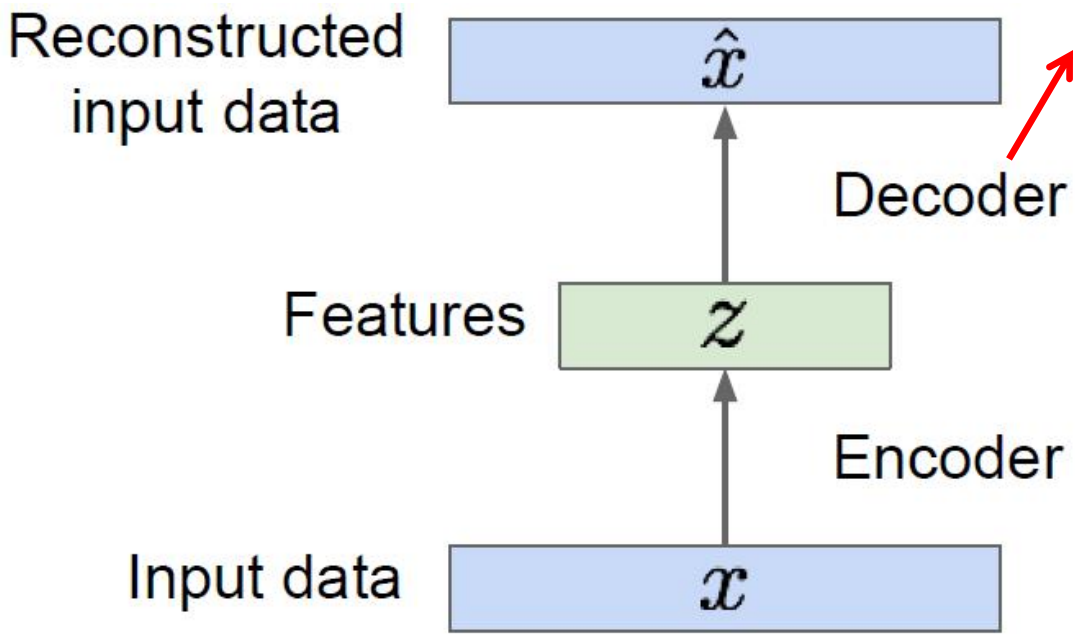

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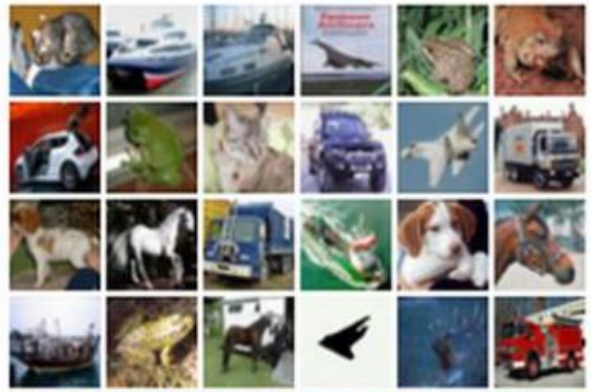

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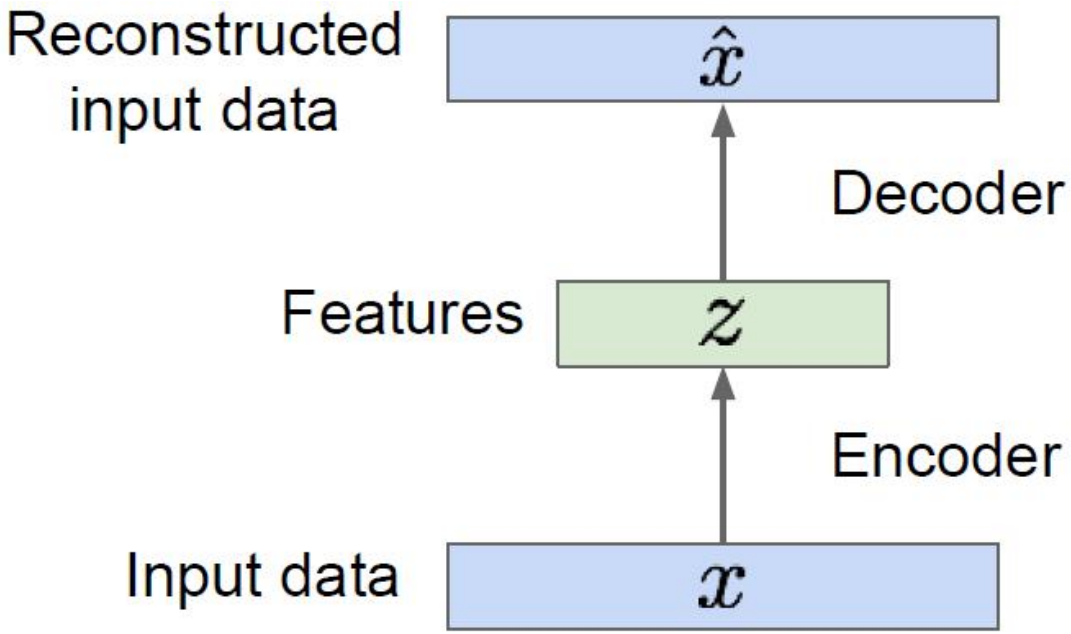
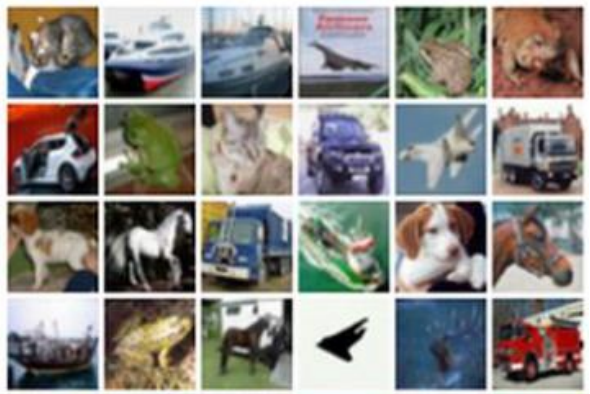


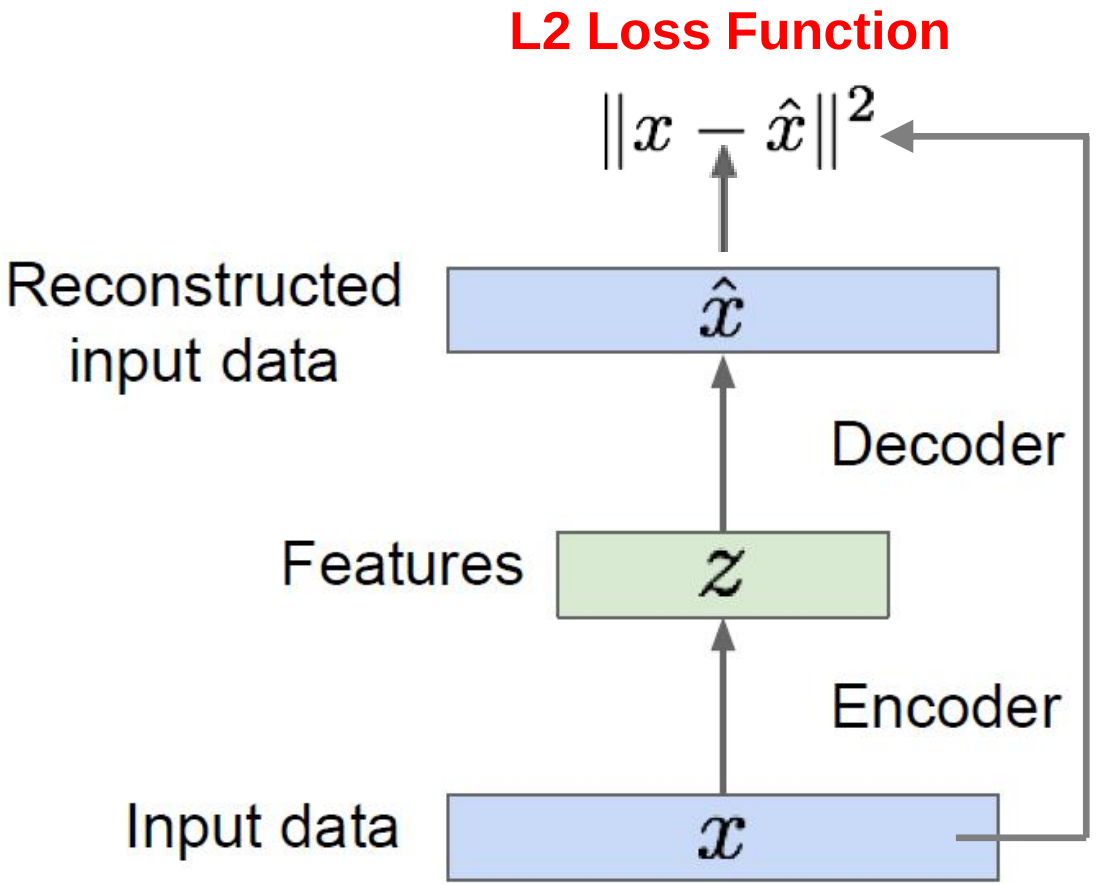
Decoder: 4-layer upconv
Encoder: 4-layer conv



Credit: cs231n, Stanford

Autoencoders

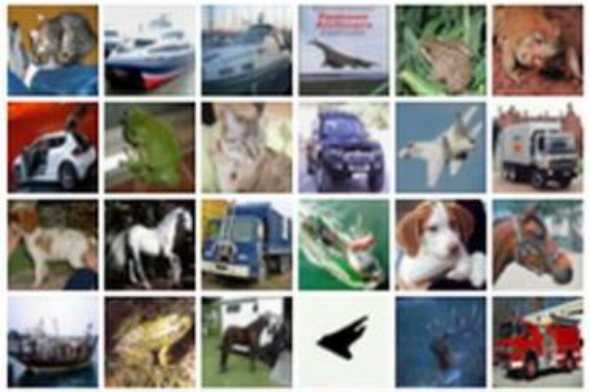
Train such that features can be used to reconstruct original data



Reconstructed Data

Decoder: 4-layer upconv
Encoder: 4-layer conv

Input Data

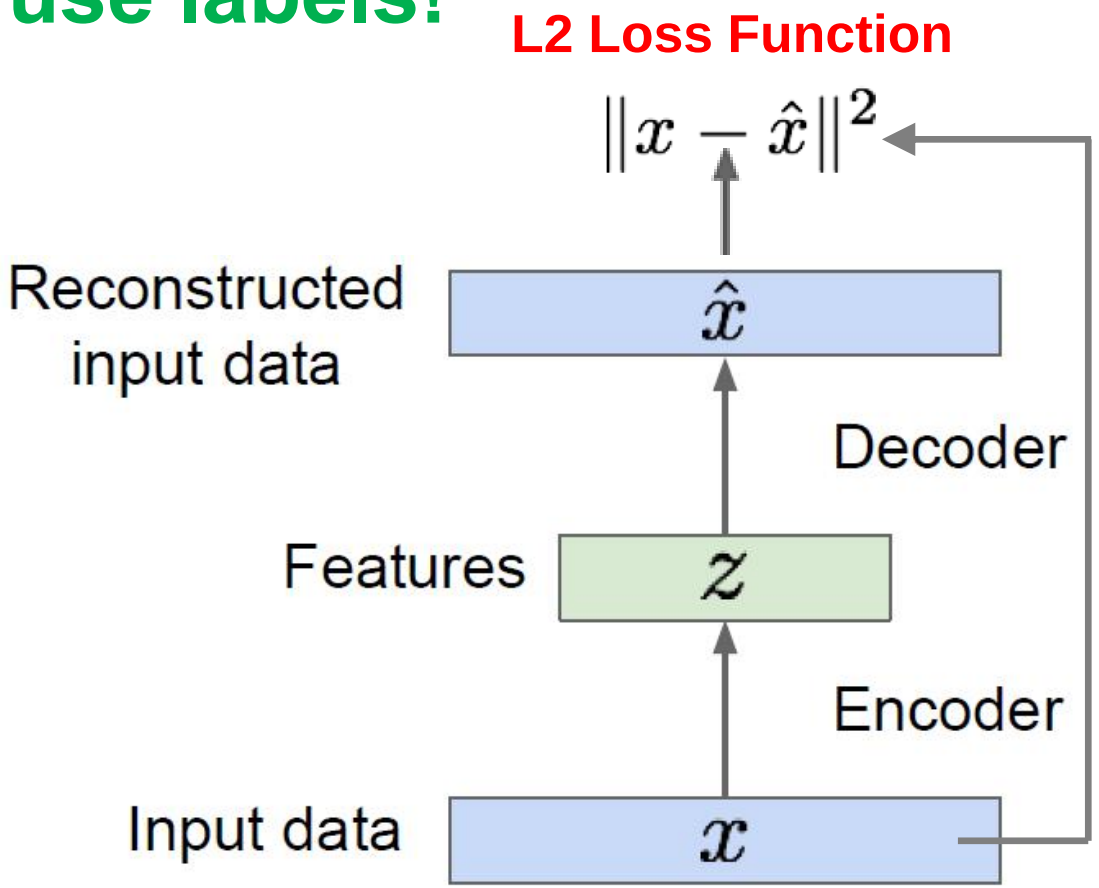


Credit: cs231n, Stanford

Autoencoders

Train such that features can be used to reconstruct original data

Doesn't use labels!



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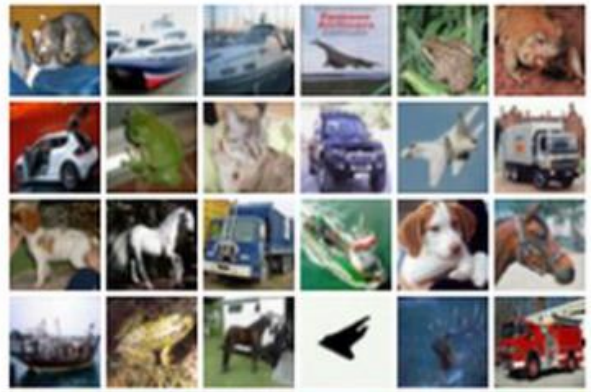
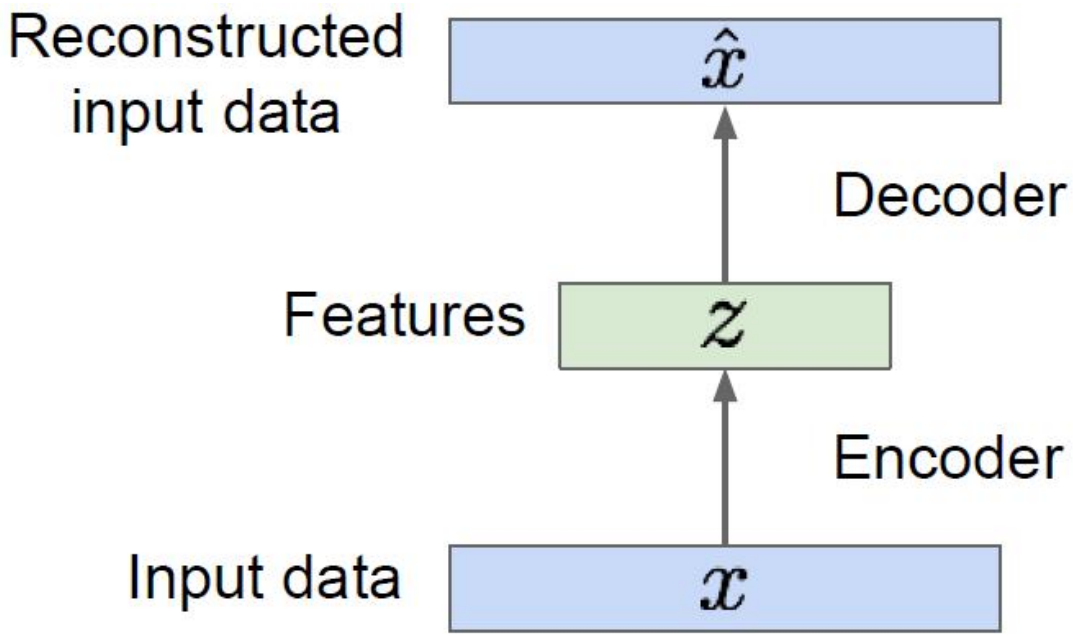


Credit: cs231n, Stanford

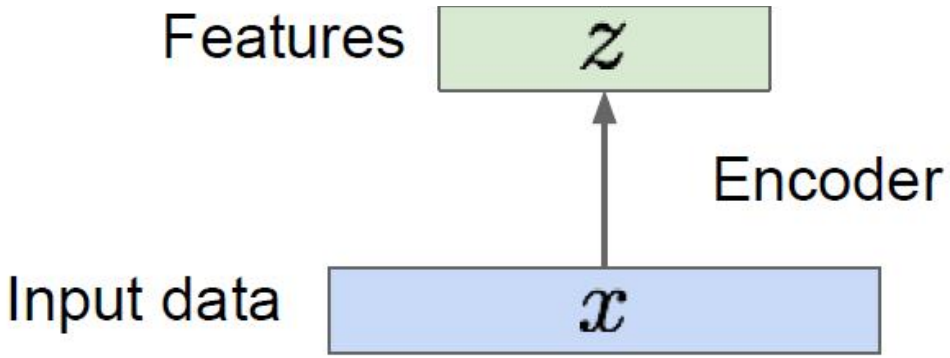
Autoencoders



After training,
throw away decoder

Credit: cs231n, Stanford

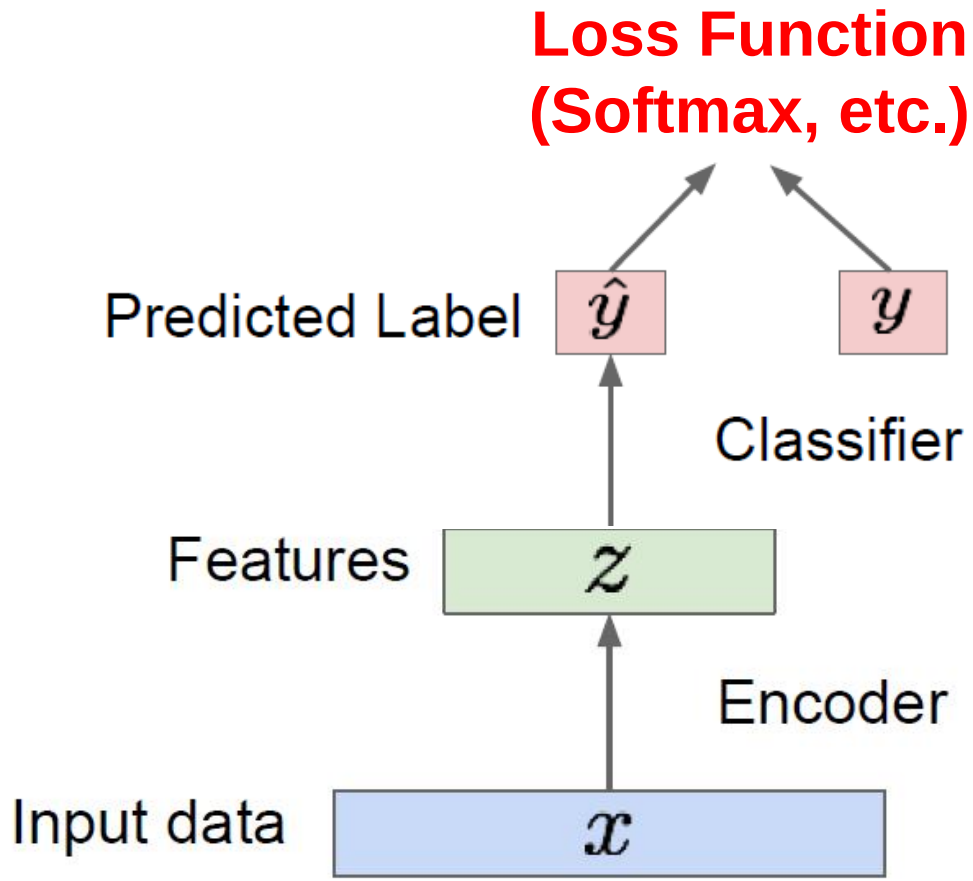
Autoencoders



Credit: cs231n, Stanford

Autoencoders

Encoder can be used to
initialize a supervised model



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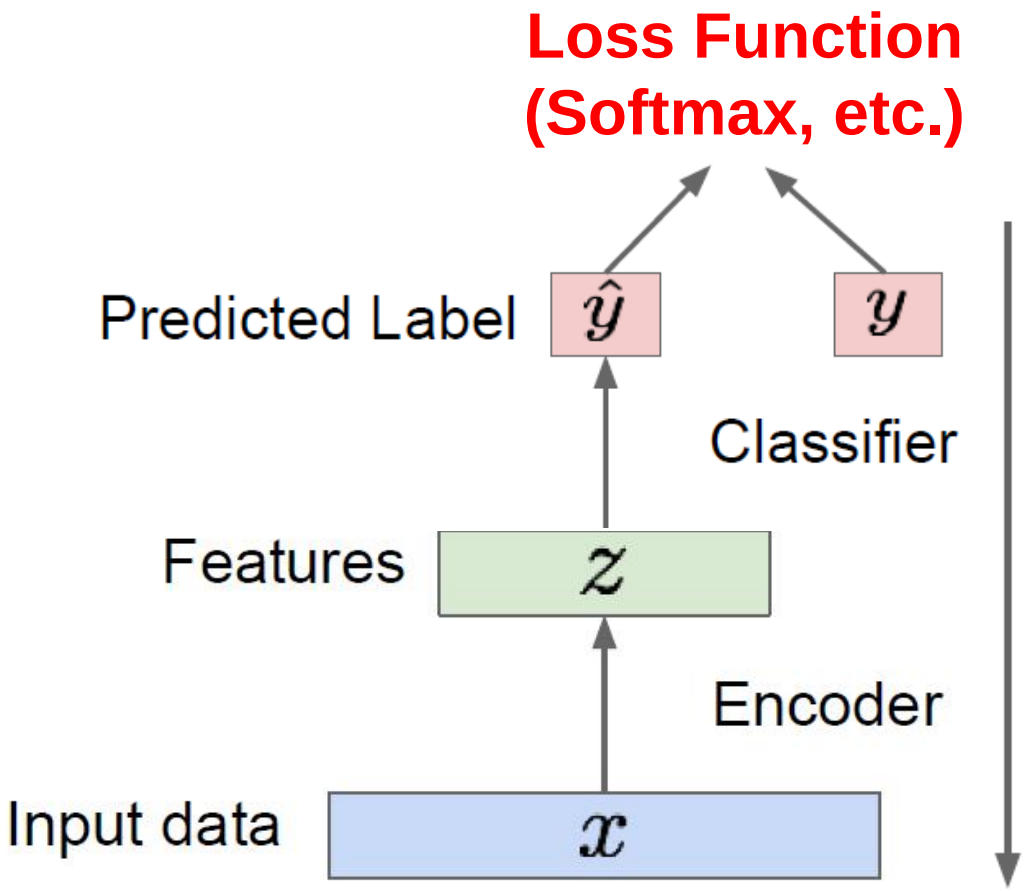


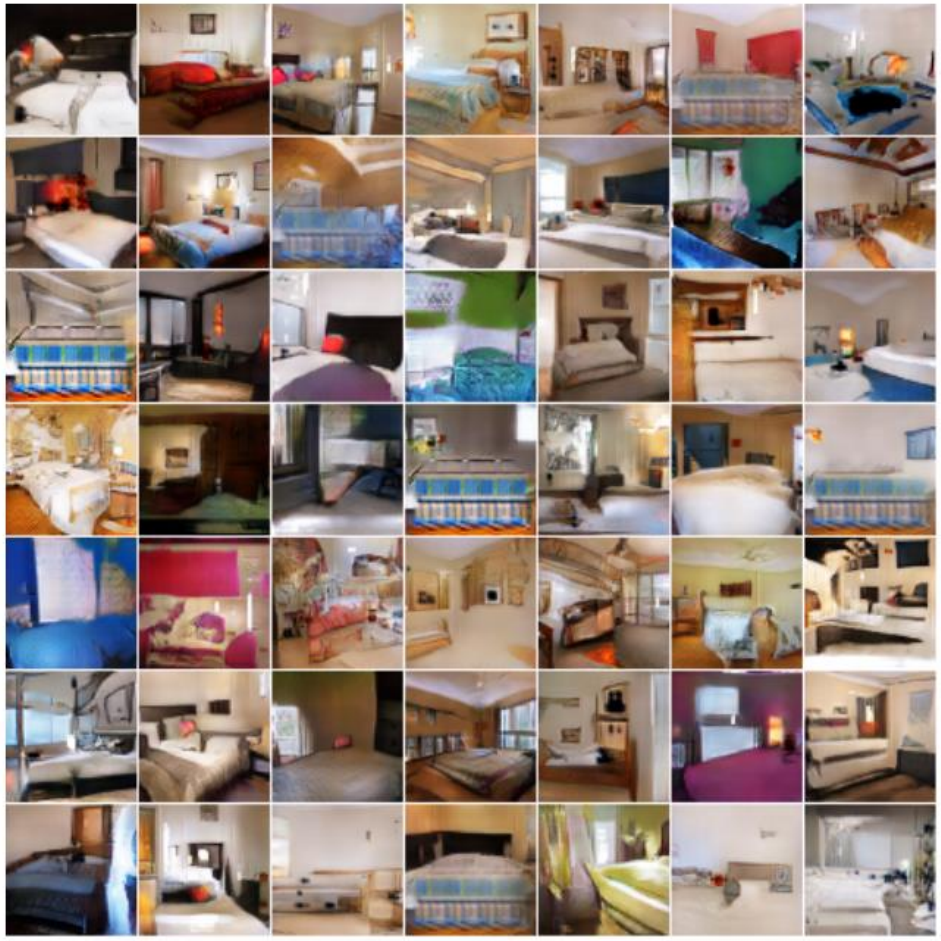
Fine-tune
encoder
jointly with
classifier

Train for final task
(sometimes with
small data)

Credit: cs231n, Stanford

Generative tasks

- Generation (from scratch): learn to sample from the distribution represented by the training set
  - *Unsupervised learning* task



Generative tasks

- Generation conditioned on class label

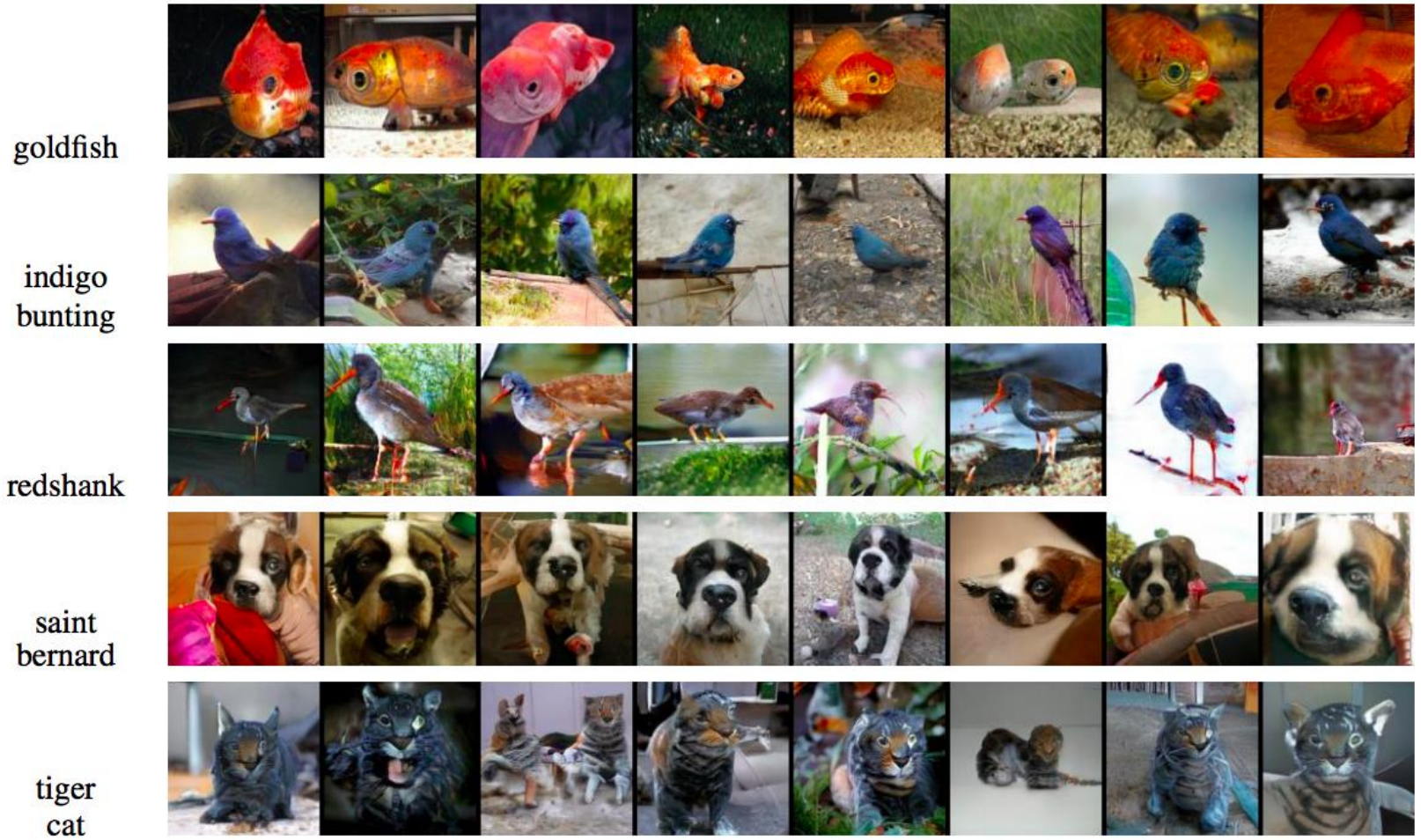
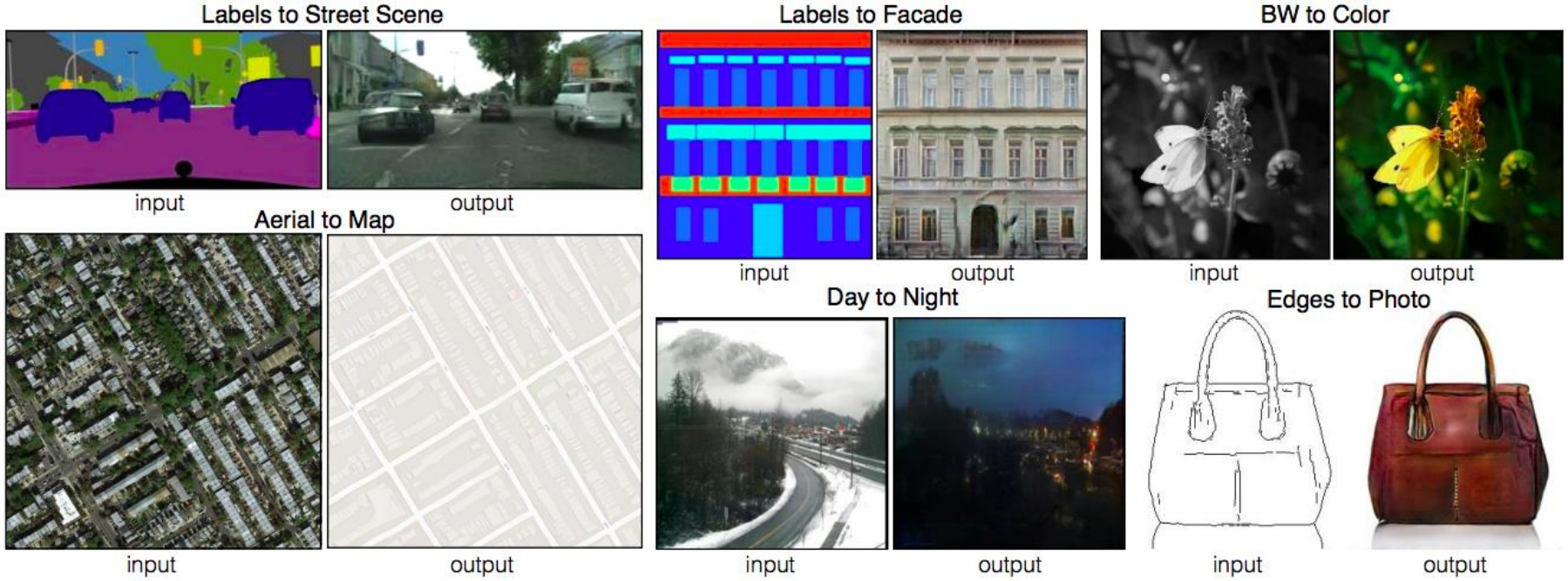


Figure source

Generative tasks

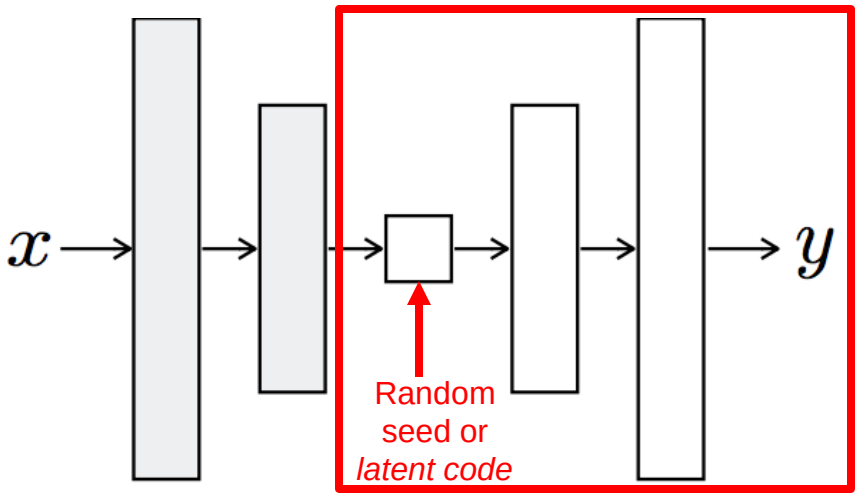
- Generation conditioned on image (image-to-image translation)



P. Isola, J.-Y. Zhu, T. Zhou, A. Efros, Image-to-Image Translation with Conditional Adversarial Networks, CVPR 2017

Designing a network for generative tasks

1. We need an architecture that can generate an image
   - Recall upsampling architectures for dense prediction



Unconditional
generation

Designing a network for generative tasks

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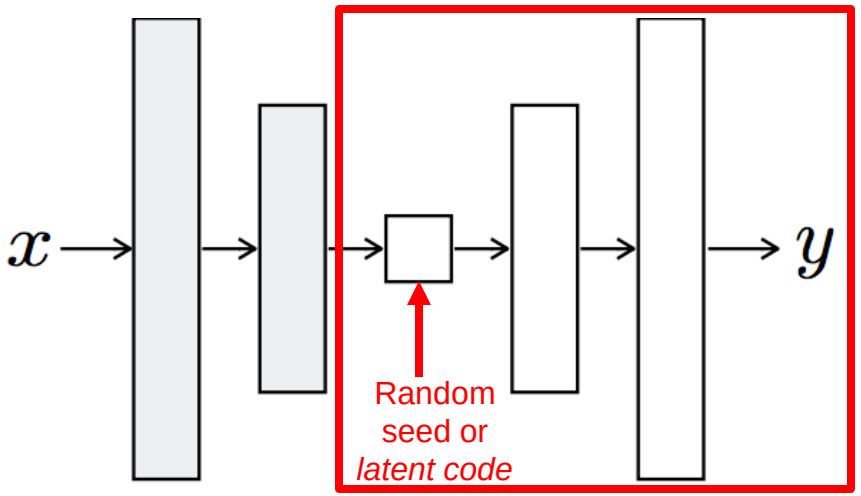
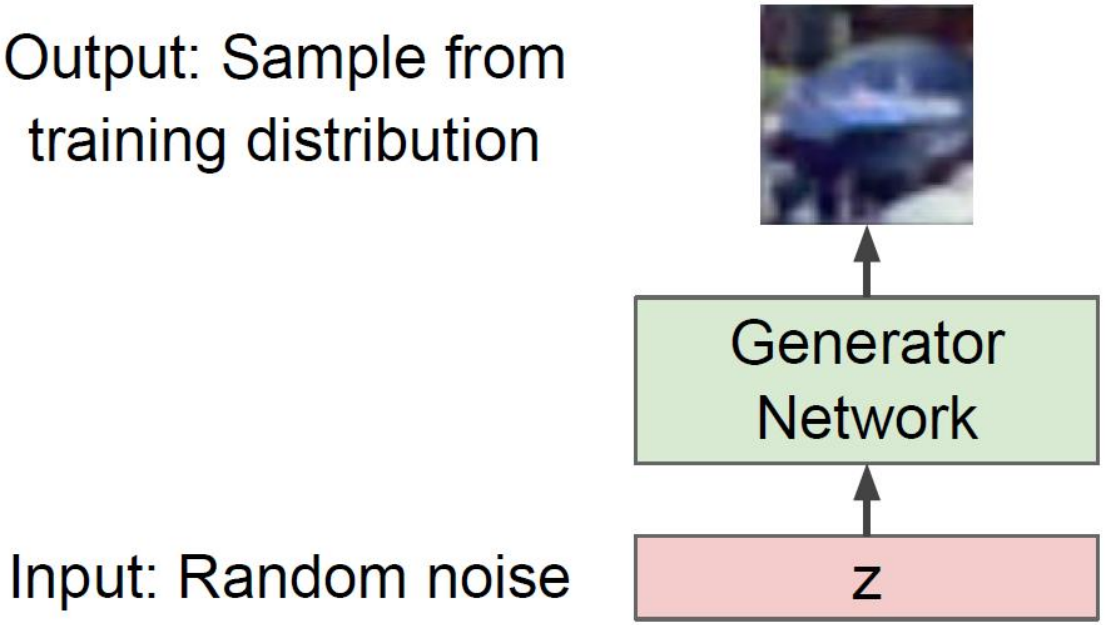


Unconditional generation

- Sample from a simple distribution, e.g. random noise.
- Learn transformation to training distribution.



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

Credit: cs231n, Stanford

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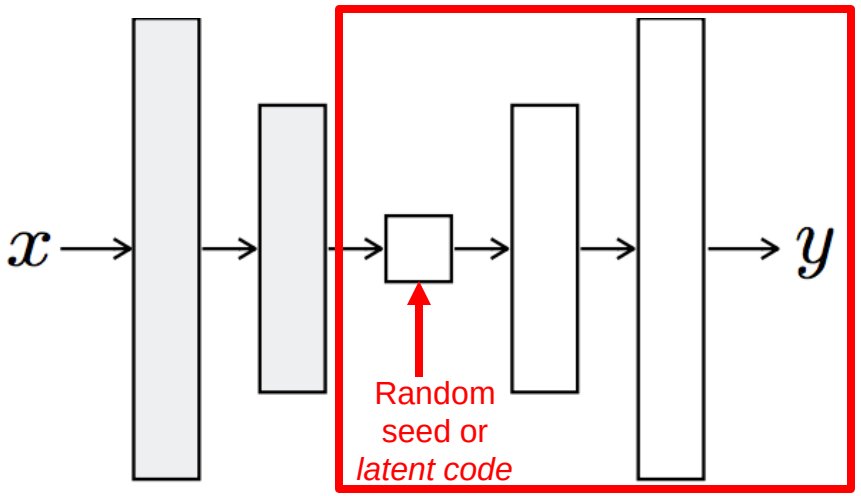


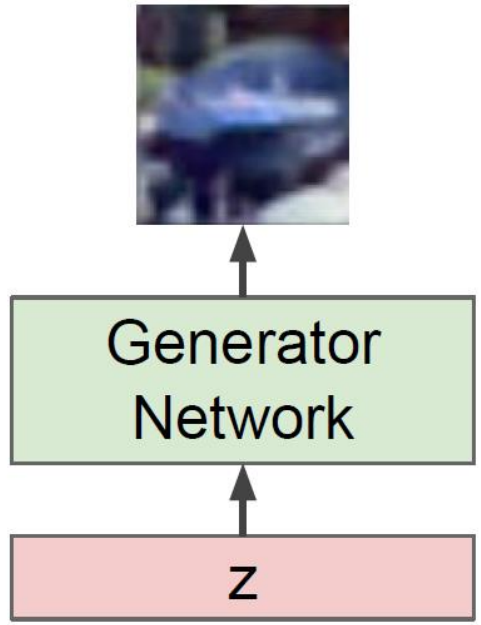
Unconditional generation

- Sample from a simple distribution, e.g. random noise.
- Learn transformation to training distribution.

Output: Sample from training distribution

A neural network can be used to represent this complex transformation?

Input: Random noise



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Designing a network for generative tasks

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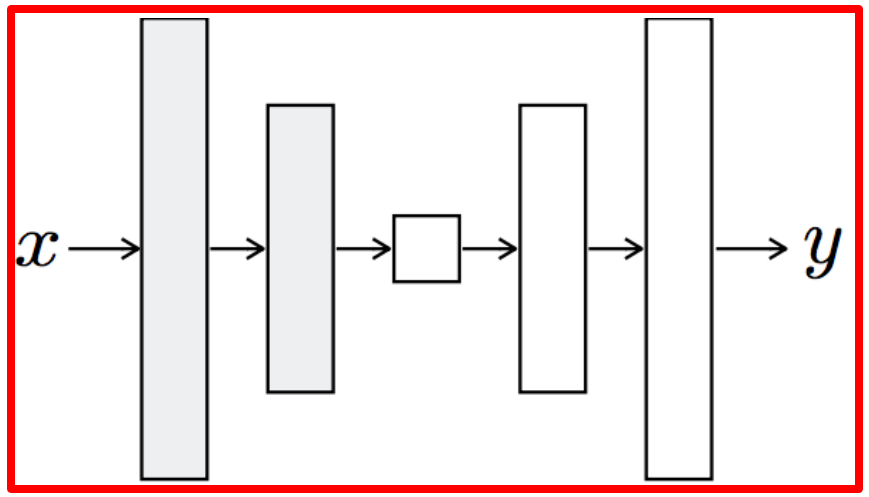


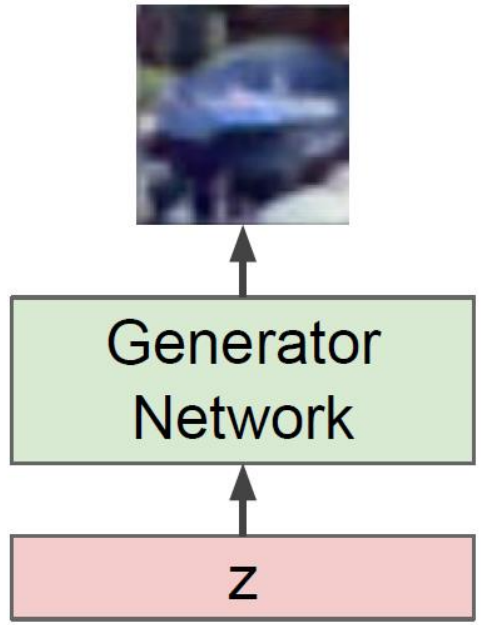
Image-to-image translation

- Sample from a simple distribution, e.g. random noise.
- Learn transformation to training distribution.

Output: Sample from training distribution

A neural network can be used to represent this complex transformation?

Input: Random noise



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

Credit: cs231n, Stanford

Designing a network for generative tasks

1. We need an architecture that can generate an image
   - Recall upsampling architectures for dense prediction
2. We need to design the right loss function

Learning to sample

Training data $x \sim p_{\text{data}}$

Generated samples $x \sim p_{\text{model}}$

We want to learn p_{model} that matches p_{data}

Adapted from Stanford CS231n

Generative adversarial networks

- Train two networks with opposing objectives:
  - **Generator:** learns to generate samples
  - **Discriminator:** learns to distinguish between generated and real samples

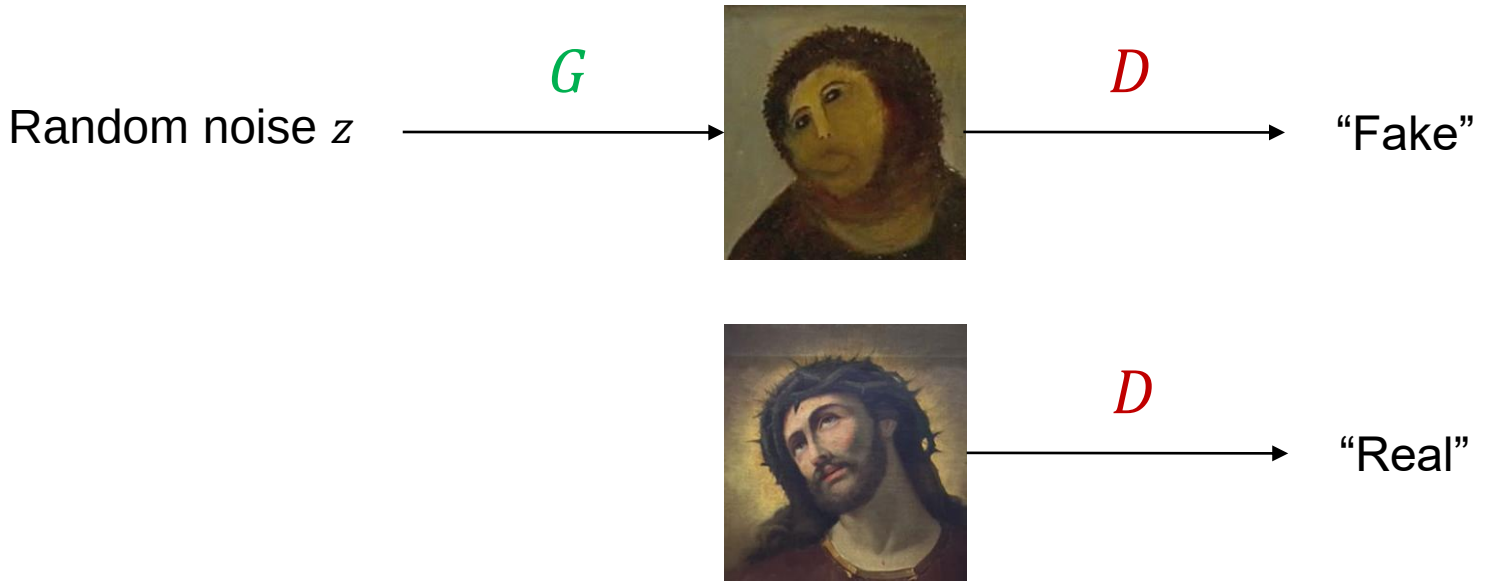


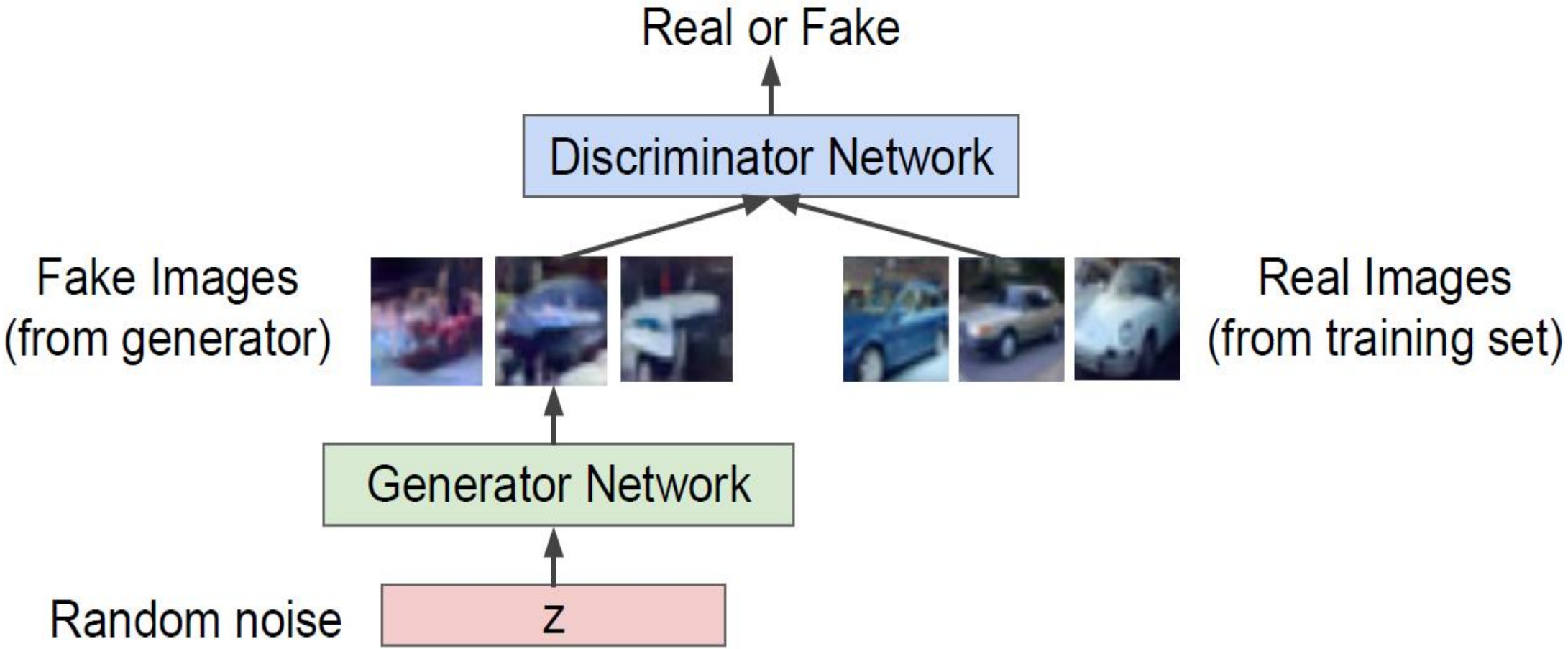
Figure adapted from F. Fleuret

I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, Y. Bengio, Generative adversarial nets, NIPS 2014

Generative adversarial networks

Generator network: try to fool the discriminator by generating real-looking images

Discriminator network: try to distinguish between real and fake images



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

Fake and real images copyright Emily Denton et al. 2015.

Credit: cs231n, Stanford

Generative adversarial networks

Generator network: try to fool the discriminator by generating real-looking images

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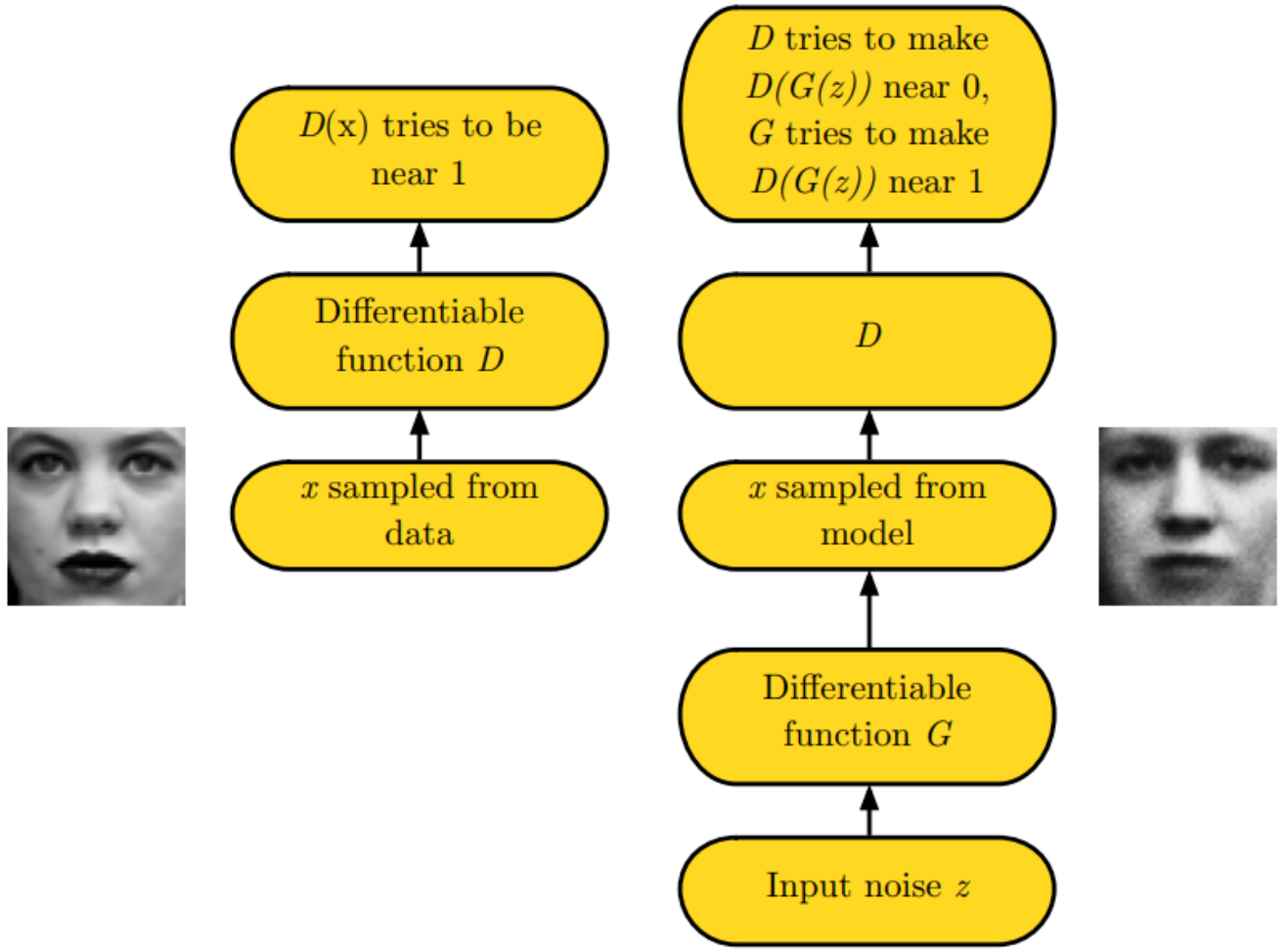

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

Fake and real images copyright Emily Denton et al. 2015.

Credit: cs231n, Stanford

GAN objective

- The discriminator $D(x)$ should output the probability that the sample x is real
  - That is, we want $D(x)$ to be close to 1 for real data and close to 0 for fake
- Expected conditional log likelihood for real and generated data:

$$\mathbb{E}_{x\sim p_{\text{data}}} \log D(x) \; + \; \mathbb{E}_{x\sim p_{\text{gen}}} \log\big(1 - D(x)\big)$$

$$= \mathbb{E}_{x\sim p_{\text{data}}} \log D(x) \; + \; \mathbb{E}_{z\sim p} \log(1 - D(G(z)))$$

We seed the generator with noise z drawn from a simple distribution p (Gaussian or uniform)

GAN objective

$$V(G, D) = \mathbb{E}_{x \sim p_{\text{data}}} \log D(x) + \mathbb{E}_{z \sim p} \log(1 - D(G(z)))$$

- The discriminator wants to correctly distinguish real and fake samples:

$$D^* = \arg\max_D V(G, D)$$

- The generator wants to fool the discriminator:

$$G^* = \arg\min_G V(G, D)$$

- Train the generator and discriminator jointly in a *minimax game*

GAN objective: Theoretical properties

$$V(G, D) = \mathbb{E}_{x \sim p_{\text{data}}} \log D(x) + \mathbb{E}_{z \sim p} \log(1 - D(G(z)))$$

- Assuming unlimited capacity for generator and discriminator and unlimited training data:
  - The objective $\min_G \max_D V(G, D)$ is equivalent to *Jensen-Shannon divergence* between p_{data} and p_{gen} and global optimum (*Nash equilibrium*) is given by $p_{\text{data}} = p_{\text{gen}}$

GAN objective: Theoretical properties

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  - The objective $\min_G \max_D V(G, D)$ is equivalent to *Jensen-Shannon divergence* between p_{data} and p_{gen} and global optimum (*Nash equilibrium*) is given by $p_{\text{data}} = p_{\text{gen}}$
  - If at each step, D is allowed to reach its optimum given G, and G is updated to decrease $V(G, D)$, then p_{gen} will eventually converge to p_{data}

GAN training

$$V(G, D) = \mathbb{E}_{x \sim p_{\text{data}}} \log D(x) + \mathbb{E}_{z \sim p} \log(1 - D(G(z)))$$

- Alternate between
  - *Gradient ascent* on discriminator:

$$D^* = \arg\max_D V(G, D)$$

  - *Gradient descent* on generator (minimize log-probability of discriminator being right):

$$G^* = \arg\min_G V(G, D)$$
$$= \arg\min_G \mathbb{E}_{z \sim p} \log(1 - D(G(z)))$$

  - In practice, do *gradient ascent* on generator (maximize log-probability of discriminator being wrong):

$$G^* = \arg\max_G \mathbb{E}_{z \sim p} \log(D(G(z)))$$

Non-saturating GAN loss (NSGAN)

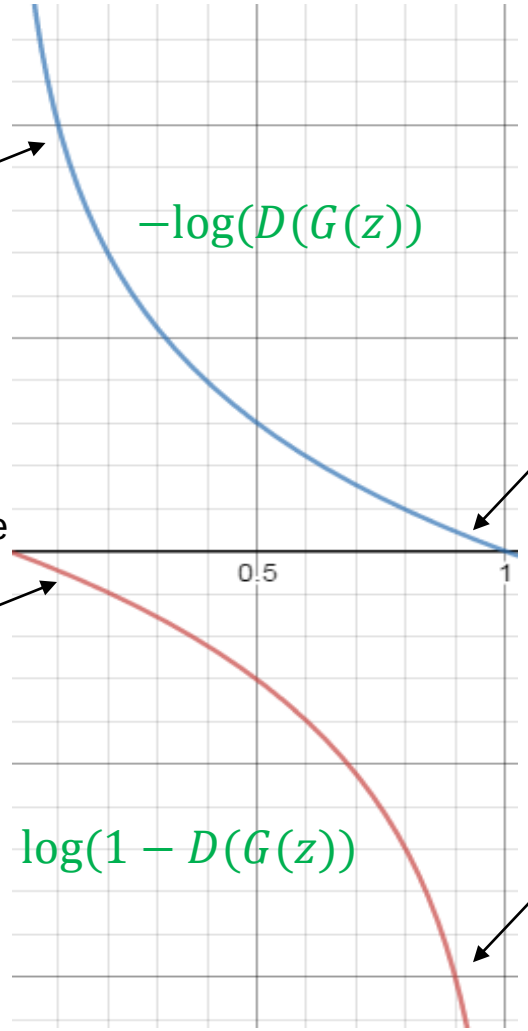
$\min_{w_G} \mathbb{E}_{z \sim p} \log(1 - D(G(z)))$ vs. $\max_{w_G} \mathbb{E}_{z \sim p} \log(D(G(z)))$

Minimize log-probability of discriminator being right

Maximize log-probability of discriminator being wrong

Non-saturating GAN loss (NSGAN)

$\min_{w_G} \mathbb{E}_{z \sim p} \log(1 - D(G(z)))$ vs. $\max_{w_G} \mathbb{E}_{z \sim p} \log(D(G(z)))$



Large gradients for low-quality samples

Small gradients for high-quality samples

Low discriminator score (low-quality samples)

High discriminator score (high-quality samples)

Want to learn from confidently rejected sample but gradients here are small

These samples already fool the discriminator so we don't need large gradients here

Figure source

NSGAN training algorithm

- Update discriminator:
  - Repeat for k steps:
    - Sample mini-batch of noise samples $z_1, \dots, z_m$ and mini-batch of real samples $x_1, \dots, x_m$
    - Update parameters of D by stochastic gradient ascent on

$$\frac{1}{m}\sum_{m}[\log D(x_m) + \log(1 - D(G(z_m)))]$$

- Update generator:
  - Sample mini-batch of noise samples $z_1, \dots, z_m$
  - Update parameters of G by stochastic gradient ascent on

$$\frac{1}{m}\sum_{m}\log D(G(z_m))$$

- Repeat until happy with results

NSGAN training algorithm

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  - Update parameters of G by stochastic gradient ascent on

$$\frac{1}{m}\sum_{m}\log D(G(z_m))$$

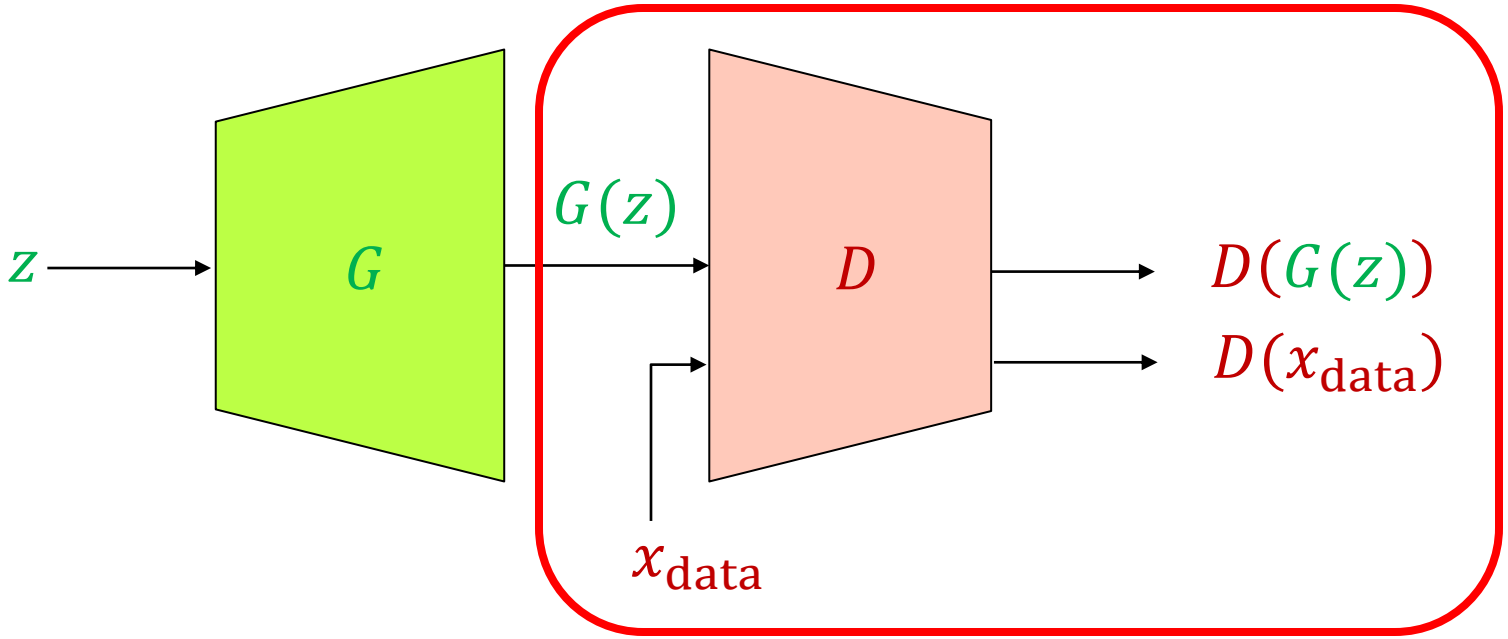
- Repeat until happy with results

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

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

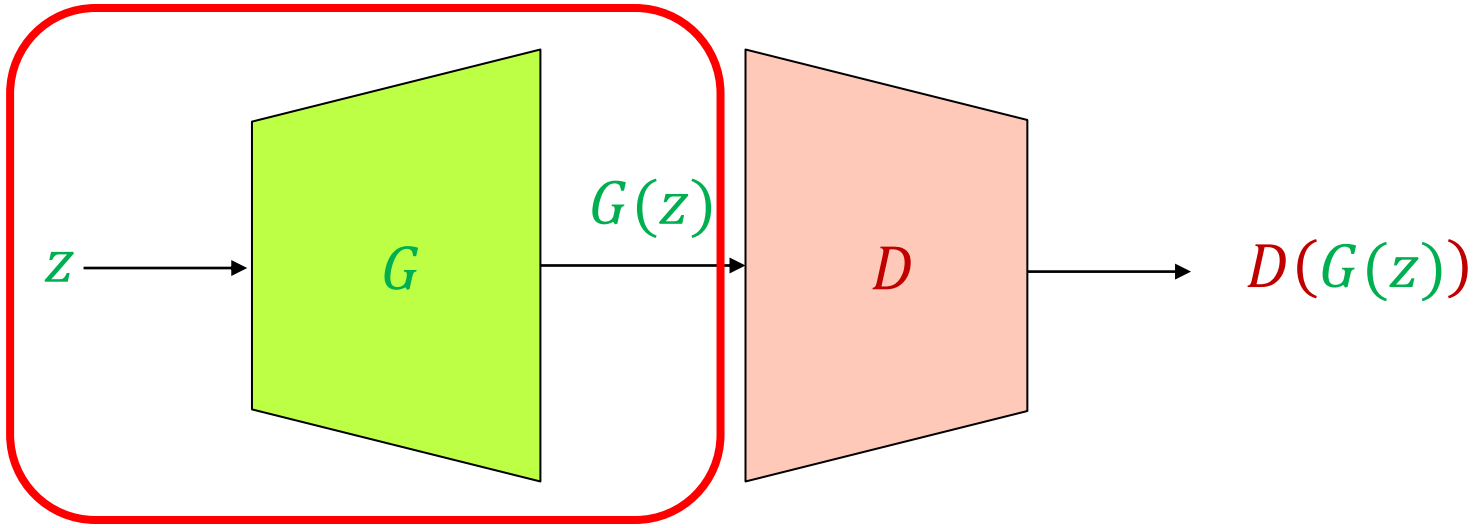
GAN: Conceptual picture

- Update discriminator: push $D(x_{\text{data}})$ close to 1 and $D(G(z))$ close to 0
  - The generator is a “black box” to the discriminator



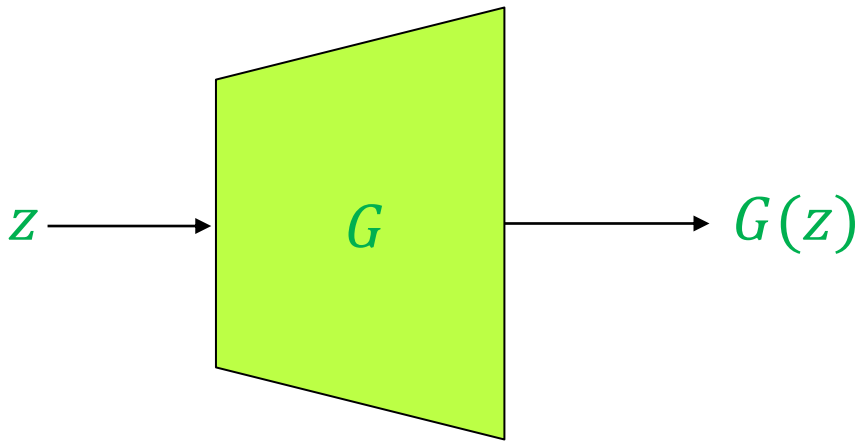
GAN: Conceptual picture

- Update generator: increase $D(G(z))$
  - Requires back-propagating through the composed generator-discriminator network (i.e., the discriminator cannot be a black box)
  - The generator is exposed to real data only via the output of the discriminator (and its gradients)



GAN: Conceptual picture

- Test time – the discriminator is discarded



Original GAN results

MNIST digits

Toronto Face Dataset

Nearest real image for
sample to the left

I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair,
A. Courville, Y. Bengio, Generative adversarial nets, NIPS 2014

Original GAN results

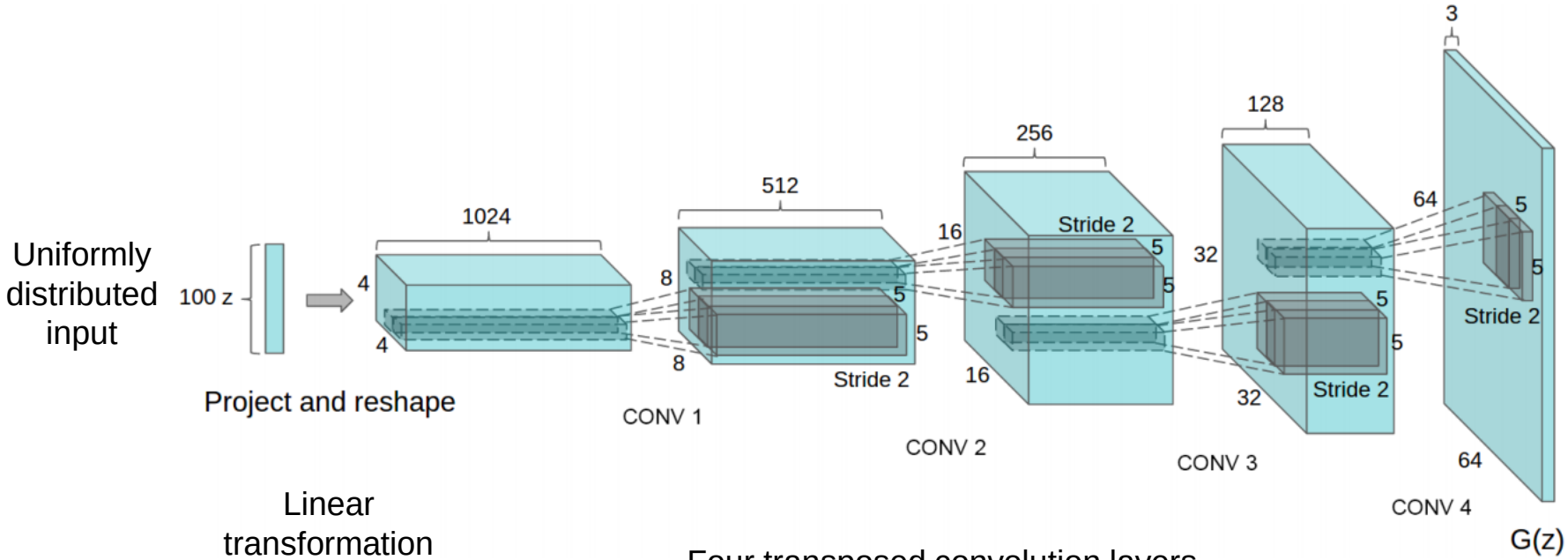
CIFAR-10 (FC networks)

CIFAR-10 (conv networks)

I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, Y. Bengio, Generative adversarial nets, NIPS 2014

DCGAN

- Early, influential convolutional architecture for generator



A. Radford, L. Metz, S. Chintala, Unsupervised representation learning with deep convolutional generative adversarial networks, ICLR 2016

DCGAN

- Early, influential convolutional architecture for generator
- Discriminator architecture:
  - Don’t use pooling, only strided convolutions
  - Use Leaky ReLU activations (sparse gradients cause problems for training)
  - Use only one FC layer before the softmax output
  - Use batch normalization after most layers (in the generator also)

A. Radford, L. Metz, S. Chintala, Unsupervised representation learning with deep convolutional generative adversarial networks, ICLR 2016

DCGAN results

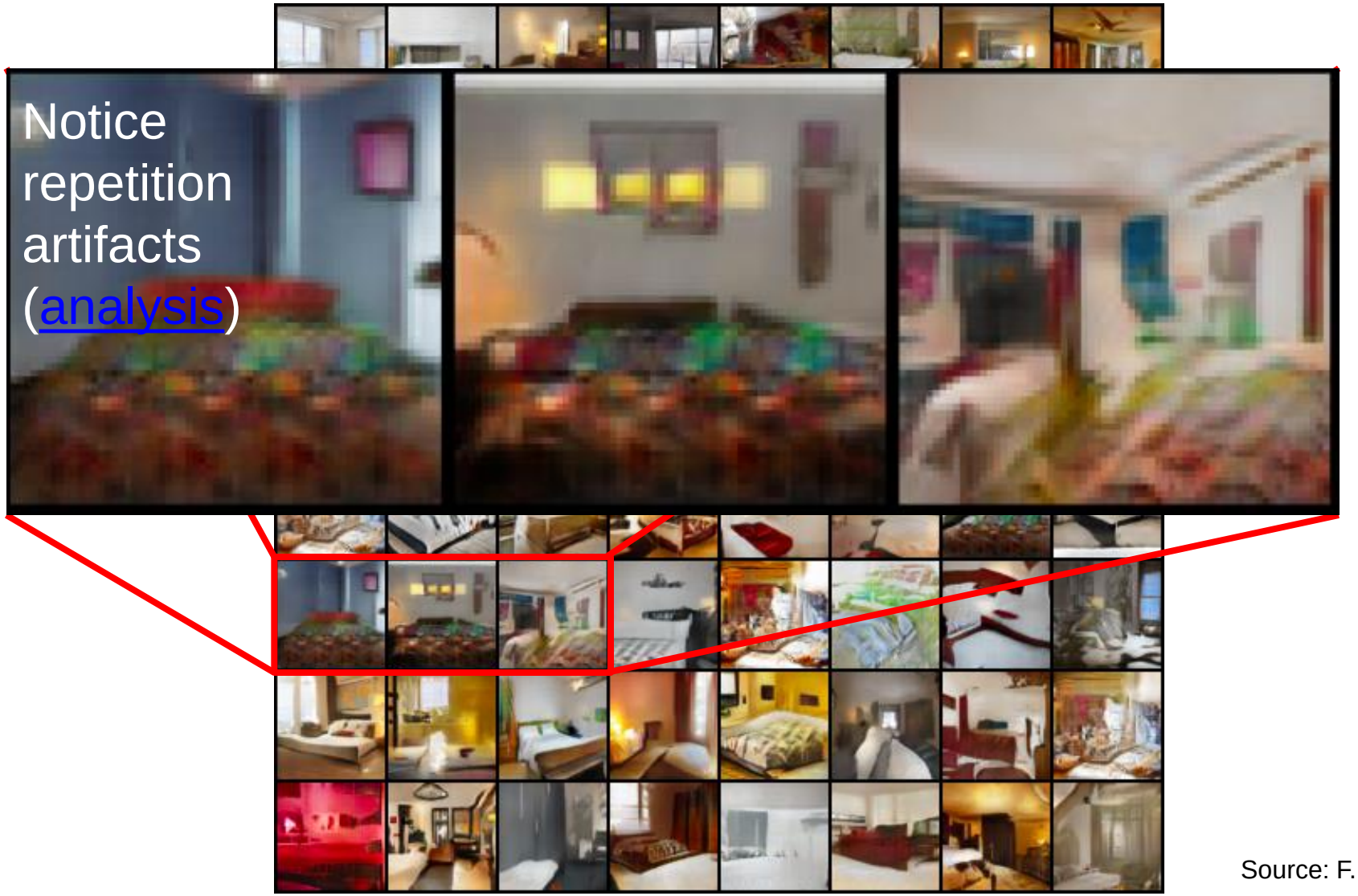
Generated bedrooms after one epoch

DCGAN results

Generated bedrooms after five epochs

DCGAN results

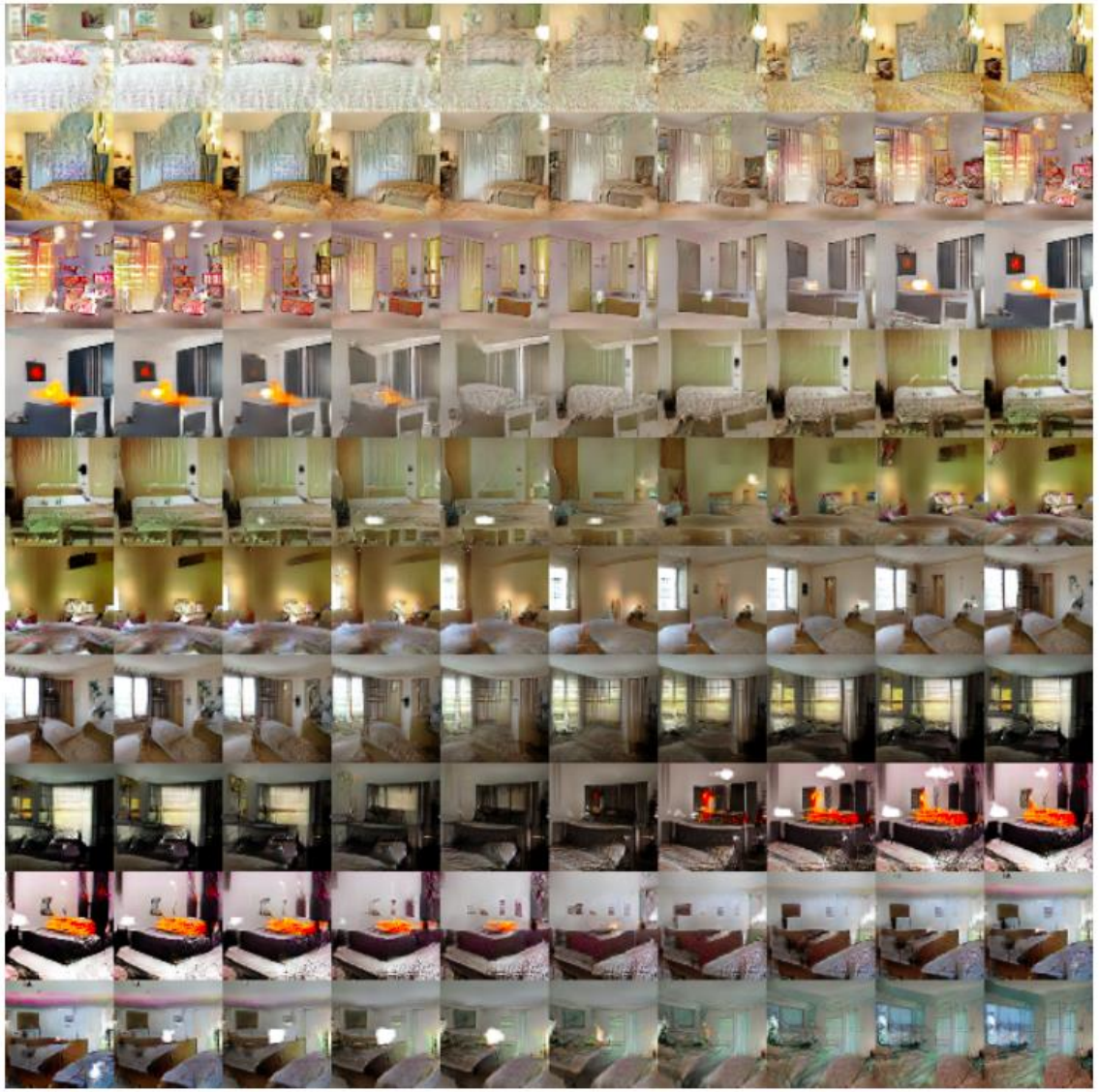
More bedrooms



Source: F. Fleuret

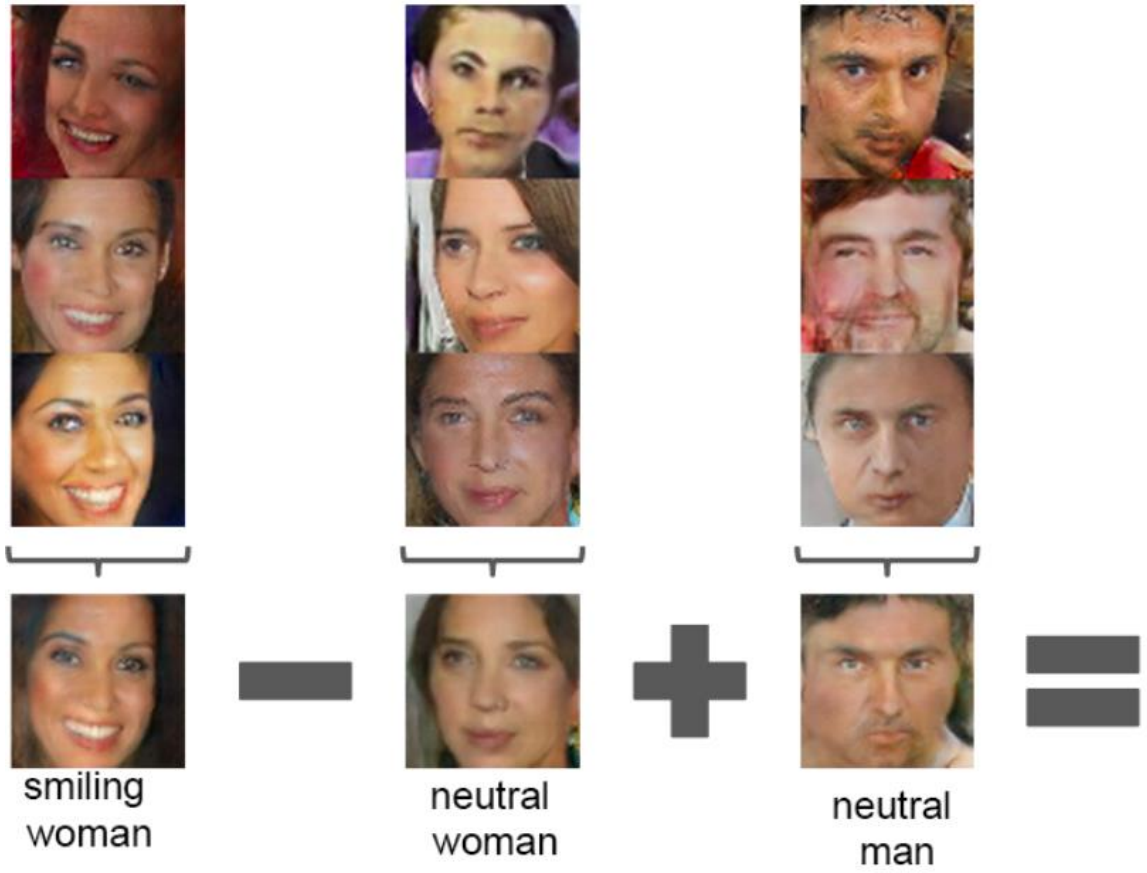
DCGAN results

Interpolation between different points in the z space



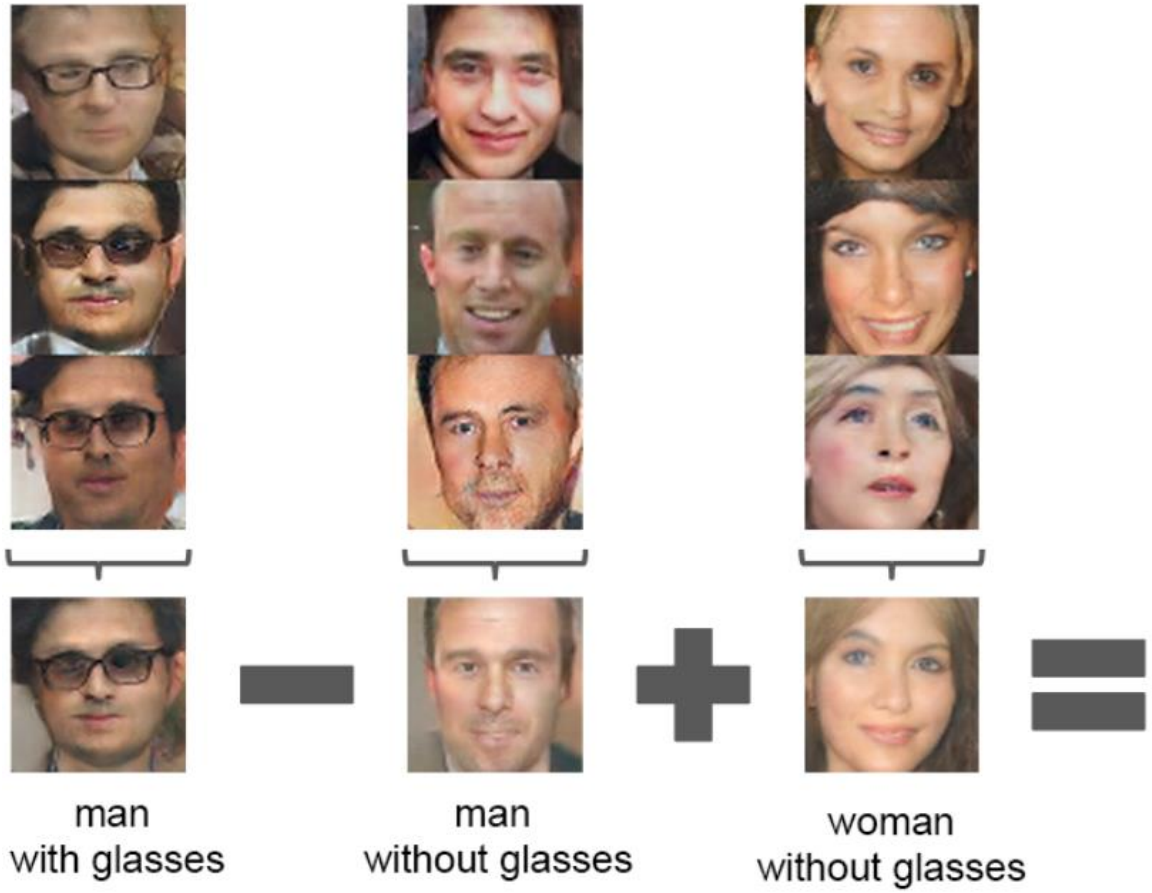
DCGAN results

- Vector arithmetic in the z space



DCGAN results

- Vector arithmetic in the z space



DCGAN results

- Pose transformation by adding a “turn” vector

Outline

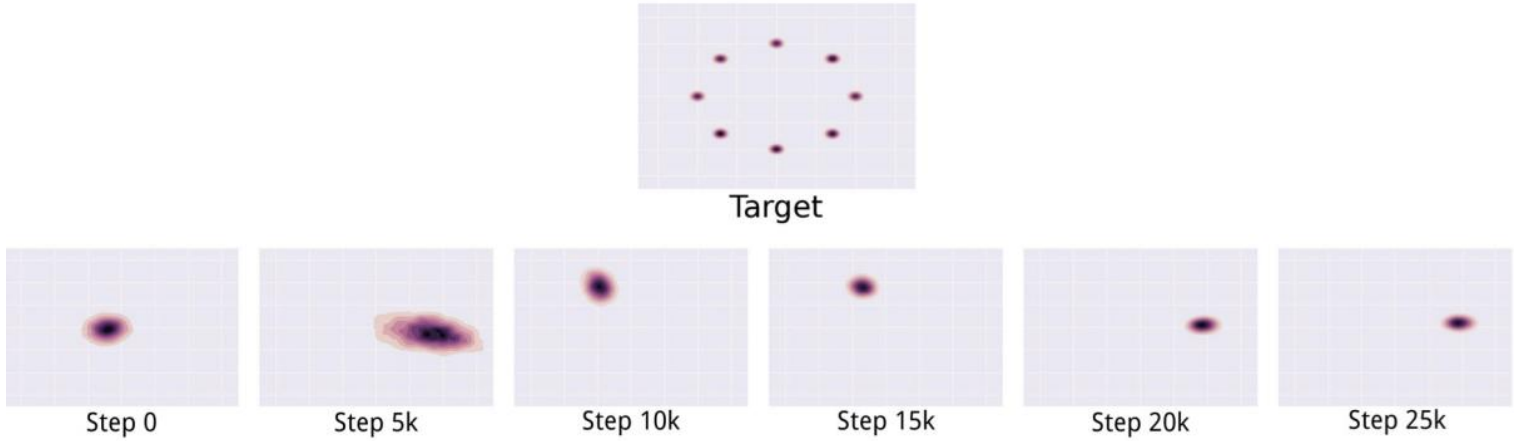
- Generative tasks
- Original GAN formulations
  - NSGAN
  - DCGAN
- Other popular formulations
  - WGAN, WGAN-GP
  - LSGAN

Problems with GAN training

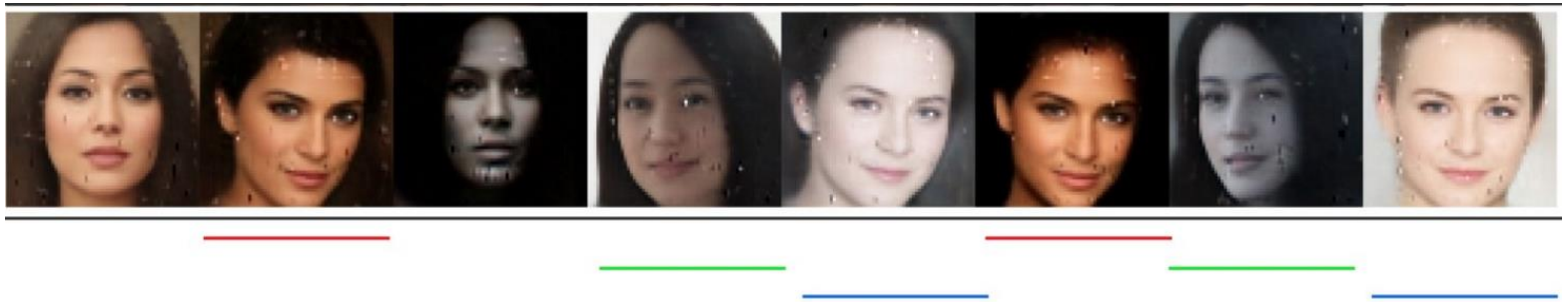
- Stability
  - Parameters can oscillate or diverge, generator loss does not correlate with sample quality
  - Behavior very sensitive to hyperparameter selection

Problems with GAN training

- Mode collapse
  - Generator ends up modeling only a small subset of the training data



Source



Source

Some popular GAN flavors

- WGAN and improved WGAN (WGAN-GP)
- LSGAN

Wasserstein GAN (WGAN)

- Motivated by *Wasserstein or Earth mover's distance*, which is an alternative to JS divergence for comparing distributions
  - In practice, use linear activation instead of sigmoid in the discriminator and drop the logs from the objective:

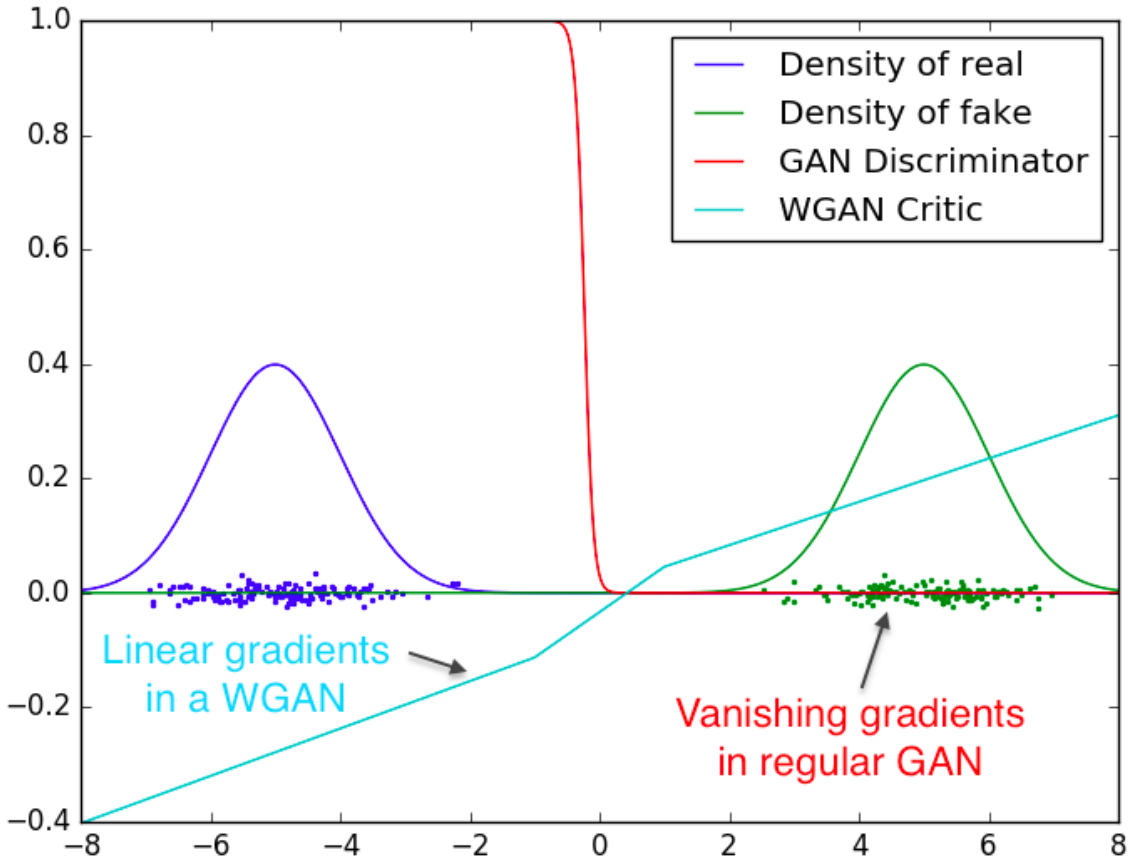
$$\min_G \max_D \left[\mathbb{E}_{x \sim p_{\text{data}}} D(x) - \mathbb{E}_{z \sim p} D(G(z)) \right]$$

  - Due to theoretical considerations, important to ensure smoothness of discriminator
  - This paper's suggested method is clipping weights to fixed range $[-c, c]$

M. Arjovsky, S. Chintala, L. Bottou, Wasserstein generative adversarial networks, ICML 2017

Wasserstein GAN (WGAN)

- Benefits (claimed)
  - Better gradients, more stable training

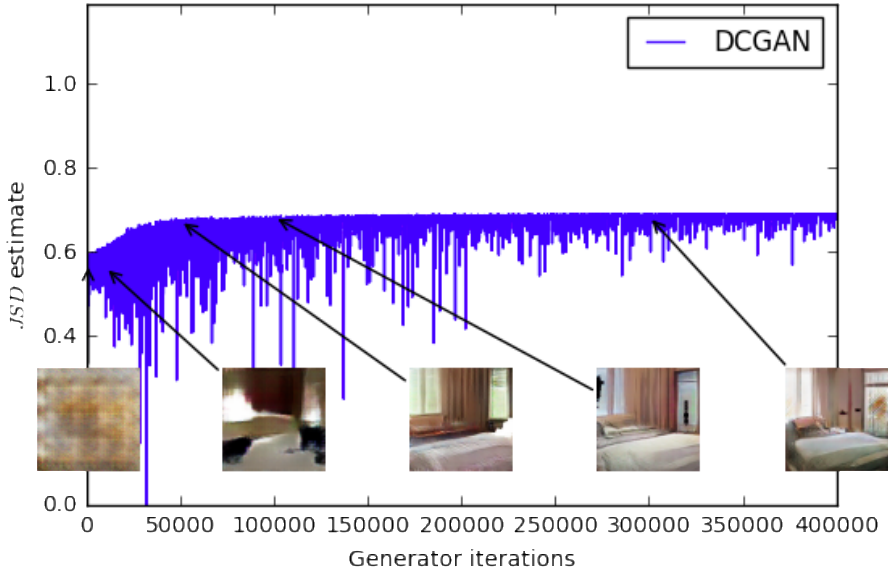


M. Arjovsky, S. Chintala, L. Bottou, Wasserstein generative adversarial networks, ICML 2017

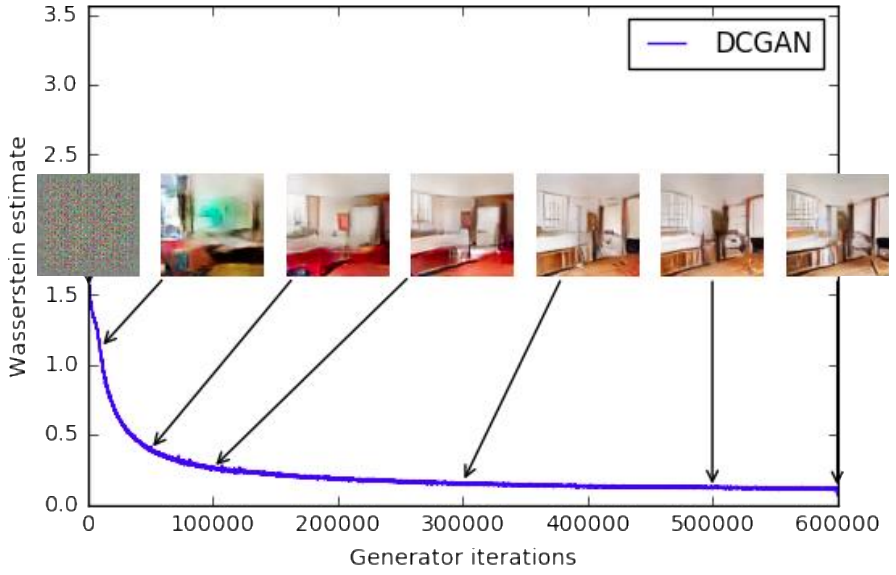
Wasserstein GAN (WGAN)

- Benefits (claimed)
  - Better gradients, more stable training
  - Objective function value is more meaningfully related to quality of generator output

Original GAN divergence



WGAN divergence



M. Arjovsky, S. Chintala, L. Bottou, Wasserstein generative adversarial networks, ICML 2017

Improved Wasserstein GAN (WGAN-GP)

- Weight clipping leads to problems with discriminator training
- Improved Wasserstein discriminator loss:

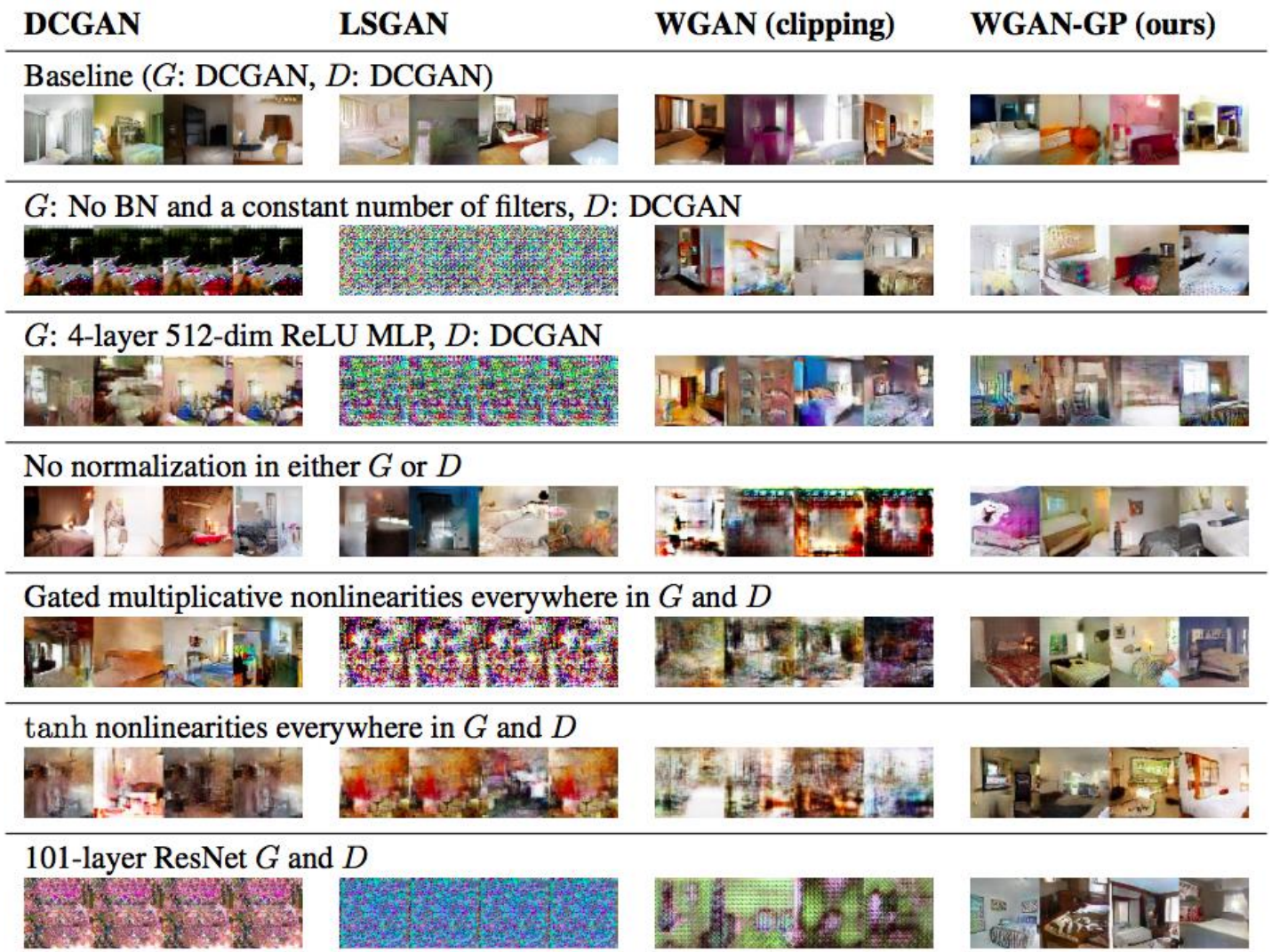
$$\mathbb{E}_{\tilde{x}\sim p_{\text{gen}}} D(\tilde{x}) - \mathbb{E}_{x\sim p_{\text{real}}} D(x)$$

$$+ \lambda\, \mathbb{E}_{\hat{x}\sim p_{\hat{x}}} [(\|\nabla_{\hat{x}} D(\hat{x})\|_2 - 1)^2]$$

Unit norm gradient penalty on points $\hat{x}$ obtained by interpolating real and generated samples

I. Gulrajani, F. Ahmed, M. Arjovsky, V. Dumoulin, A. Courville, Improved training of Wasserstein GANs, NIPS 2017

Improved Wasserstein GAN: Results



I. Gulrajani, F. Ahmed, M. Arjovsky, V. Dumoulin, A. Courville, Improved training of Wasserstein GANs, NIPS 2017

Least Squares GAN (LSGAN)

- Use least squares cost for generator and discriminator
  - Equivalent to minimizing Pearson χ^2 divergence

$$D^* = \arg\min_D \left[\mathbb{E}_{x \sim p_{\text{data}}} (D(x) - 1)^2 + \mathbb{E}_{z \sim p} (D(G(z)))^2 \right]$$

Push discrim. response on real data close to 1

Push response on generated data close to 0

$$G^* = \arg\min_G \mathbb{E}_{z \sim p} (D(G(z)) - 1)^2$$

Push response on generated data close to 1

X. Mao, Q. Li, H. Xie, R. Y. Lau, Z. Wang, and S. P. Smolley, Least squares generative adversarial networks, ICCV 2017

Least Squares GAN (LSGAN)

- Benefits (claimed)
  - Higher-quality images

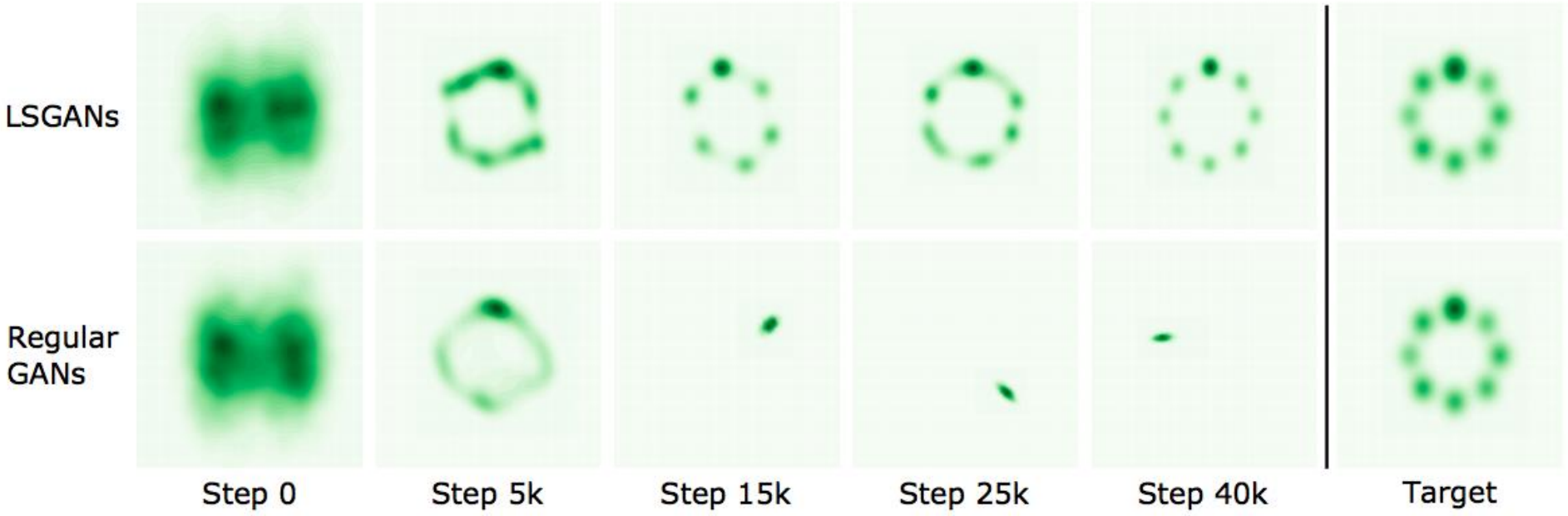
(a) Generated images (112 × 112) by LSGANs.

(b) Generated images (112 × 112) by DCGANs.

X. Mao, Q. Li, H. Xie, R. Y. Lau, Z. Wang, and S. P. Smolley, Least squares generative adversarial networks, ICCV 2017

Least Squares GAN (LSGAN)

- Benefits (claimed)
  - Higher-quality images
  - More stable and resistant to mode collapse



X. Mao, Q. Li, H. Xie, R. Y. Lau, Z. Wang, and S. P. Smolley, Least squares generative adversarial networks, ICCV 2017

Are GANs created equal?

- From the abstract:

"We find that most models can reach similar scores with enough hyperparameter optimization and random restarts. This suggests that improvements can arise from a higher computational budget and tuning more than fundamental algorithmic changes … ***We did not find evidence that any of the tested algorithms consistently outperforms the non-saturating GAN introduced in Goodfellow et al. (2014)****"*

M. Lucic, K. Kurach, M. Michalski, O. Bousquet, S. Gelly, Are GANs created equal? A large-scale study, NIPS 2018

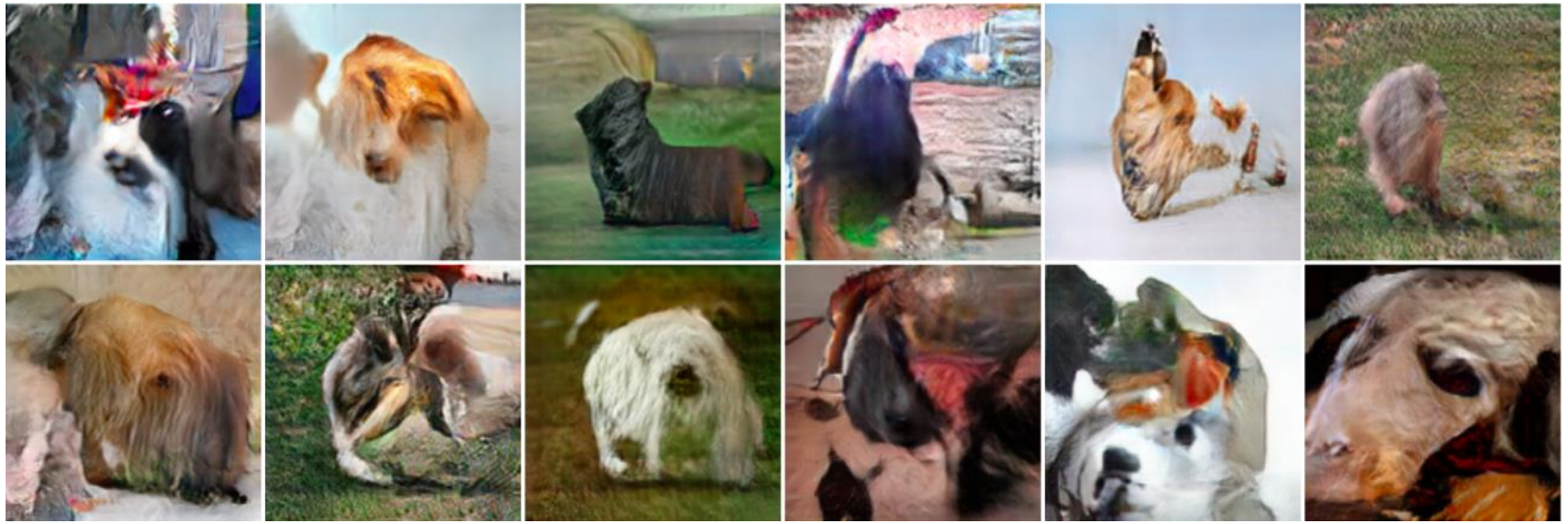
Outline

- Generative tasks
- Original GAN formulations
  - NSGAN
  - DCGAN
- Other popular formulations
  - WGAN, WGAN-GP
  - LSGAN
- State-of-the-art architectures
  - Progressive GAN, StyleGAN

Recent progress in GANs

Recent progress in GANs

EBGAN (2017)



ENERGY-BASED GAN

BigGAN (2018)

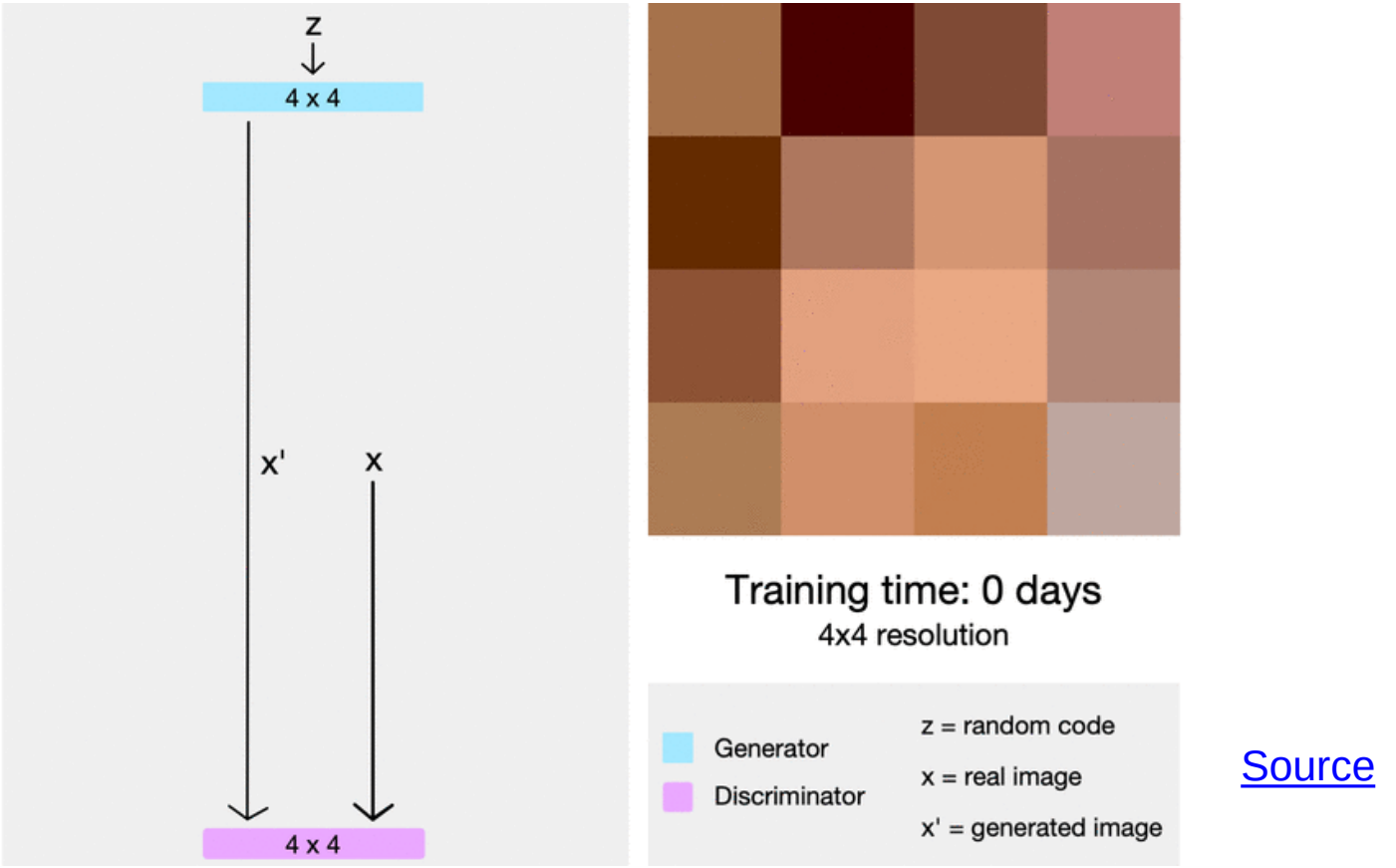
Progressive GANs

Realistic face images up to 1024 x 1024 resolution

T. Karras, T. Aila, S. Laine, J. Lehtinen. Progressive Growing of GANs for Improved Quality, Stability, and Variation. ICLR 2018

Progressive GANs

- Key idea: train lower-resolution models, gradually add layers corresponding to higher-resolution outputs



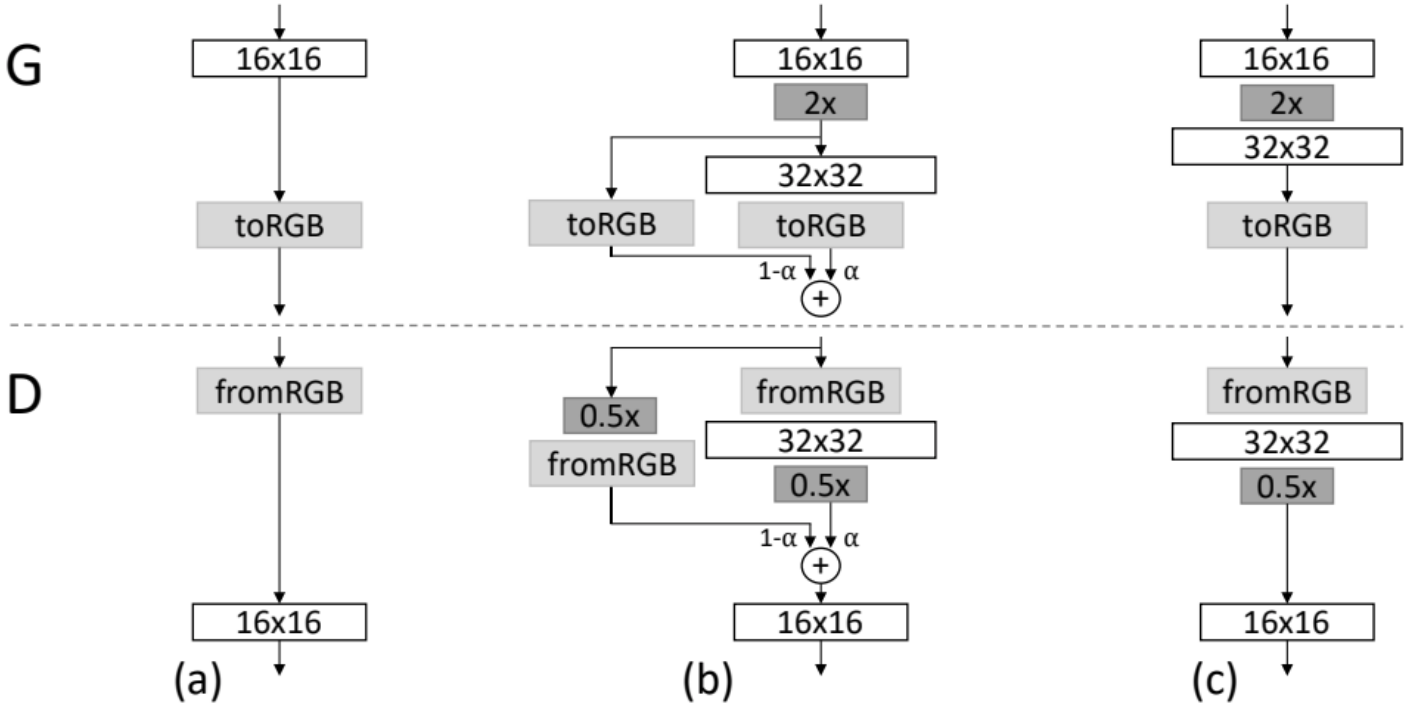
Source

T. Karras, T. Aila, S. Laine, J. Lehtinen. Progressive Growing of GANs for Improved Quality, Stability, and Variation. ICLR 2018

Progressive GANs

- Key idea: train lower-resolution models, gradually add layers corresponding to higher-resolution outputs

Transition from 16x16 to 32x32 images



T. Karras, T. Aila, S. Laine, J. Lehtinen. Progressive Growing of GANs for Improved Quality, Stability, and Variation. ICLR 2018

Progressive GANs: Implementation details

- Loss: WGAN-GP loss (preferred) or LSGAN
- Architectures:
  - Nearest neighbor upsampling (2x2 replication) followed by regular convolutions instead of transposed conv layers
  - Average pooling instead of striding for downsampling in discriminator
  - Leaky ReLUs used in discriminator and generator
  - Per-pixel response normalization in generator: rescale feature vector in each pixel to unit length after each conv layer
- Use of minibatch standard deviation in discriminator (append to feature map)
- Exponential moving average of generator weights for display

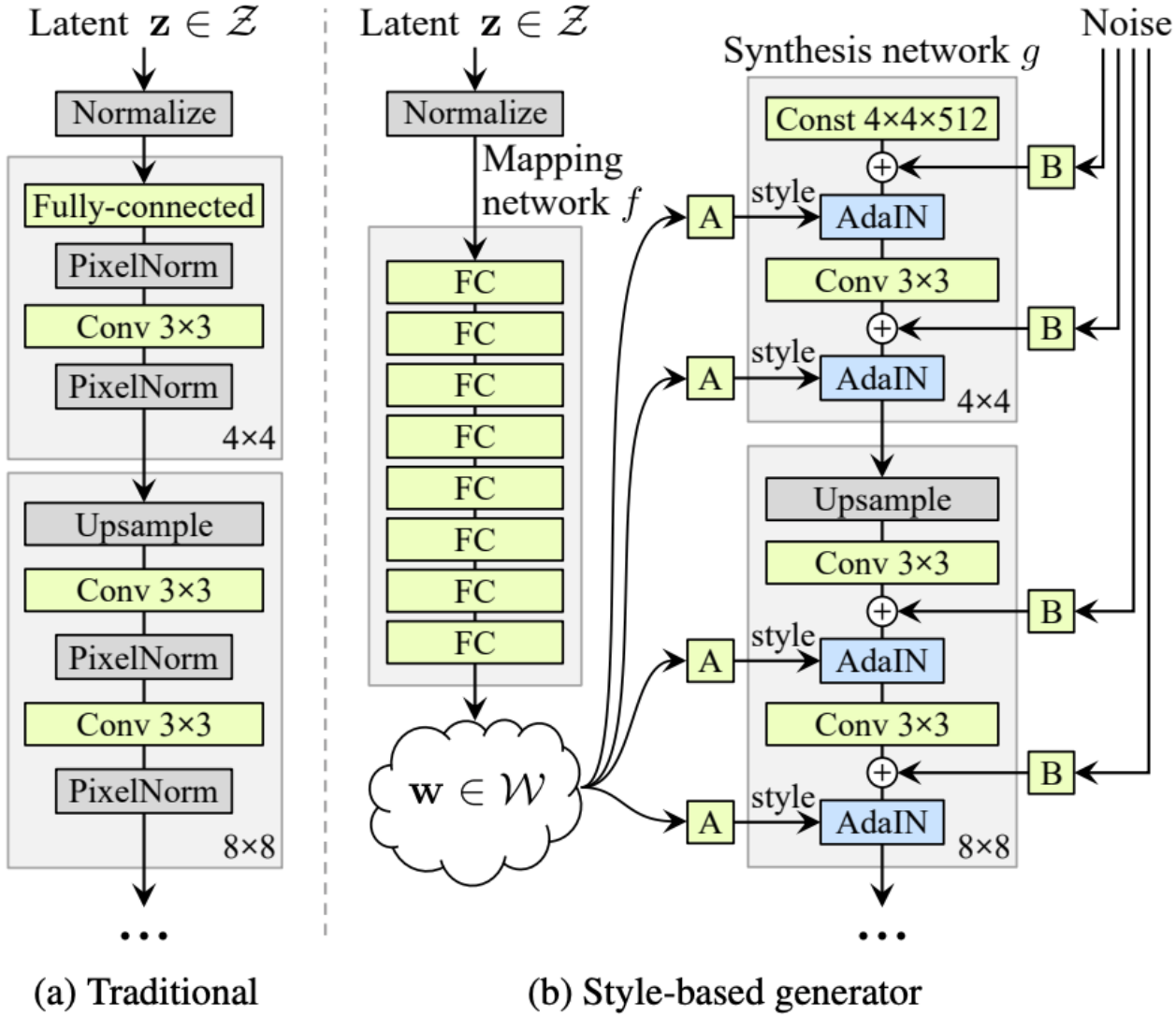
T. Karras, T. Aila, S. Laine, J. Lehtinen. Progressive Growing of GANs for Improved Quality, Stability, and Variation. ICLR 2018

Progressive GANs: Results

256 x 256 results for LSUN categories

StyleGAN

- Built on top of Progressive GAN
- Start with learned constant (instead of noise vector)
- Use a mapping network to produce a *style code w* using learned affine transformations *A*
- Use *adaptive instance normalization* (AdaIN): scale and bias each feature map using learned style values
- Add noise after each convolution and before nonlinearity (enables stochastic detail)



T. Karras, S. Laine, T. Aila. A Style-Based Generator Architecture for Generative Adversarial Networks. CVPR 2019

StyleGAN: Results

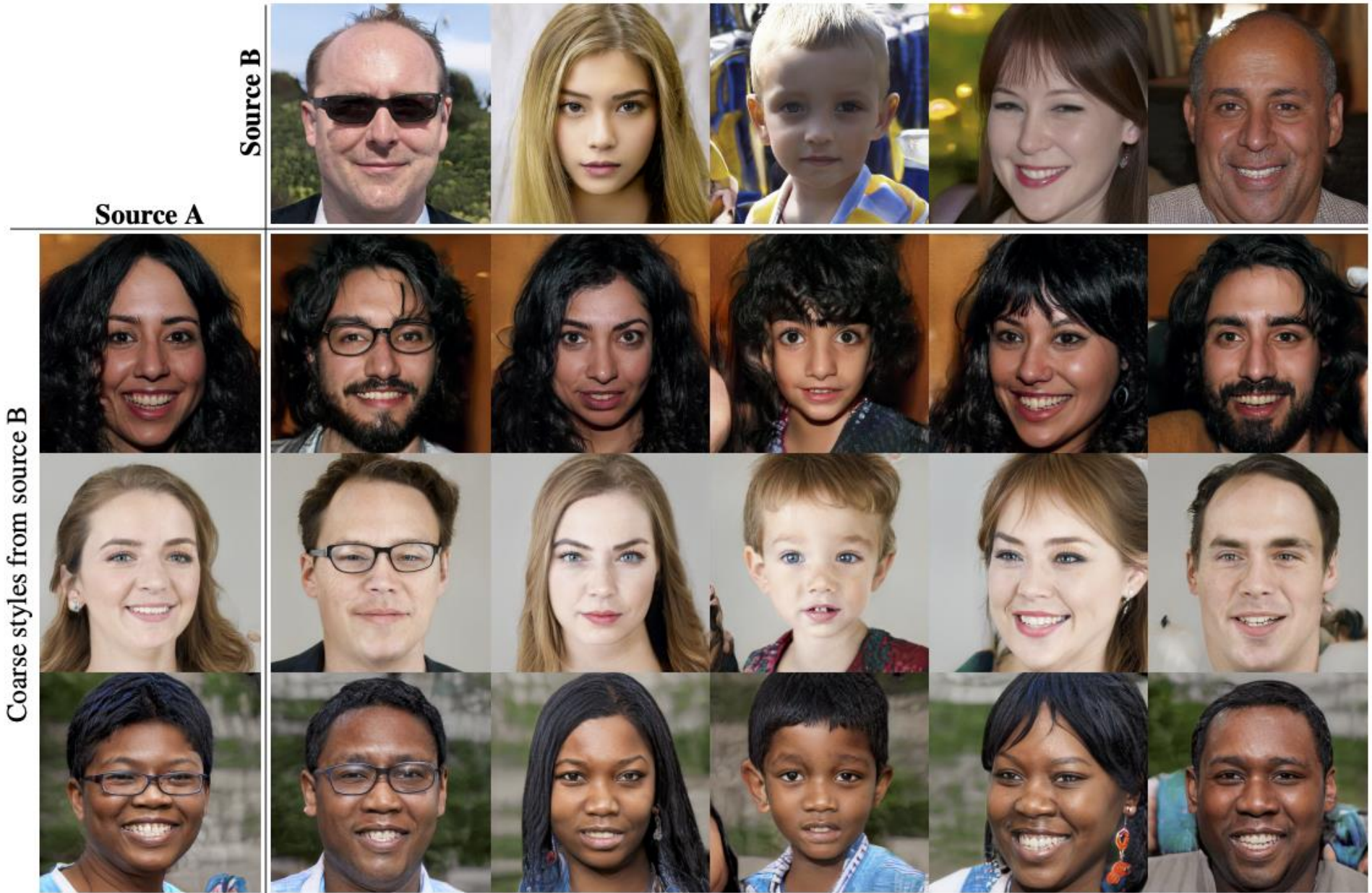
T. Karras, S. Laine, T. Aila. A Style-Based Generator Architecture for Generative Adversarial Networks. CVPR 2019

Mixing styles

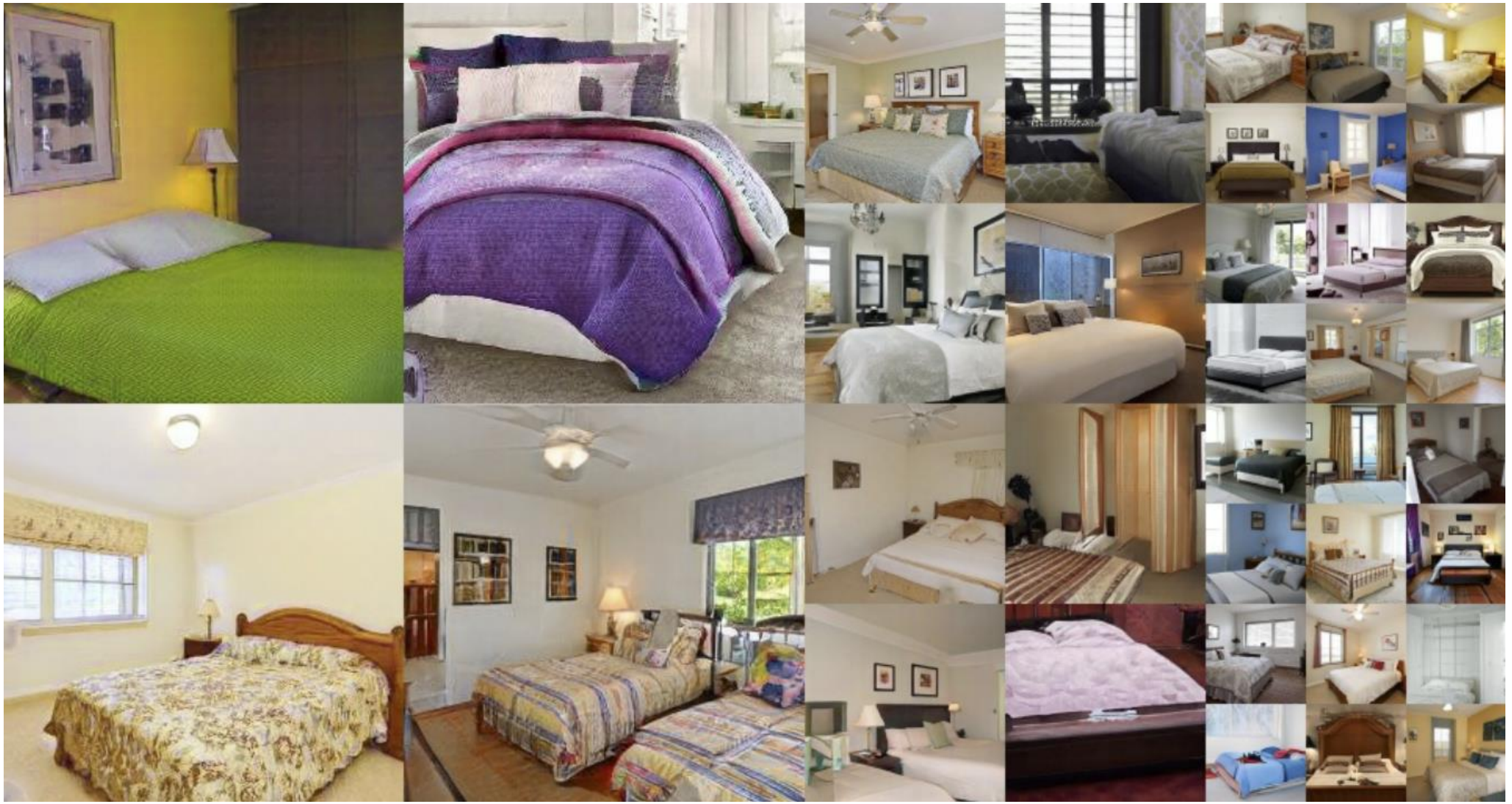
“Two sets of images were generated from their respective latent codes (sources A and B); the rest of the images were generated by copying a specified subset of styles from source B and taking the rest from source A.”

Mixing styles

Mixing styles



StyleGAN: Bedrooms



T. Karras, S. Laine, T. Aila. A Style-Based Generator Architecture for Generative Adversarial Networks. CVPR 2019

StyleGAN: Cars

T. Karras, S. Laine, T. Aila. A Style-Based Generator Architecture for Generative Adversarial Networks. CVPR 2019

StyleGAN2

- Change normalization, remove progressive growing to address StyleGAN artifacts

Figure 1. Instance normalization causes water droplet -like artifacts in StyleGAN images. These are not always obvious in the generated images, but if we look at the activations inside the generator network, the problem is always there, in all feature maps starting from the 64x64 resolution. It is a systemic problem that plagues all StyleGAN images.

Figure 6. Progressive growing leads to "phase" artifacts. In this example the teeth do not follow the pose but stay aligned to the camera, as indicated by the blue line.

T. Karras et al. Analyzing and Improving the Image Quality of StyleGAN. CVPR 2020

Outline

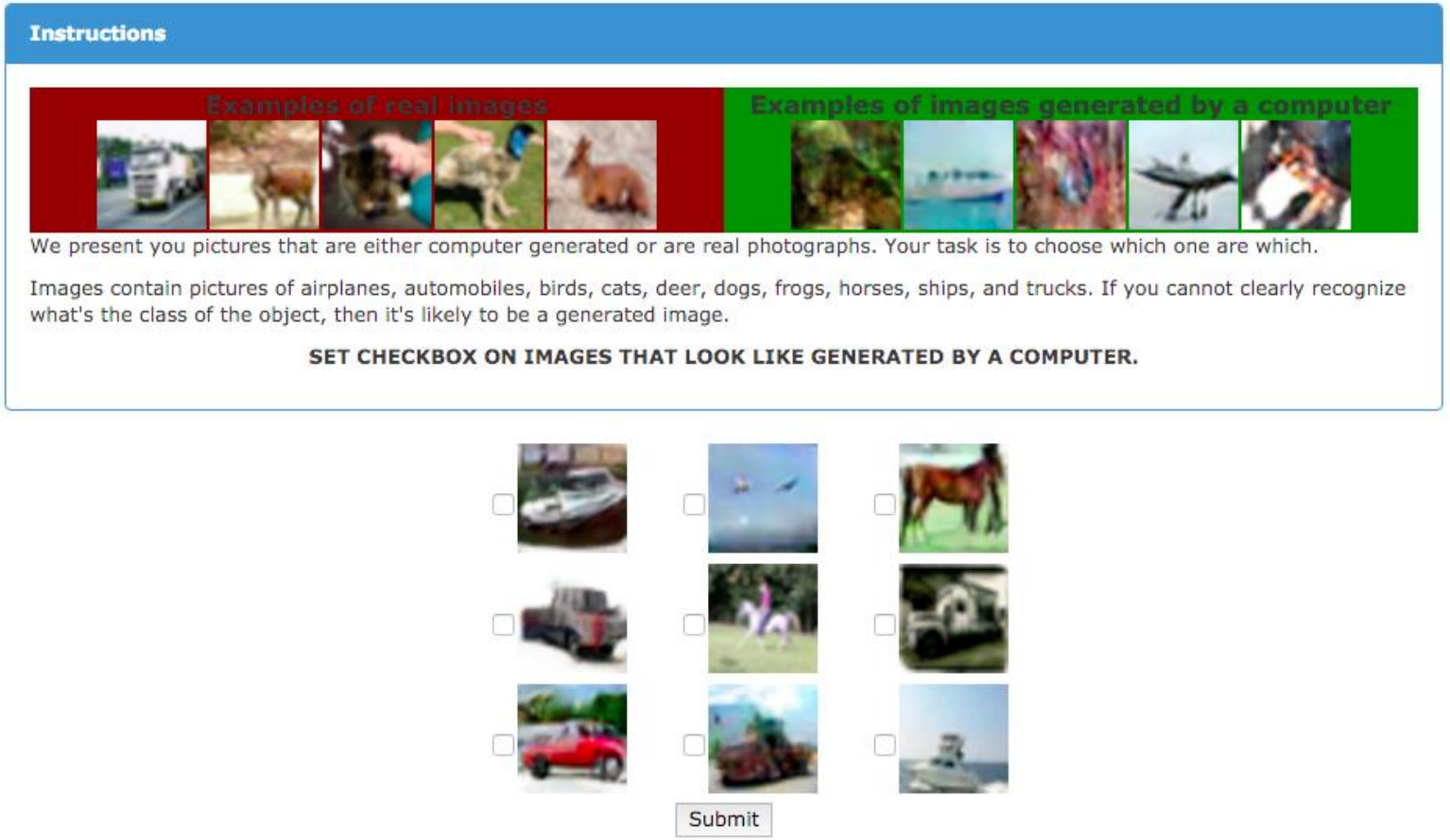
- Generative tasks
- Original GAN formulations
  - NSGAN
  - DCGAN
- Other popular formulations
  - WGAN, WGAN-GP
  - LSGAN
- State-of-the-art architectures
  - Progressive GAN, StyleGAN
- Evaluating GANs

How to evaluate GANs?

- Showing pictures of samples is not enough, especially for simpler datasets like MNIST, CIFAR, faces, bedrooms, etc.
- We cannot directly compute the likelihoods of high-dimensional samples (real or generated), or compare their distributions
- Many GAN approaches claim mainly to improve stability, which is hard to evaluate

GAN evaluation: Human studies

- Example: Turing test



T. Salimans, I. Goodfellow, W. Zaremba, V. Cheung, A. Radford, X. Chen, Improved techniques for training GANs, NIPS 2016

GAN evaluation: Inception score (IS)

- Key idea: generators should produce images with a variety of recognizable object classes
- Defined as $IS(G) = \exp[\mathbb{E}_{x\sim G}\, KL(P(y|x) \parallel P(y))]$ where $P(y|x)$ is the posterior label distribution returned by an image classifier (e.g., InceptionNet) for sample x
  - If x contains a recognizable object, entropy of $P(y|x)$ should be low
  - If generator generates images of diverse objects, the marginal distribution $P(y)$ should have high entropy

T. Salimans, I. Goodfellow, W. Zaremba, V. Cheung, A. Radford, X. Chen, Improved techniques for training GANs, NIPS 2016

GAN evaluation: Inception score (IS)

- Disadvantages
  - A GAN that simply memorizes the training data (overfitting) or outputs a single image per class (mode dropping) could still score well
  - Is sensitive to network weights, not necessarily valid for generative models not trained on ImageNet, can be gamed (Barratt & Sharma 2018)

Figure 1. Sample of generated images achieving an Inception Score of 900.15. The maximum achievable Inception Score is 1000, and the highest achieved in the literature is on the order of 10.

GAN evaluation: Fréchet Inception Distance (FID)

- Key idea: fit simple distributions (Gaussians) to statistics of feature activations for real and generated data; estimate divergence parametrically
  - Pass generated samples through a network (InceptionNet), compute activations for a chosen layer
  - Estimate multivariate mean and covariance of activations, compute Fréchet distance to those of real data

M. Heusel, H. Ramsauer, T. Unterthiner, B. Nessler, S. Hochreiter, GANs trained by a two time-scale update rule converge to a local Nash equilibrium, NIPS 2017

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In mathematics, the **Fréchet distance** is a measure of similarity between curves that takes into account the location and ordering of the points along the curves. It is named after Maurice Fréchet. ---------- Source: en.wikipedia.org

M. Heusel, H. Ramsauer, T. Unterthiner, B. Nessler, S. Hochreiter, GANs trained by a two time-scale update rule converge to a local Nash equilibrium, NIPS 2017

GAN evaluation: Fréchet Inception Distance (FID)

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  - Pass generated samples through a network (InceptionNet), compute activations for a chosen layer
  - Estimate multivariate mean and covariance of activations, compute Fréchet distance to those of real data
- Advantages: correlated with visual quality of samples and human judgment, can detect mode dropping (unlike IS)
- Disadvantage: cannot detect overfitting (like IS)

M. Heusel, H. Ramsauer, T. Unterthiner, B. Nessler, S. Hochreiter, GANs trained by a two time-scale update rule converge to a local Nash equilibrium, NIPS 2017

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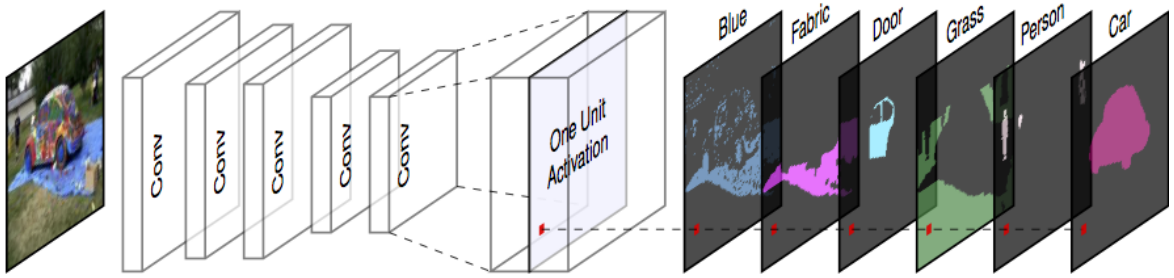
- Visualizing and controlling GANs

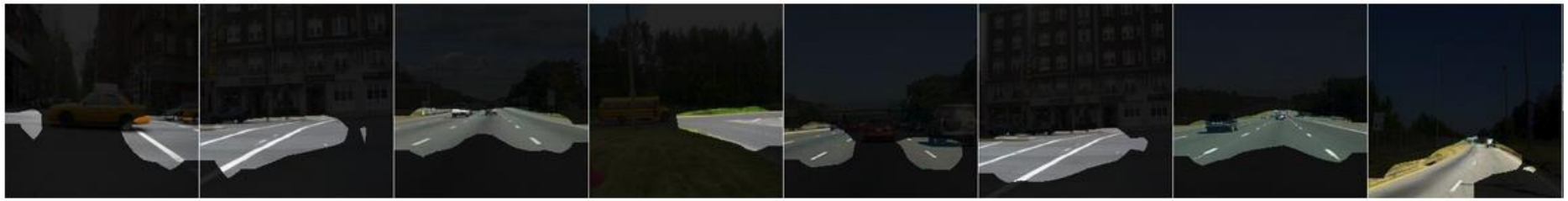
GAN Dissection

- Recall: network dissection



conv5 unit 79 car (object) IoU=0.13

conv5 unit 107 road (object) IoU=0.15



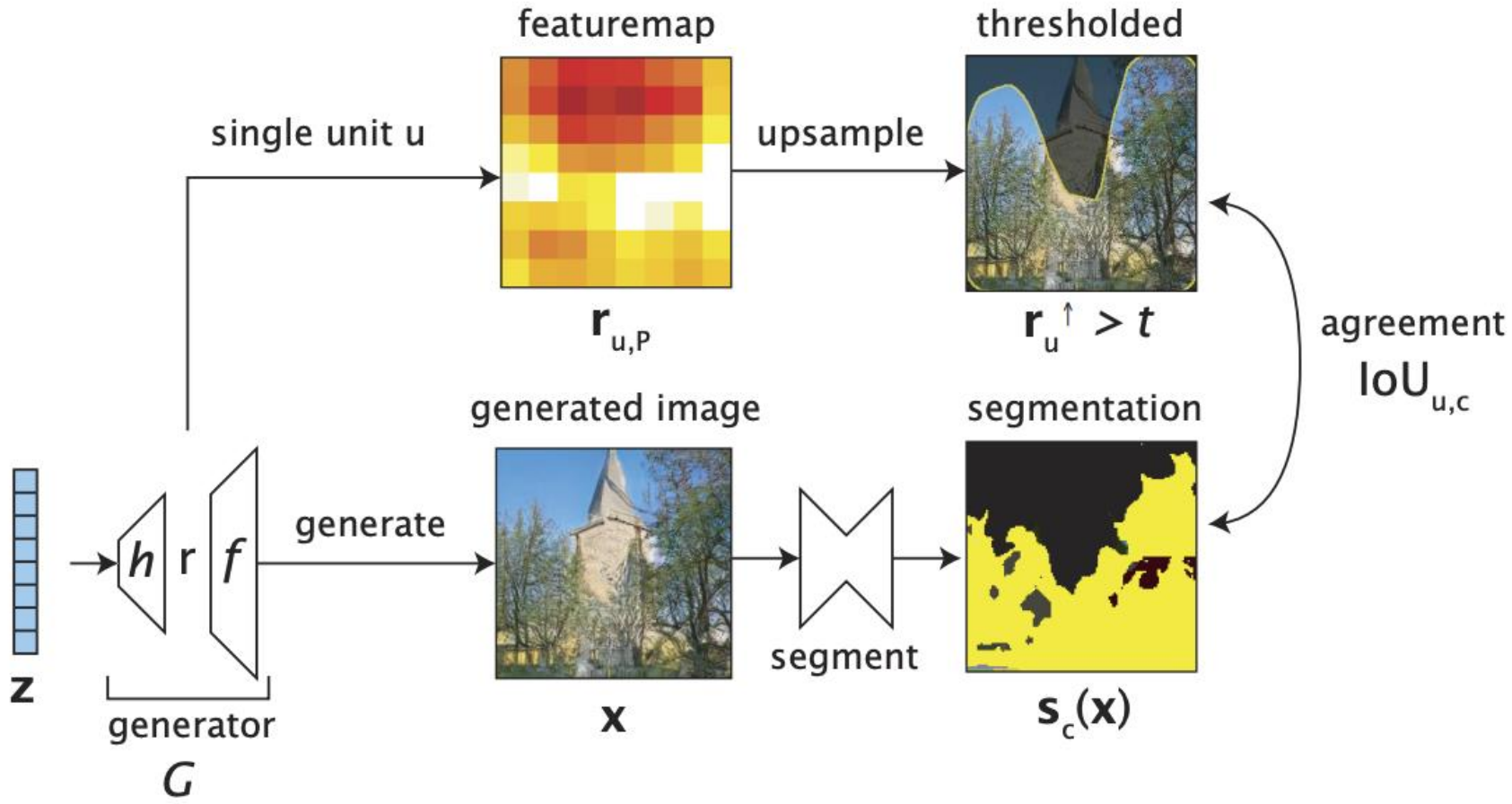
D. Bau, B. Zhou, A. Khosla, A. Oliva, A. Torralba, Network Dissection: Quantifying Interpretability of Deep Visual Representations, CVPR 2017

GAN Dissection

D. Bau et al. GAN Dissection: Visualizing and understanding generative adversarial networks. ICLR 2019

GAN Dissection

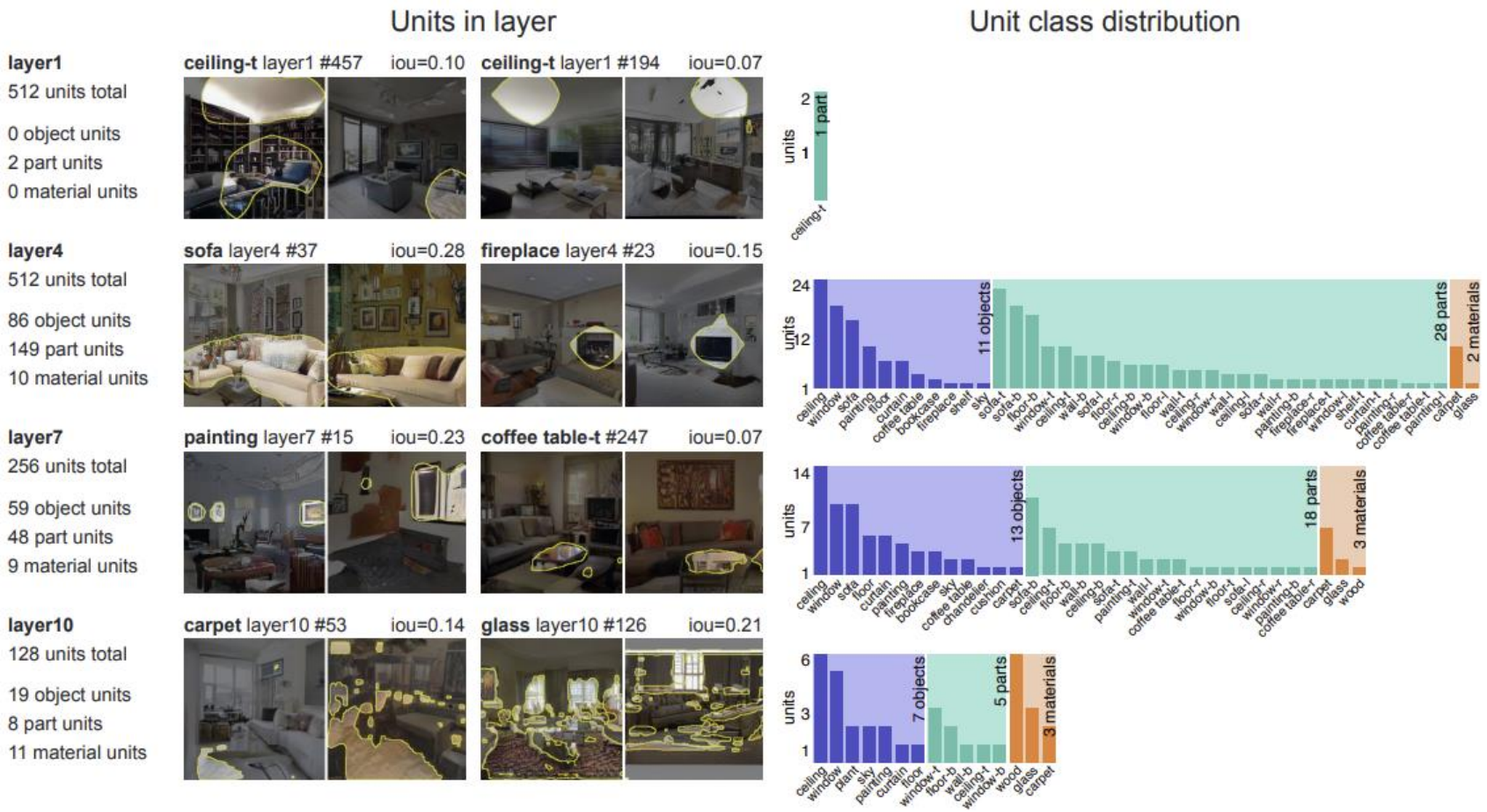
- Dissection:



D. Bau et al. [GAN Dissection: Visualizing and understanding generative adversarial networks](). ICLR 2019

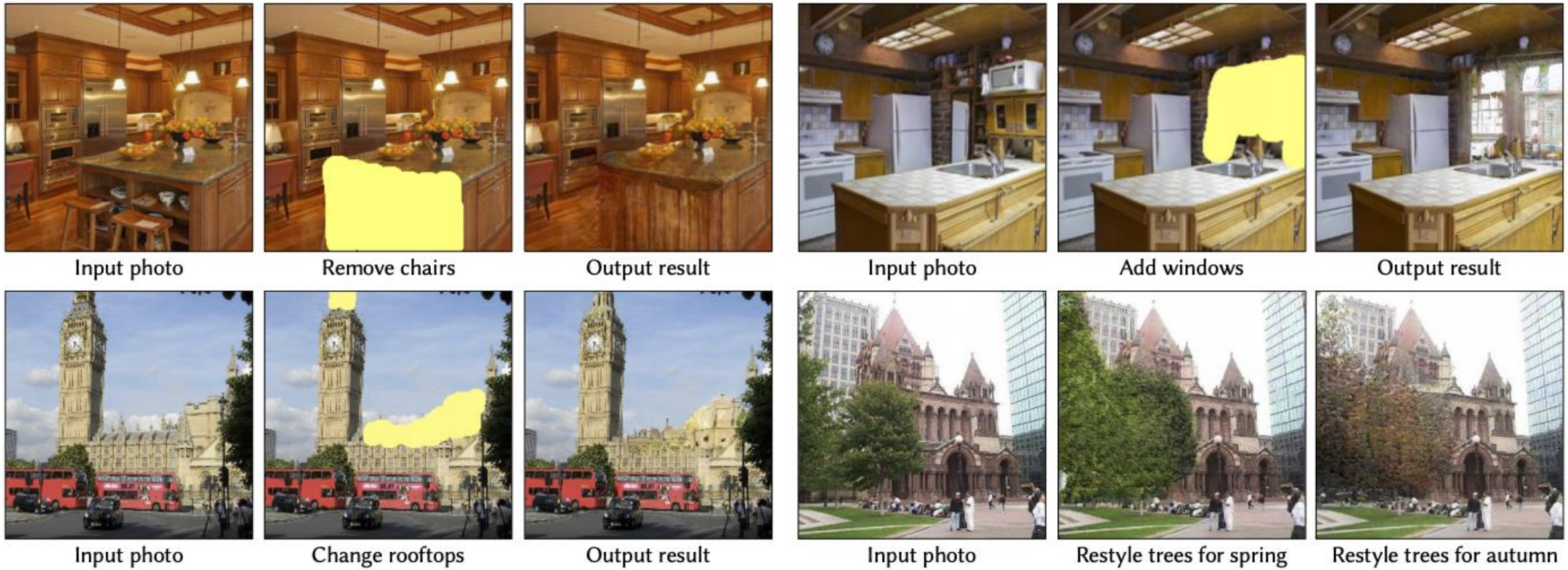
GAN Dissection

- Interpreting units at different levels of a progressive GAN (trained on “bedroom”):



D. Bau et al. [GAN Dissection: Visualizing and understanding generative adversarial networks](). ICLR 2019

GANPaint demo

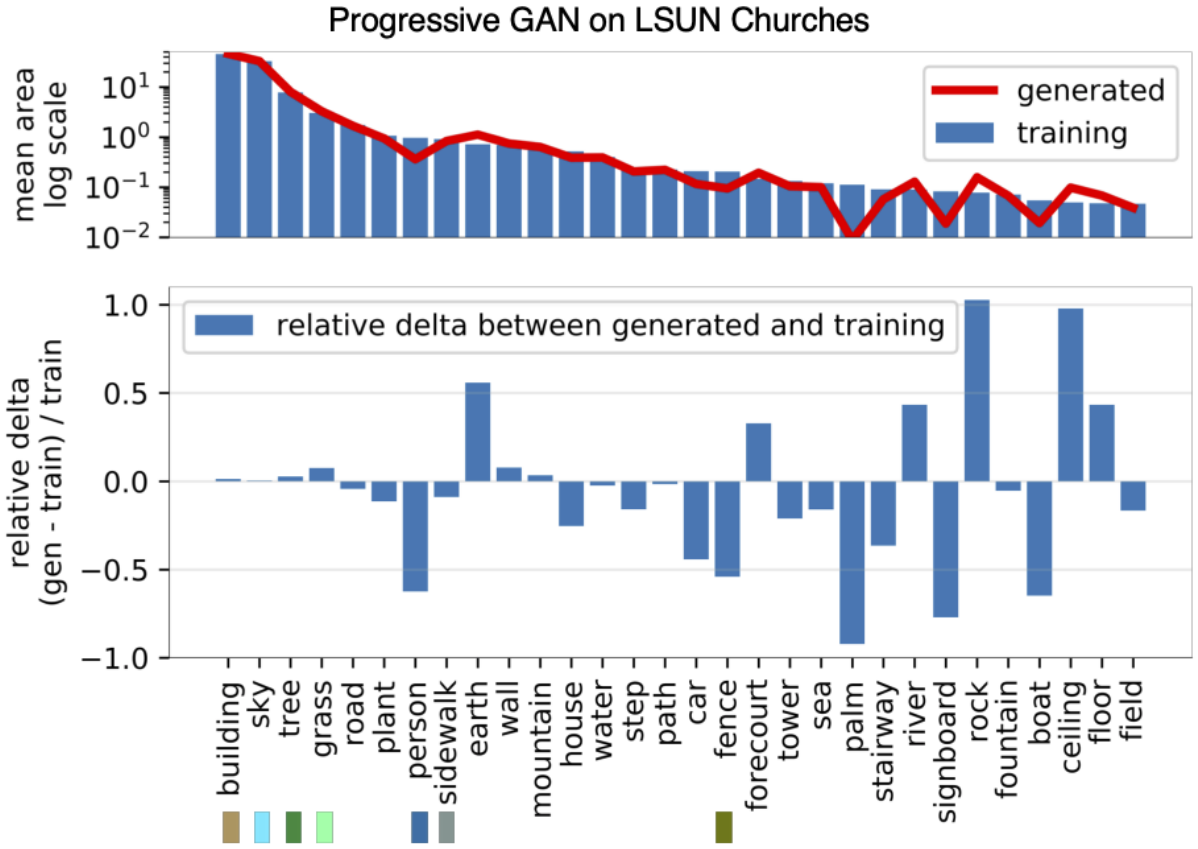


https://ganpaint.io/demo/?project=church

D. Bau et al. Semantic Photo Manipulation with a Generative Image Prior. SIGGRAPH 2019

Seeing what a GAN cannot generate

- Compare semantic segmentations of real and generated images, see which classes get dropped by the GAN

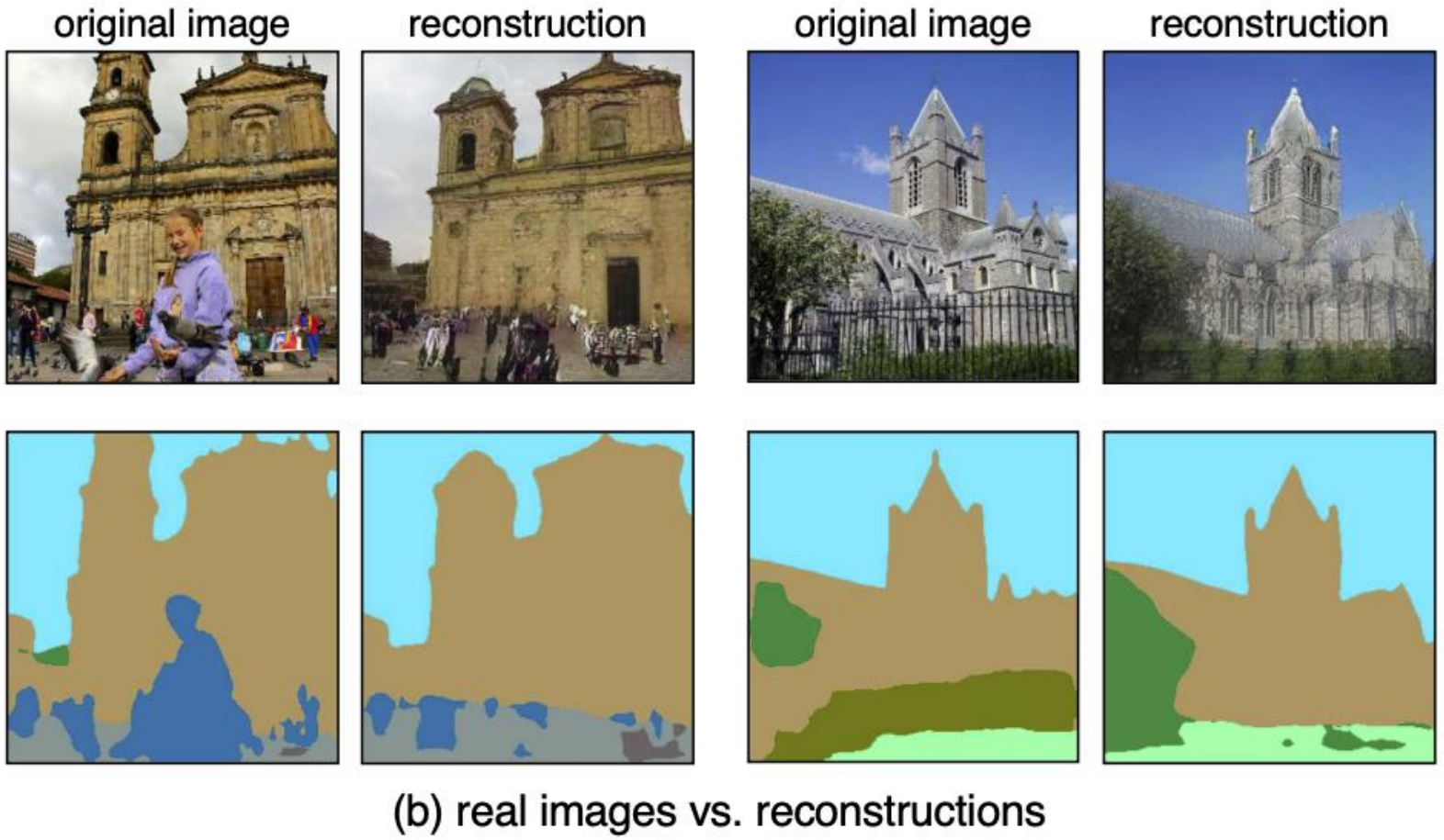


(a) generated vs training object segmentation statistics

D. Bau et al. Seeing what a GAN cannot generate. ICCV 2019

Seeing what a GAN cannot generate

- Given real images, try to find “closest” generated images and see what gets omitted

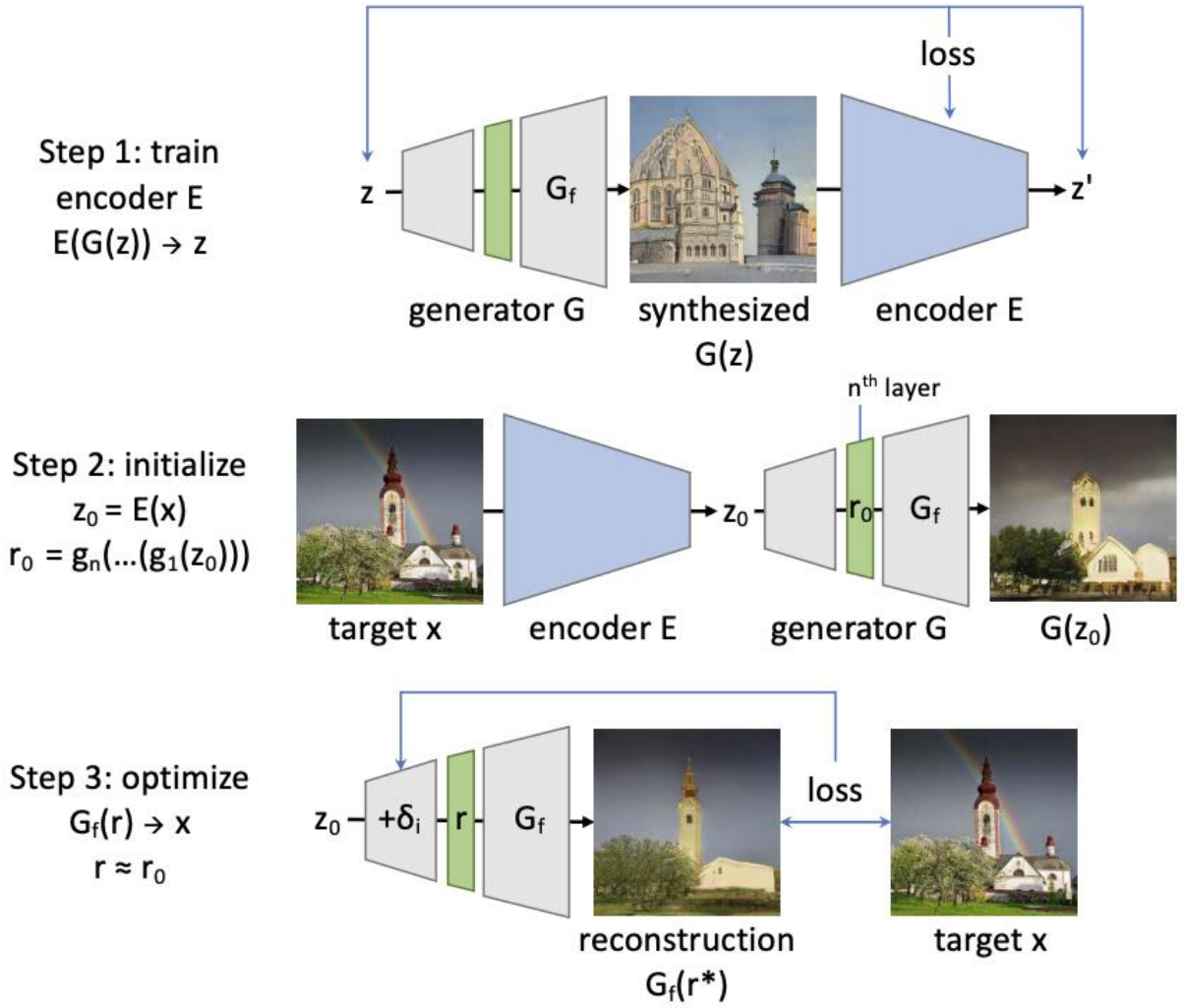


(b) real images vs. reconstructions

D. Bau et al. Seeing what a GAN cannot generate. ICCV 2019

Seeing what a GAN cannot generate

- Layer inversion method:



D. Bau et al. Seeing what a GAN cannot generate. ICCV 2019

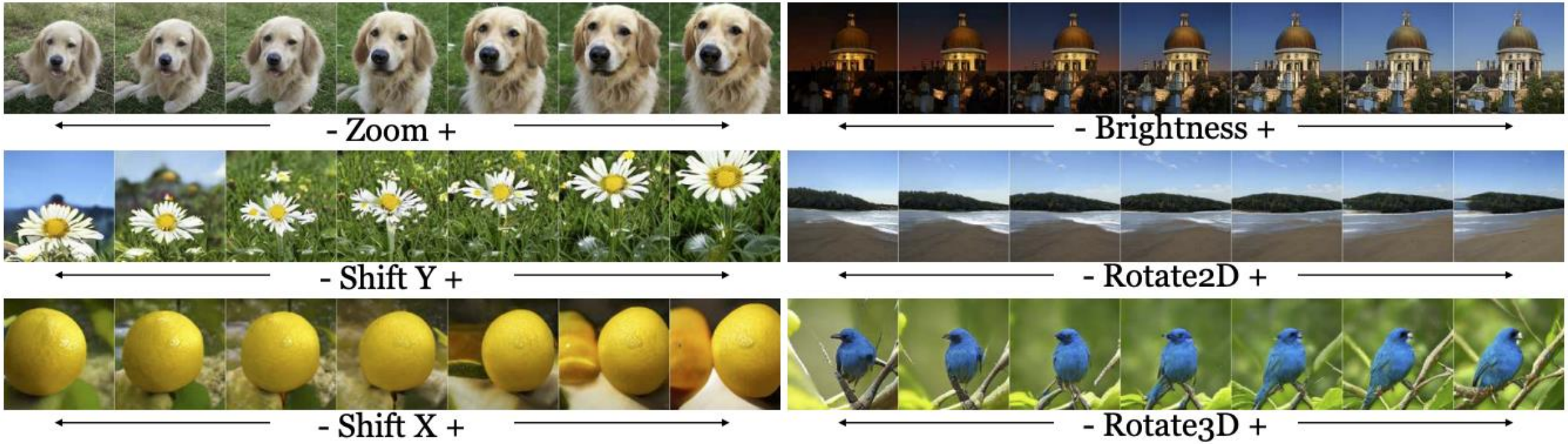
Seeing what a GAN cannot generate

- Reconstruction results for “bedroom” GAN

D. Bau et al. Seeing what a GAN cannot generate. ICCV 2019

Traversing the GAN latent space

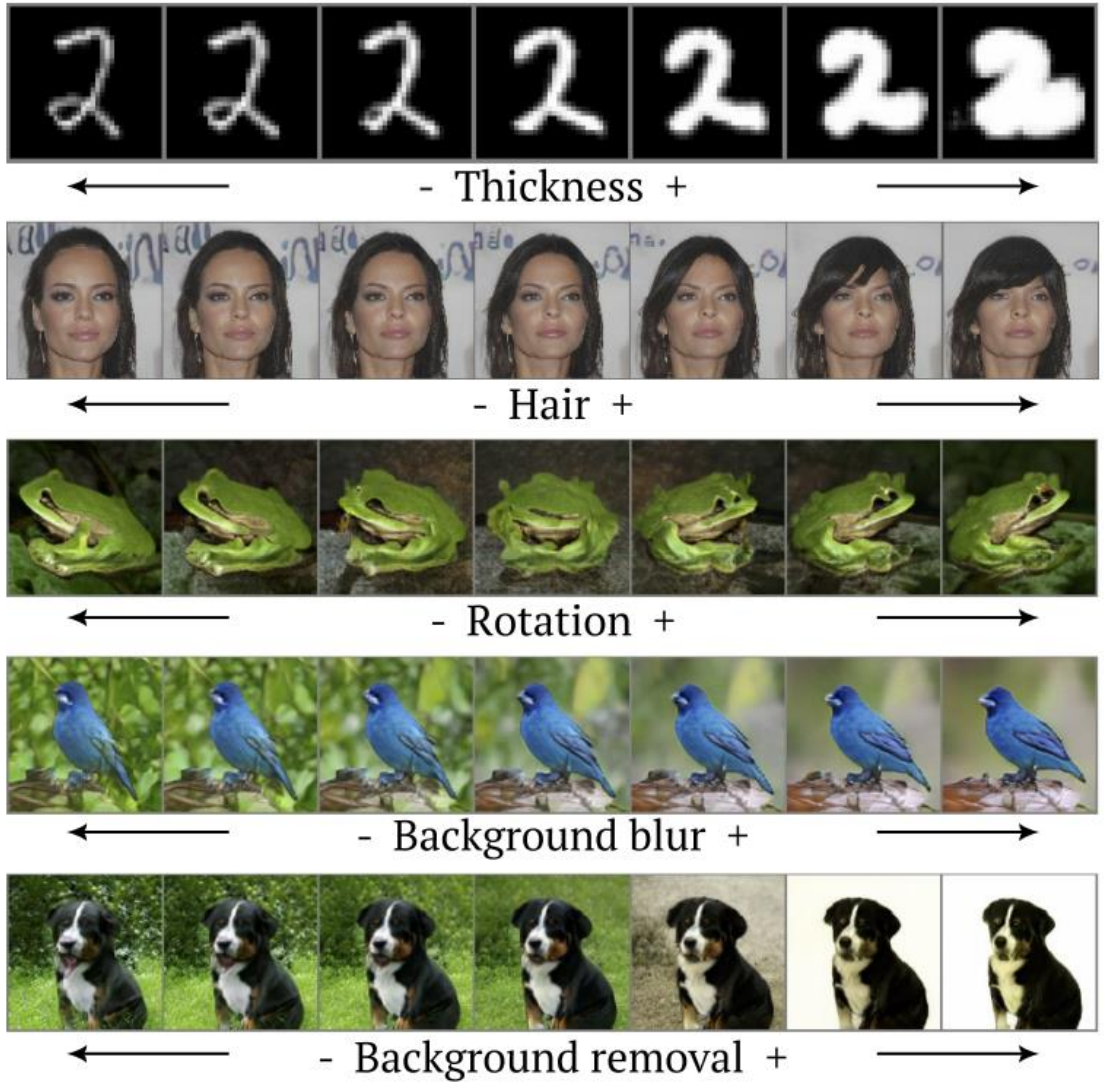
- Try to find simple “walks” in the latent space of GANs to achieve various meaningful transformations to explore structure of that space and test GANs’ ability to interpolate between training samples



A. Jahanian, L. Chai, and P. Isola. On the "steerability" of generative adversarial networks. ICLR 2020

Traversing the GAN latent space

- Goal: learn a set of directions inducing “disentangled” image transformations that are easy to distinguish from each other



A.Voynov and A. Babenko. Unsupervised Discovery of Interpretable Directions in the GAN Latent Space. ICML 2020

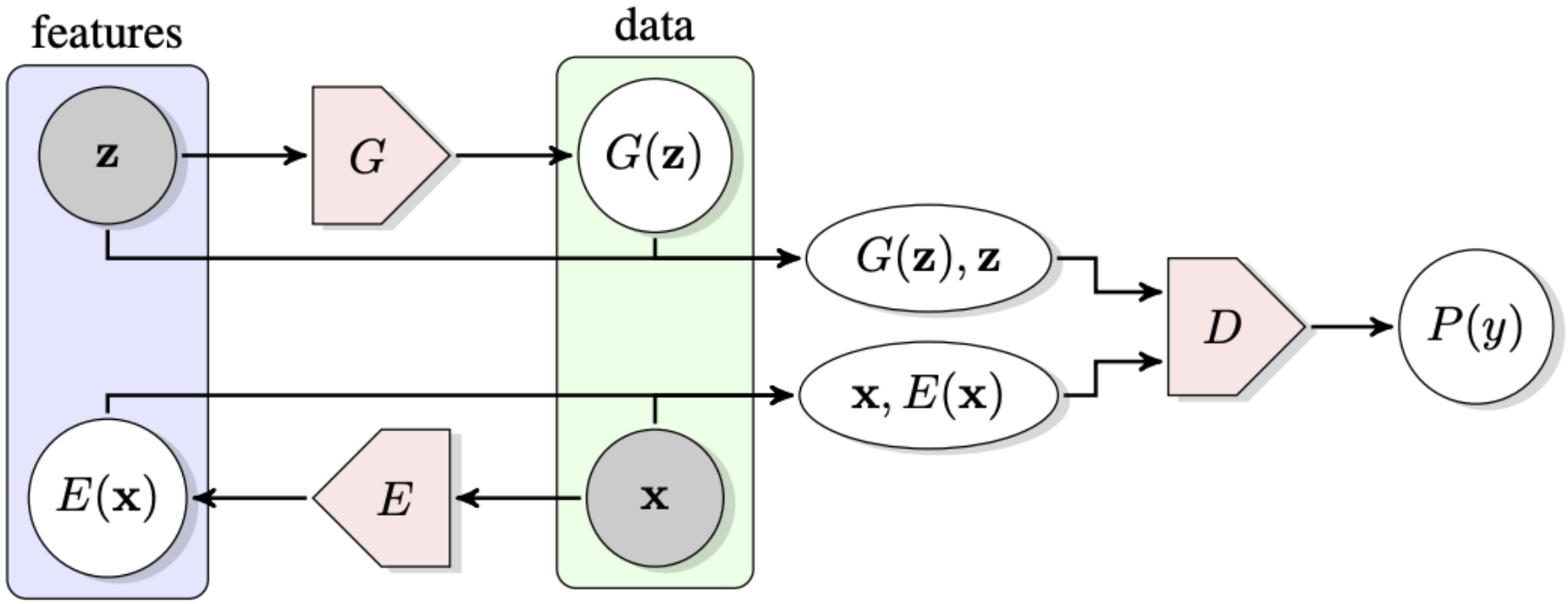
GAN editing

- Supervised training to find latent space directions corresponding to pose, smile, age, gender, eyeglasses

Y. Shen, J. Gu, X. Tang, B. Zhou. Interpreting the Latent Space of GANs for Semantic Face Editing. CVPR 2020

GANs for representation learning

- Bidirectional GAN (BiGAN): simultaneously train generator and encoder (mapping from images to z vectors or approximate inverse of the generator), show that the encoder creates a latent representation useful for other tasks



J. Donahue, P. Krähenbühl, T. Darrell, Adversarial Feature Learning, ICLR 2017

GANs for representation learning: BigBiGAN

- Train BiGAN with BigGAN architecture on ImageNet
- Show that bidirectional framework improves image generation
- Encoder representation gives results comparable to state-of-the-art self-supervised models on ImageNet classification

J. Donahue, K. Simonyan, Large Scale Adversarial Representation Learning, NeurIPS 2019

GANs for representation learning: BigBiGAN

Real images x

Reconstructions $G(E(x))$

J. Donahue, K. Simonyan, Large Scale Adversarial Representation Learning, NeurIPS 2019

Acknowledgement

Thanks to the following courses and corresponding researchers for making their teaching/research material online

- Deep Learning, Stanford University
- Introduction to Deep Learning, University of Illinois at Urbana-Champaign
- Introduction to Deep Learning, Carnegie Mellon University
- Convolutional Neural Networks for Visual Recognition, Stanford University
- Natural Language Processing with Deep Learning, Stanford University
- And Many More .....