TTIC 31230, Fundamentals of Deep Learning

David McAllester, Winter 2020

Generative Adversarial Networks (GANs)

Representing a Distribution with a Generator

z $\qquad\qquad\qquad\qquad\qquad\qquad$ $y_\Phi(z)$

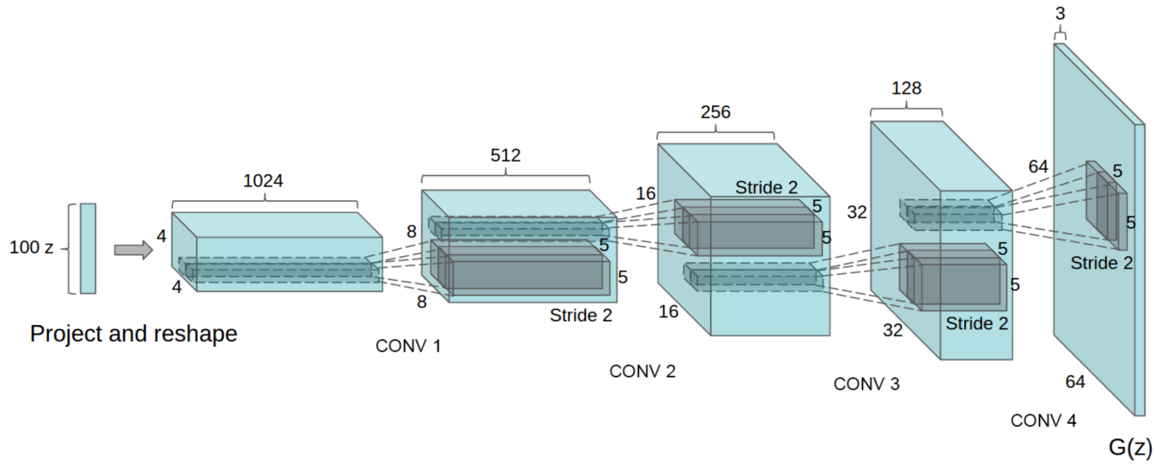


Figure 1: DCGAN generator used for LSUN scene modeling. A 100 dimensional uniform distribution Z is projected to a small spatial extent convolutional representation with many feature maps.

The random input z defines a probability density on images $y_\Phi(z)$. We will write this as $p_\Phi(y)$ for the image y.

Representing a Distribution with a Generator

z $\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad$ $y_\Phi(z)$

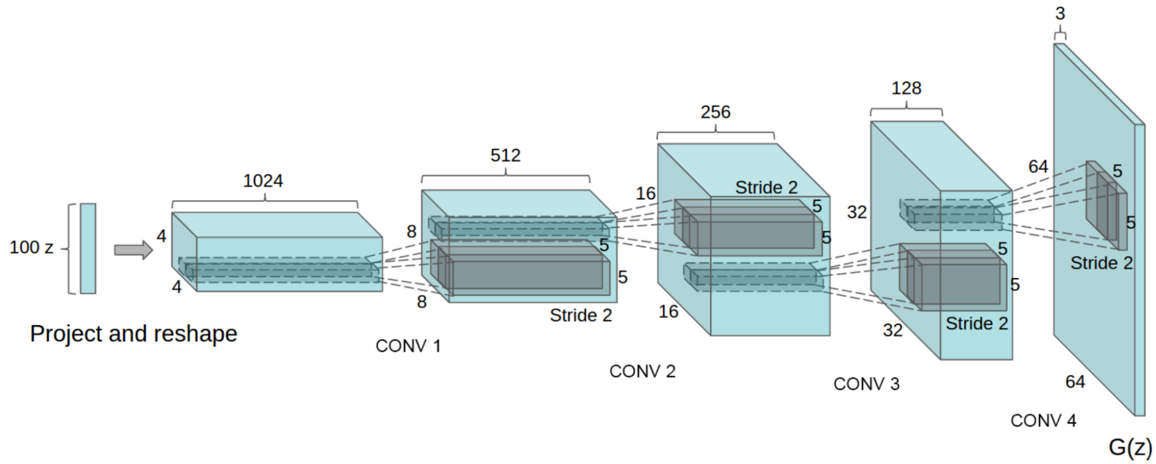


Figure 1: DCGAN generator used for LSUN scene modeling. A 100 dimensional uniform distribution Z is projected to a small spatial extent convolutional representation with many feature maps.

We want $p_\Phi(y)$ to model a natural image distribution such as the distribution over human faces.

Increasing Spatial Dimension (ConvTranspose in PyTorch)

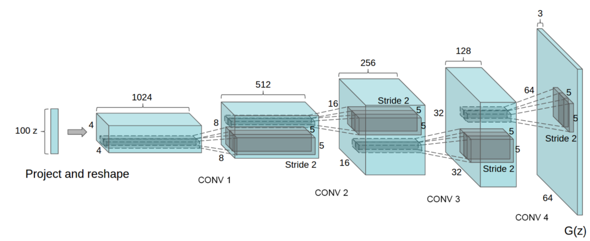


Figure 1: DCGAN generator used for LSUN scene modeling. A 100 dimensional uniform distribution Z is projected to a small spatial extent convolutional representation with many feature maps.

To increase spatial dimension we use 4 times the desired number of output features.

$$L'_{\ell+1}[x, y, i] = \sigma\left(W[\Delta X, \Delta Y, J, i]\ L'_{\ell}[x + \Delta X, y + \Delta Y, J]\right)$$

We then reshape $L'_{\ell+1}[X, Y, I]$ to $L'_{\ell+1}[2X, 2Y, I/4]$.

Generative Adversarial Networks (GANs)

Let y range over images. We have a generator p_Φ. For $i \in \{-1, 1\}$ we define a probability distribution over pairs $\langle i, y\rangle$ by

$$\begin{aligned} \tilde{p}_\Phi(i = 1) &= 1/2 \\ \tilde{p}_\Phi(y|i = 1) &= \mathrm{pop}(y) \\ \tilde{p}_\Phi(y|i = -1) &= p_\Phi(y) \end{aligned}$$

We also have a discriminator $P_\Psi(i|y)$ that tries to determine the source i given the image y.

The generator tries to fool the discriminator.

$$\Phi^* = \operatorname*{argmax}_\Phi \; \min_\Psi \; E_{\langle i, y\rangle \sim \tilde{p}_\Phi} \; - \ln P_\Psi(i|y)$$

GANs

The generator tries to fool the discriminator.

$$\Phi^* = \operatorname*{argmax}_{\Phi} \; \min_{\Psi} \; E_{\langle i, y \rangle \sim \tilde{p}_\Phi} \; -\ln P_\Psi(i|y)$$

Assuming universality of both the generator p_Φ and the discriminator P_Ψ we have $p_{\Phi^*} = \mathrm{pop}$.

GANS

To take gradients with respect to Φ we write

$$E_{\langle i,y\rangle\sim\tilde{p}_\Phi}\;-\ln P_\Psi(i|y)$$

as

$$\frac{1}{2}E_{y\sim\mathrm{pop}}\;-\ln P_\Psi(1|y)\quad+\quad\frac{1}{2}E_z\;-\ln P_\Psi(-1|y_\Phi(z))$$

Generative Adversarial Nets

Goodfellow et al., June 2014

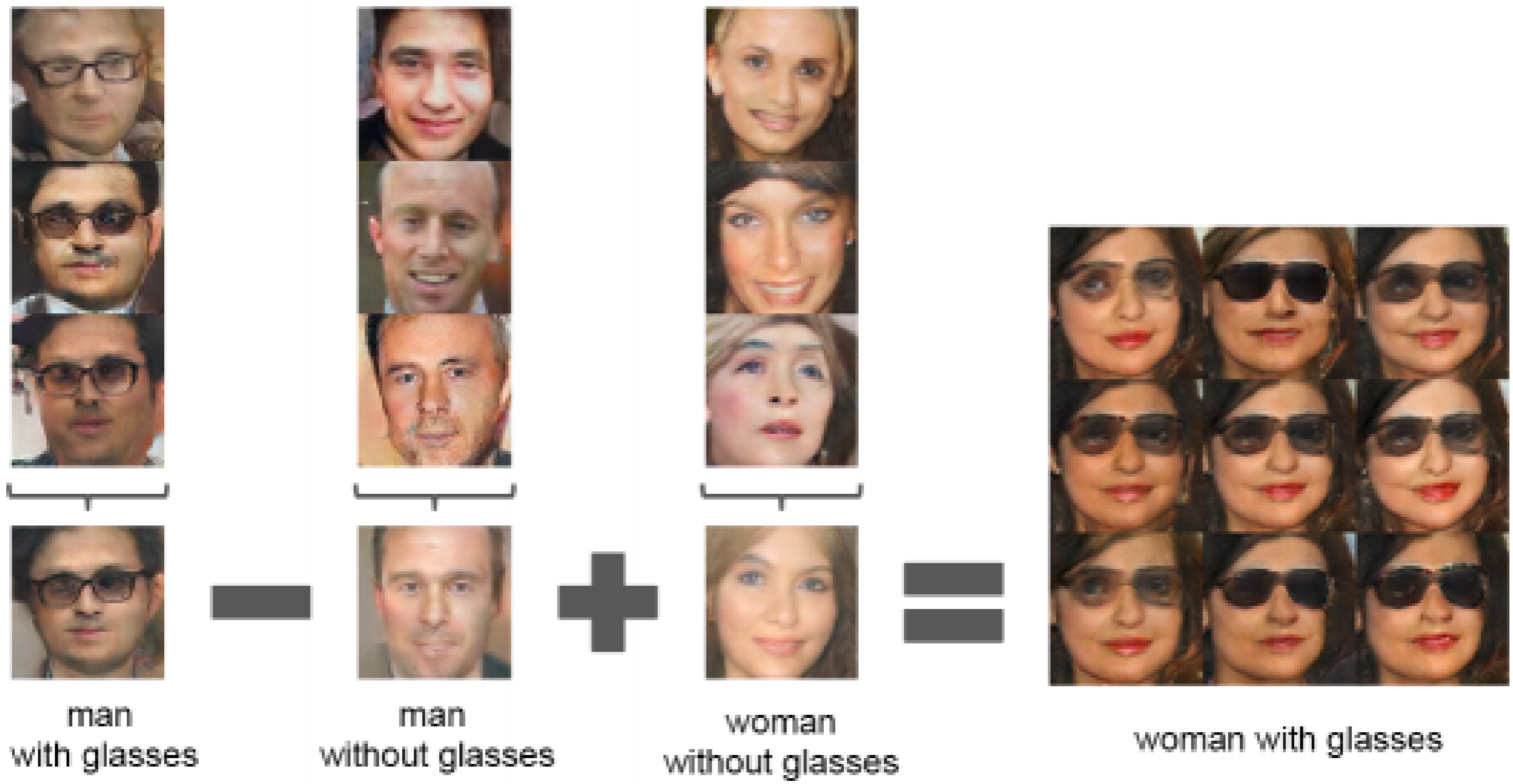
The rightmost column (yellow boarders) gives the nearest neighbor in the training data to the adjacent column.

Unsupervised Representation Learning ... (DC GANS)

Radford et al., Nov. 2015

Unsupervised Representation Learning ... (DC GANS)

Radford et al., Nov. 2015



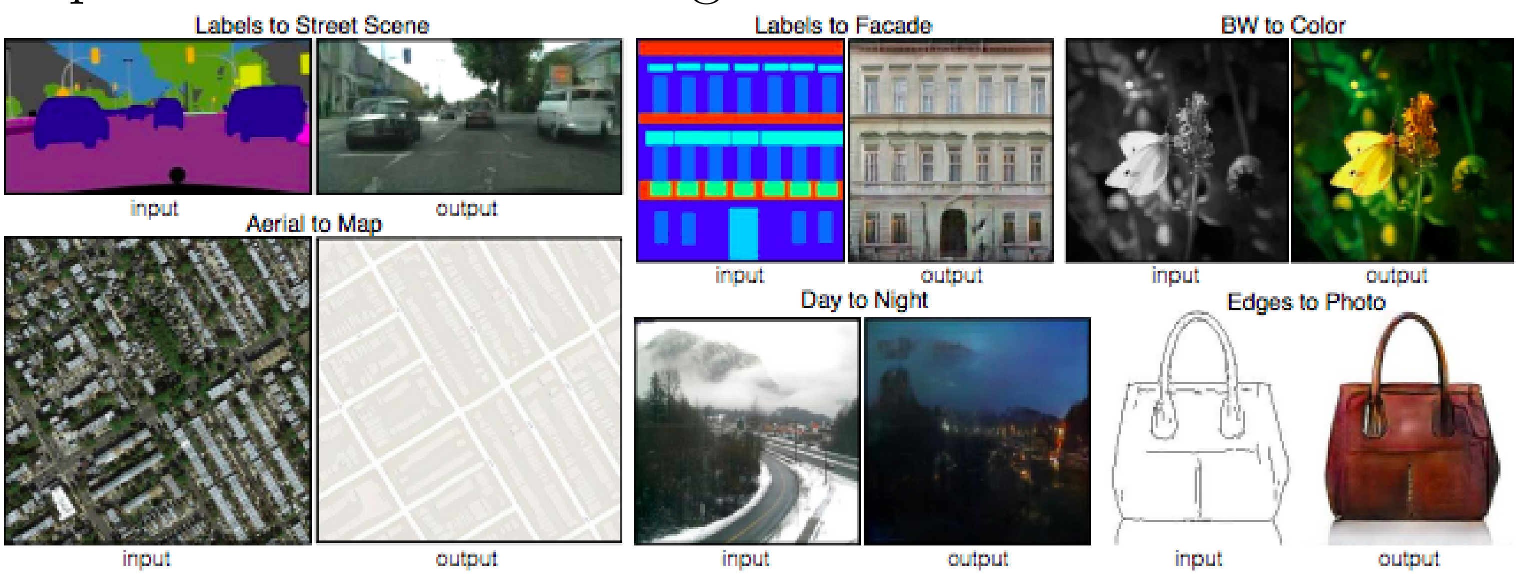
Interpolated Faces

[Ayan Chakrabarti, January 2017]

Image-to-Image Translation (Pix2Pix)

Isola et al., Nov. 2016

We assume a corpus of "image translation pairs" such as images paired with semantic segmentations.



Conditional GANS

In the conditional case we have a population distribution over pairs $\langle x, y \rangle$. For conditional GANs we have a generator $p_\Phi(y|x)$ and a discriminator $P_\Psi(i|x,y)$ For $i \in \{-1, 1\}$ we define a probability distribution over triples $\langle x, y, i \rangle$ by

$$
\begin{aligned}
\tilde{p}_\Phi(i = 1) &= 1/2 \\
\tilde{p}_\Phi(y|i = 1) &= \mathrm{pop}(y|x) \\
\tilde{p}_\Phi(y|i = -1) &= p_\Phi(y|x)
\end{aligned}
$$

$$
\Phi^* = \operatorname*{argmax}_\Phi \; \min_\Psi \; E_{\langle x, y, i \rangle \sim \tilde{p}_\Phi} \; - \ln P_\Psi(i|x, y)
$$

Adversarial Discrimination as an Additional Loss

$$\Phi^* = \operatorname*{argmin}_{\Phi} \; E_{(x,y)\sim\text{pop}} \; ||y - y_\Phi(x)||^2 \; + \; \lambda \, \mathcal{L}_{\text{Discr}}(\Phi)$$

$$\mathcal{L}_{\text{Discr}}(\Phi) = \max_{\Psi} \; E_{x,y,i\sim\tilde{p}_\Phi} \; \ln P_\Psi(i|y,x)$$

Discrimination as an Additional Loss

$$\text{L1}: \quad \Phi^* = \mathrm{argmin}_\Phi \; E_{(x,y)\sim\mathrm{pop}} \; ||y - y_\Phi(x)||_1$$

$$\text{cGAN}: \quad \Phi^* = \mathrm{argmin}_\Phi \; \mathcal{L}_{\mathrm{Discr}}(\Phi)$$

$$\text{L1} + \text{cGAN}: \quad \Phi^* = \mathrm{argmin}_\Phi \; E_{(x,y)\sim\mathrm{pop}} \; ||y - y_\Phi(x)||_1 \; + \; \lambda \, \mathcal{L}_{\mathrm{Discr}}(\Phi)$$

Image-to-Image Translation (Pix2Pix)

Isola et al., Nov. 2016

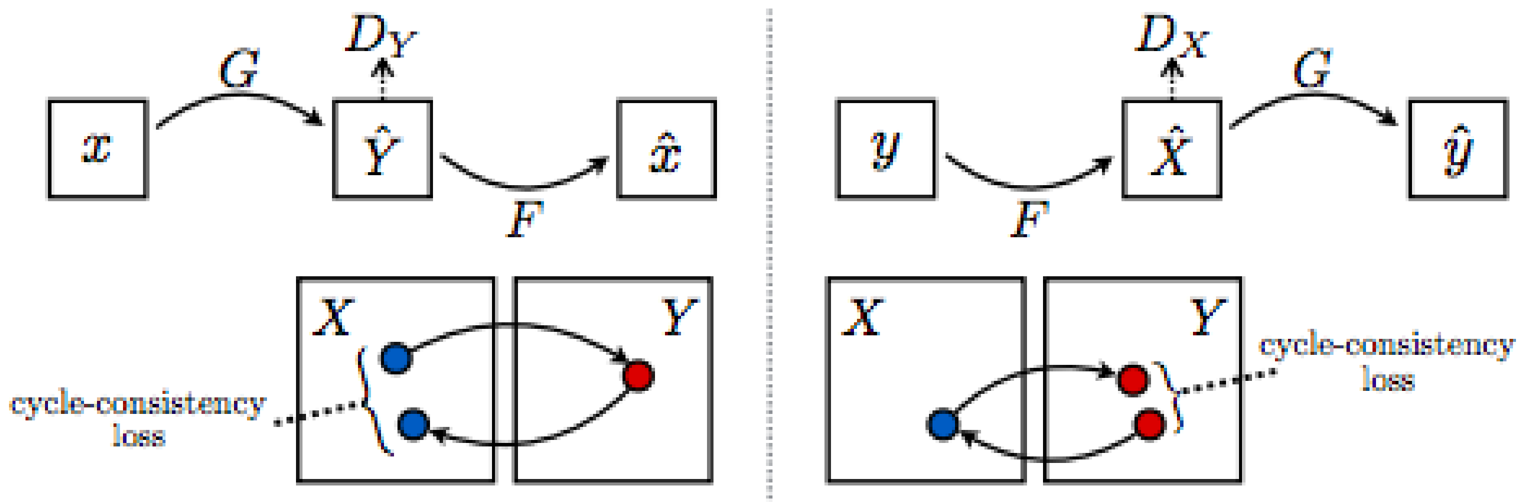
Arial Photo to Map and Back

Unpaired Image-to-Image Translation (Cycle GANs)

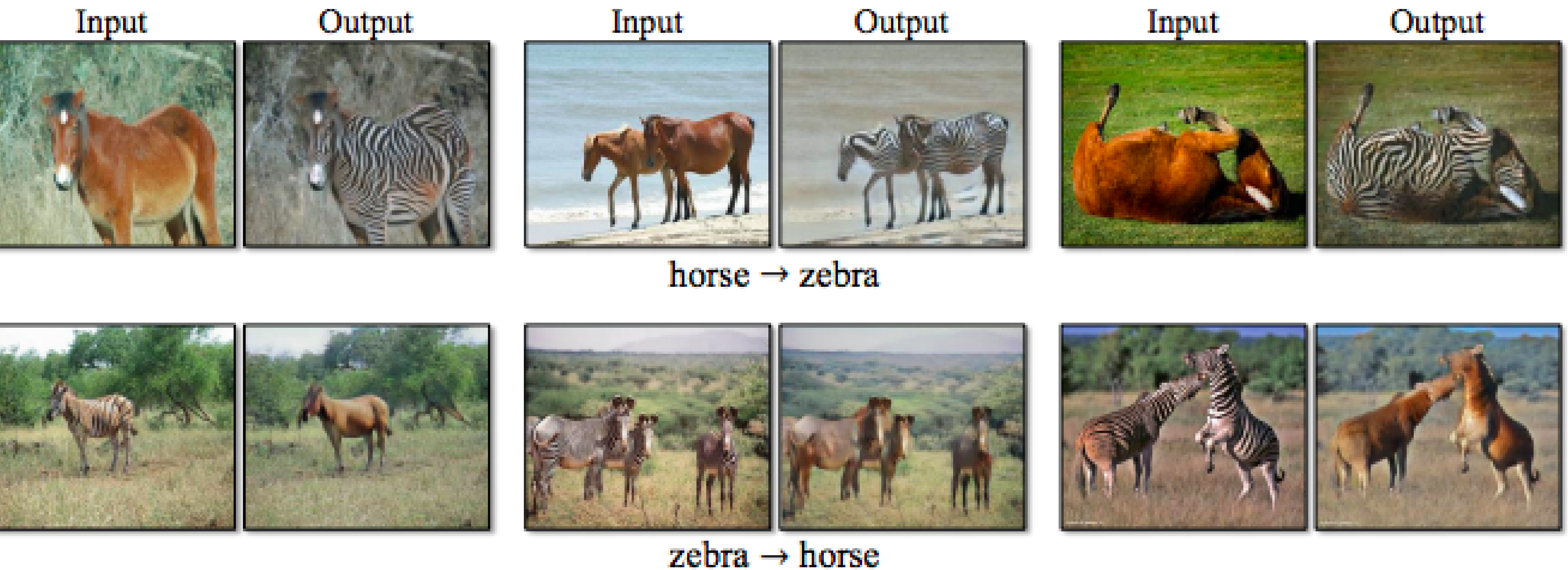
Zhu et al., March 2017

We have two corpora of images, say images of zebras and unrelated images of horses, or photographs and unrelated paintings by Monet.

We want to construct translations between the two classes.



Cycle Gans

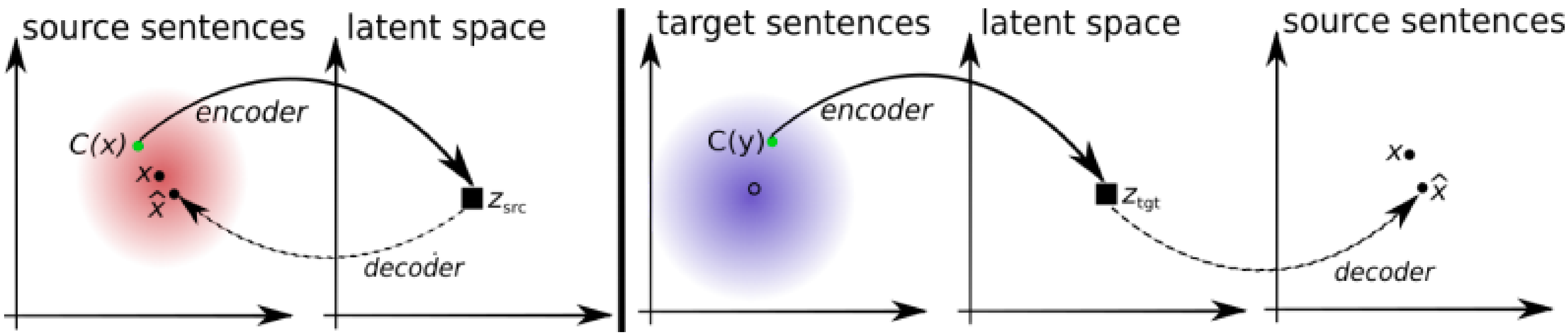

Input
Output
Input
Output
Input
Output
horse → zebra
zebra → horse

Cycle Gans

Horse → Zebra

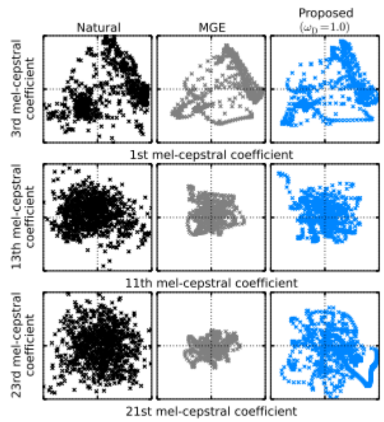
Unsupervised Machine Translation (UMT)

Lample et al, Oct. 2017, also Artetxe et al., Oct. 2017



Feature Alignment by Discrimination

Text to Speech (Saito et al. Sept. 2017)

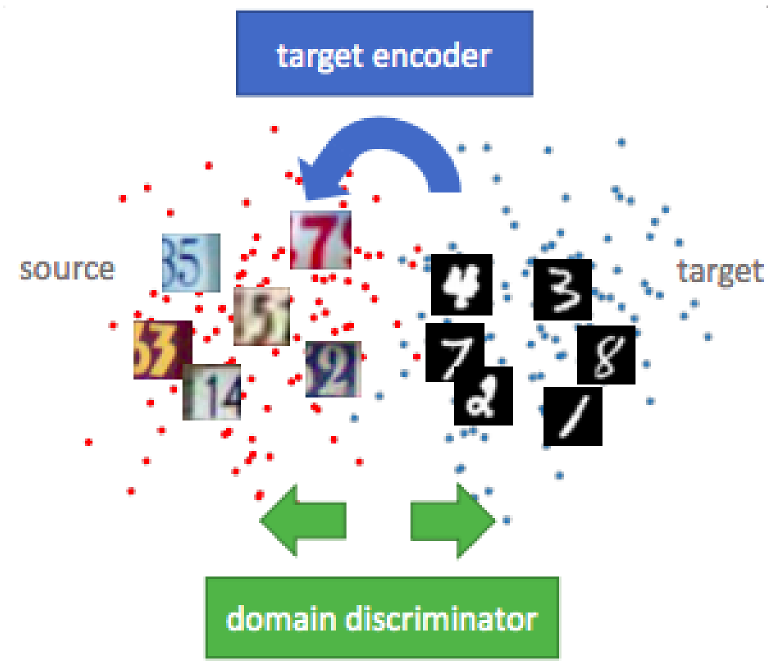


Minimum Generation Error (MGE) uses perceptual distortion — a distance between the feature vector of the generated sound wave and the feature vector of the original.

Perceptual Naturalness can be enforced by a feature discrimination loss.

Adversarial Discriminative Domain Adaptation

Tzeng et al. Feb. 2017



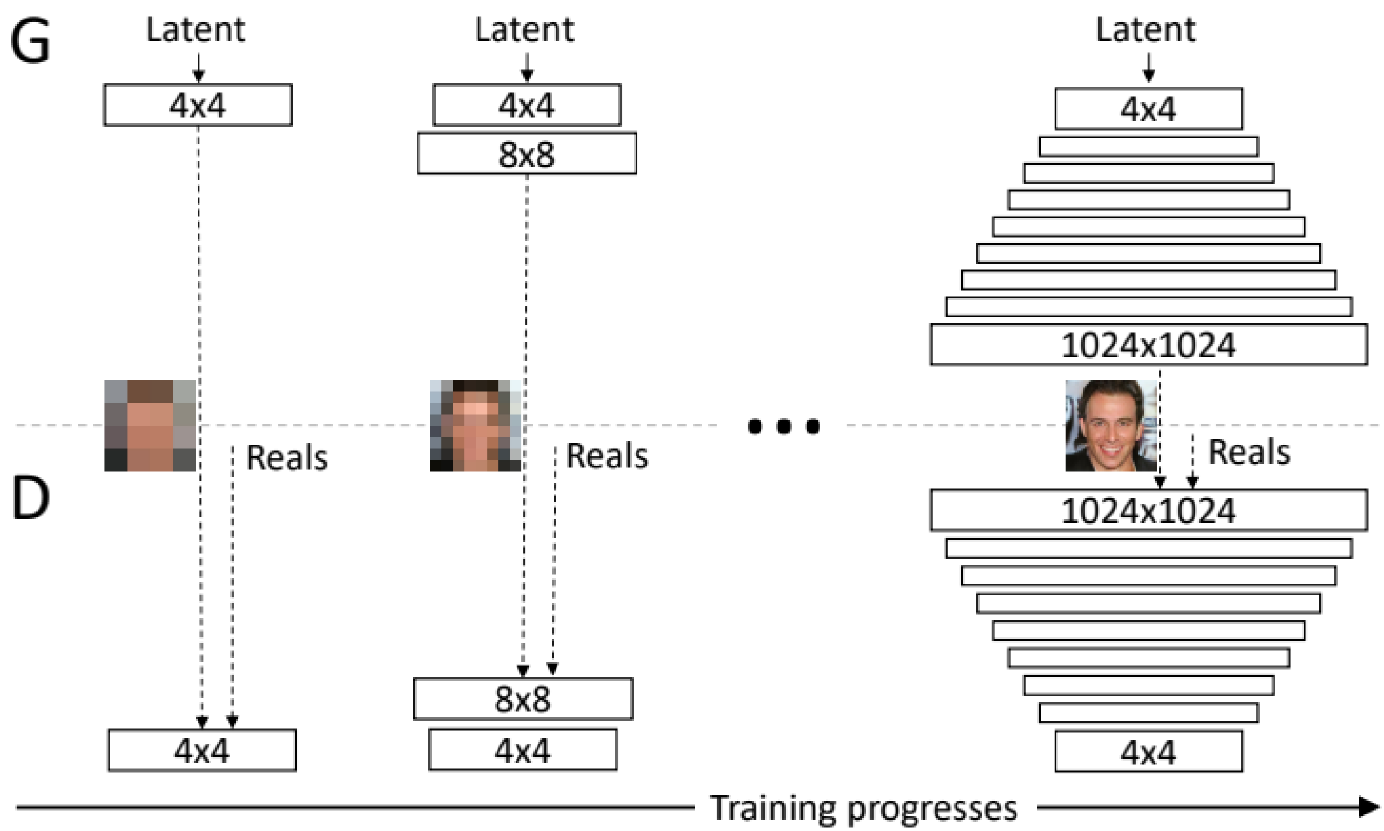
A feature discrimination loss can be used to align source and target features.

Progressive GANs

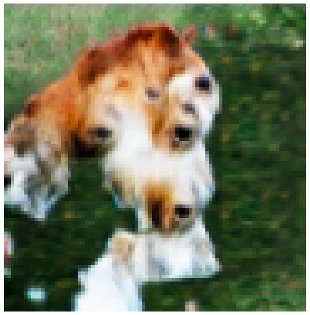
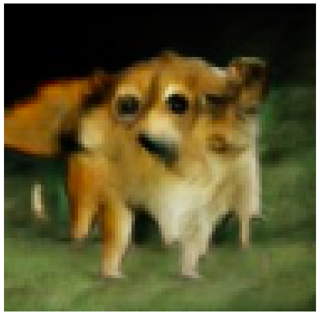
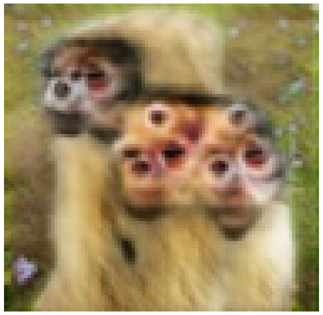
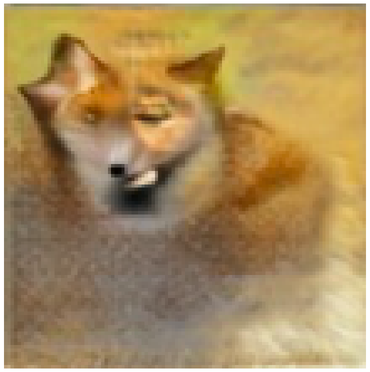
Progressive Growing of GANs, Karras et al., Oct. 2017

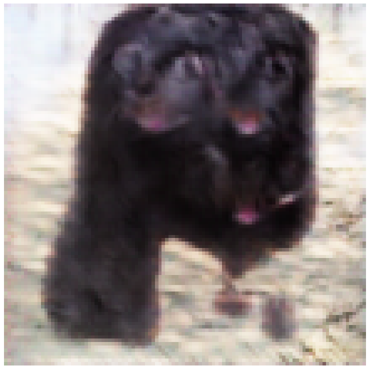
Figure 5: 1024×1024 images generated using the CELEBA-HQ dataset. See Appendix F for a larger set of results, and the accompanying video for latent space interpolations.

Progressive GANs



Early GANs on ImageNet



BigGans

Large Scale GAN Training, Brock et al., Sept. 2018

Figure 1: Class-conditional samples generated by our model.

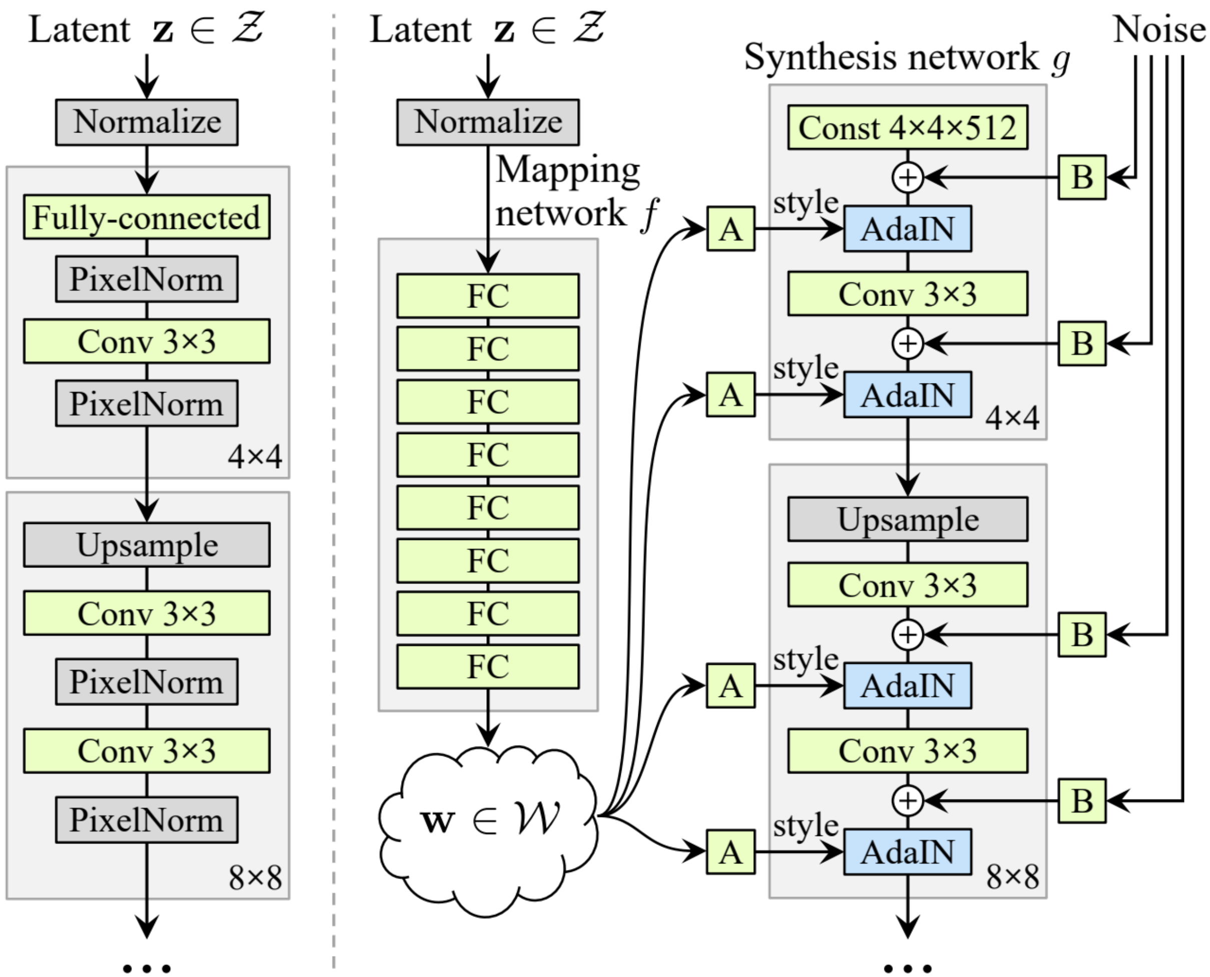
This is a class-conditional GAN — it is conditioned on the imagenet class label.

This generates 512 X 512 images without using progressive training.

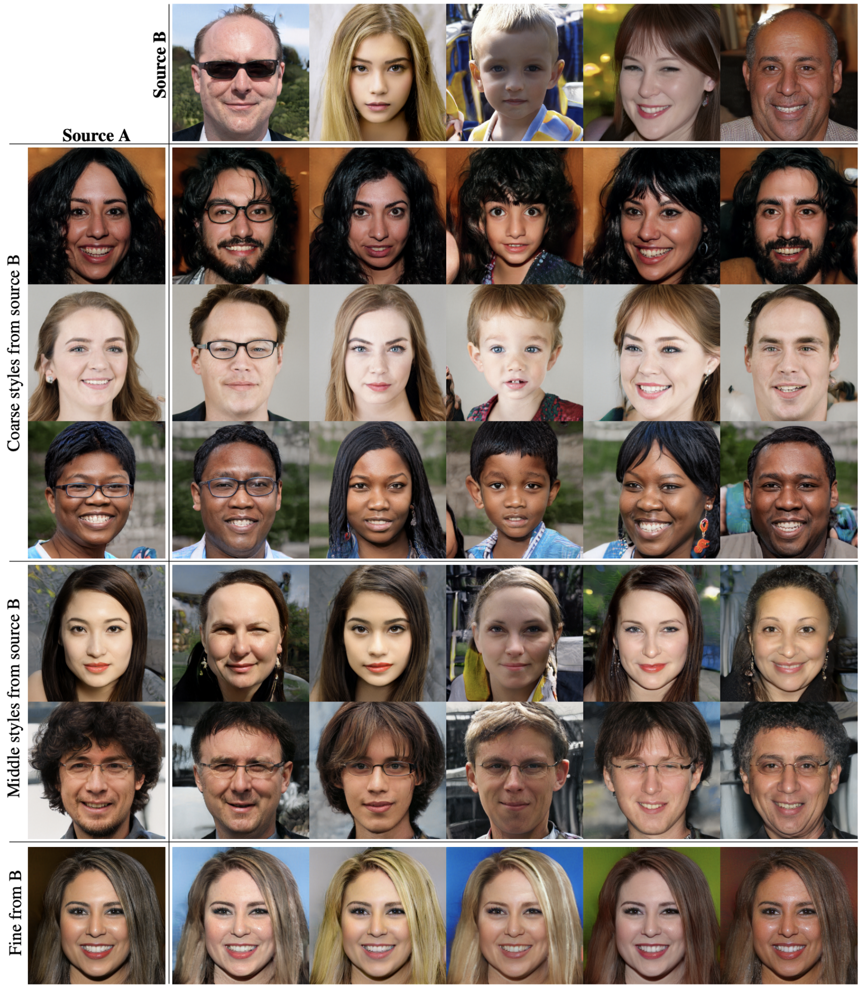
StyleGANs

A Style-Based Generator Architecture for Generative Adversarial Networks, Karras et al., Dec. 2018

StyleGans: Architecture



StyleGans: Style Transfer



StyleGans: Noise Variation

Comments

I predict that in a few years adversarial discrimination will be limited to enforcing perceptual naturalness in the generation of sounds and images.

Cooperative discrimination seems more useful for predictive tasks. We will see that cooperative discrimination has been effective in pretraining.

END