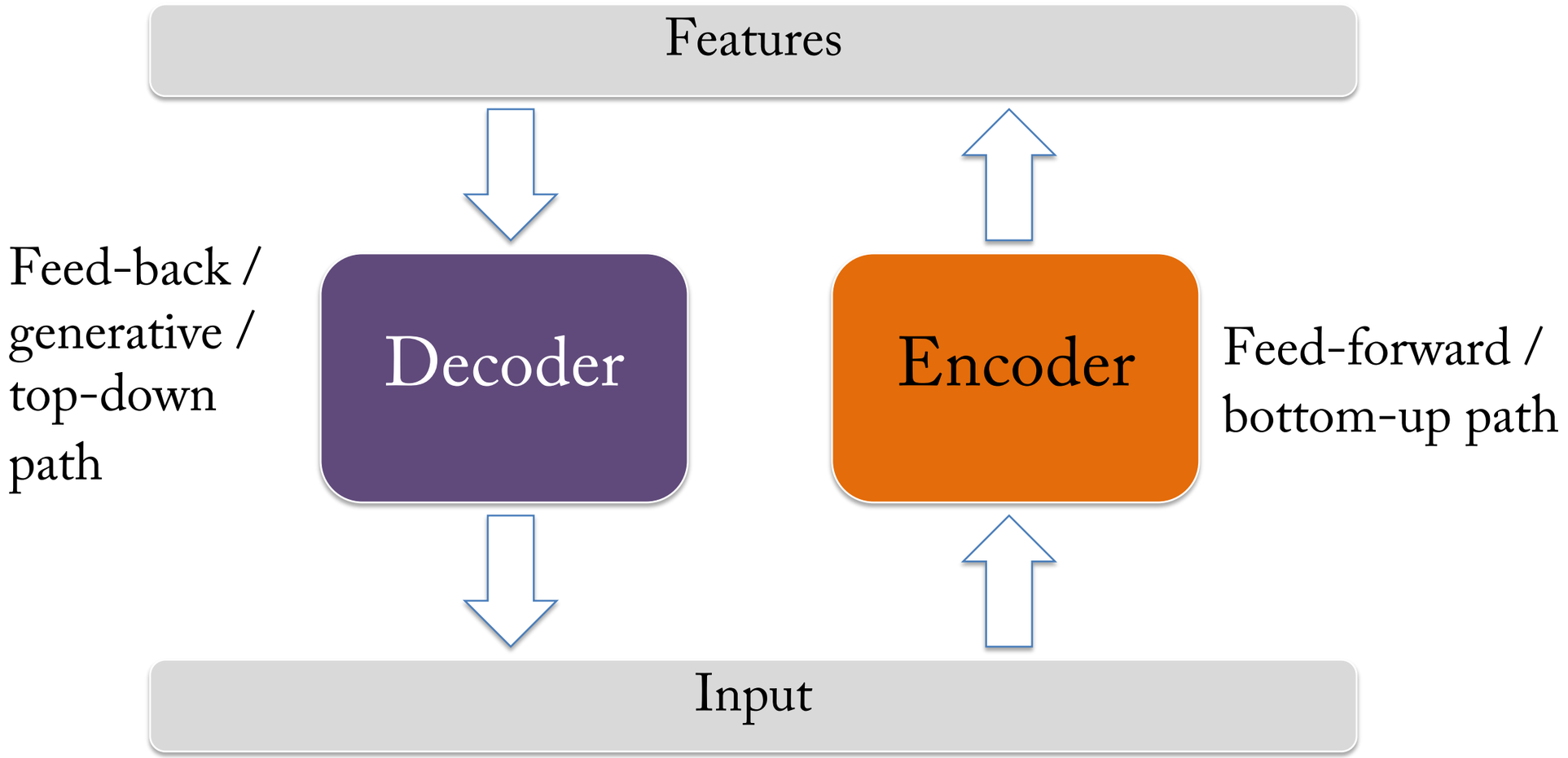
Overview of Unsupervised Learning
&
Generative Adversarial Networks

Lecture 10

Slides from: Emily Denton, Ian Goodfellow, Soumith Chintala

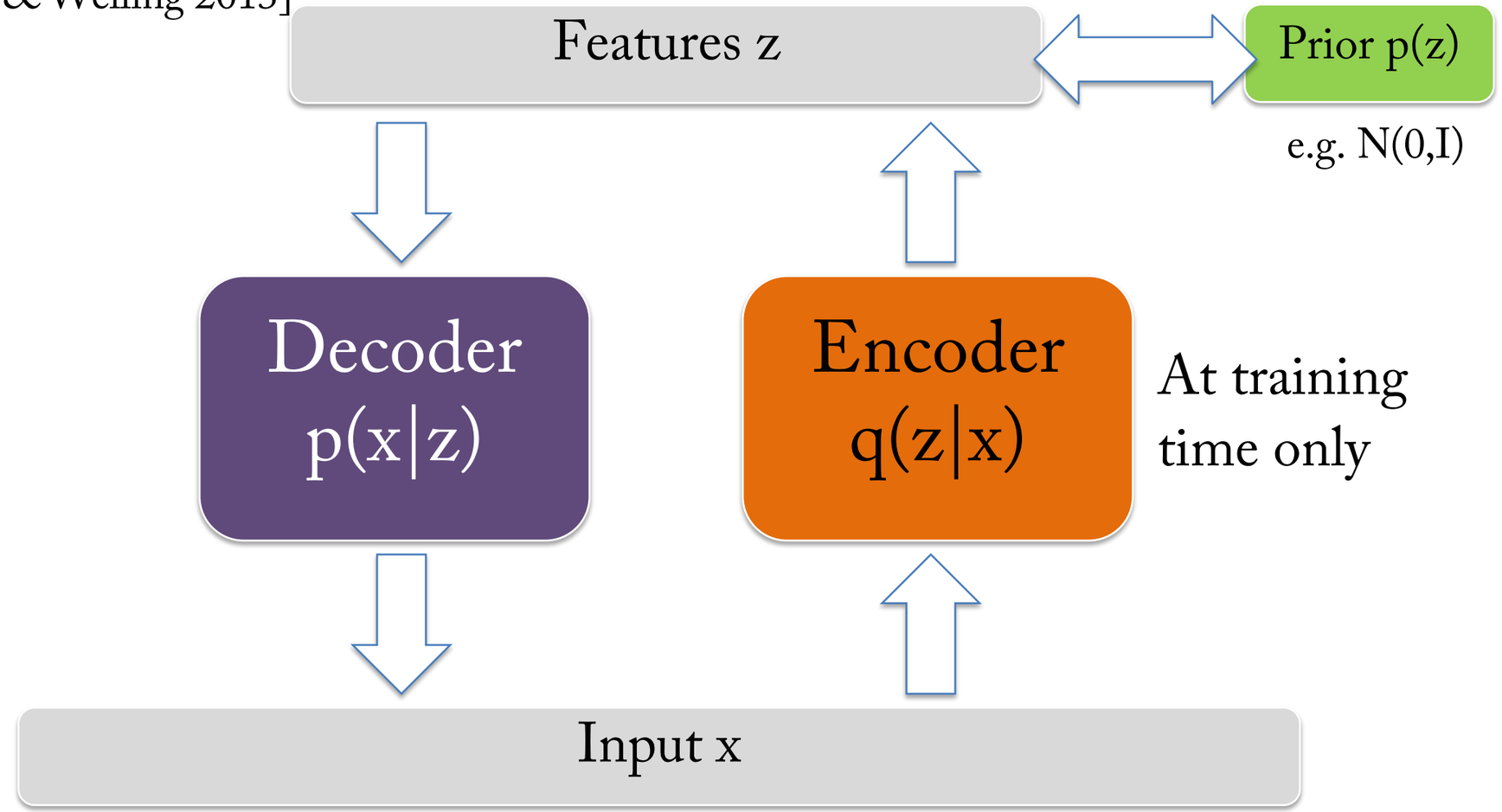
Auto-Encoder



- Encoder/Decoder will be deep network
- Slightly different architectures for decoder (needs to output image)
- Architecture depends on application

Variational Auto-Encoder

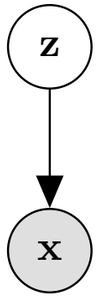
[Kingma & Welling 2013]



- Makes auto-encoder into a true generative model

$$\underbrace{\mathbb{E}_{q(z|x)} \log p(x|z)}_{\text{Reconstruction term}} - \underbrace{D_{KL}(q(z|x)||p(z))}_{\text{Prior term}}$$

Directed graphical models



- We assume data is generated by:

$$z \sim p(z) \qquad x \sim p(x|z)$$

- z is latent/hidden x is observed (image)
- Use θ to denote parameters of the generative model

Parameter estimation

- Given dataset $\{x_1, ..., x_n\}$, maximize likelihood of data under model:

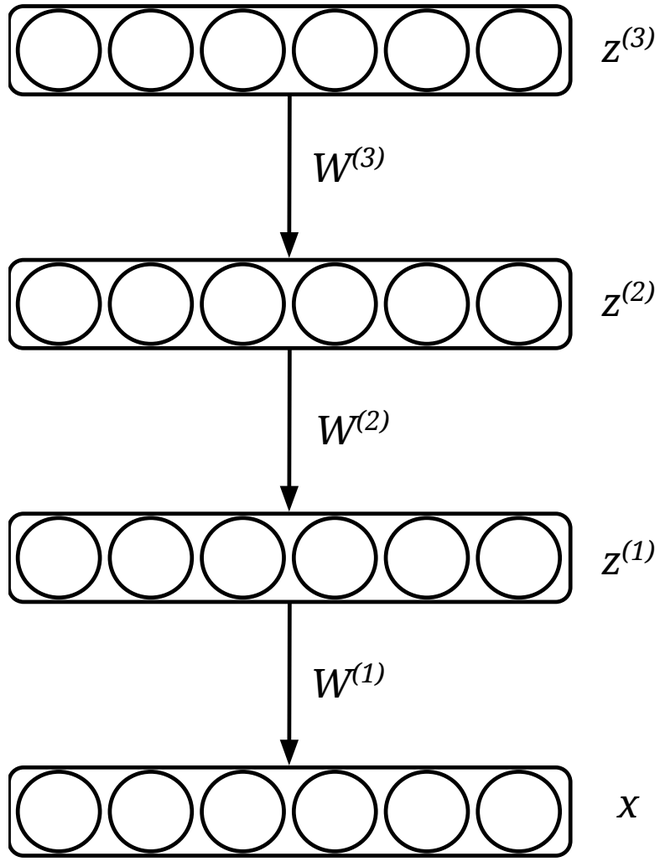
$$\max_\theta \sum_{i=1}^{n} \log p(x_i; \theta) = \max_\theta \sum_{i=1}^{n} \sum_z \log p(x_i, z; \theta)$$

- This quantity often intractable, difficult to optimize directly

- Can be optimized with iterative Expectation Maximization (EM) algorithm
  - Fix parameters and compute log likelihood wrt $p(z|x; \theta^t)$
  - Fix z find parameters $\theta^{(t+1)}$ to maximize log likelihood

Parameter estimation

- Standard EM requires access to posterior $p(z|x)$
- For the deep neural net models we care about this is infeasible
- Solution: introduce *variational* approximation $q(z;\phi)$ to $p(z|x)$
- Will give bound on log likelihood



Bounding the marginal likelihood

Recall Jenson's inequality: When f is concave, $f(\mathbb{E}[x]) \geq \mathbb{E}[f(x)]$

$$
\begin{aligned}
\log p(x) &= \log \int_z p(x,z) \\
&= \log \int_z q(z) \frac{p(x,z)}{q(z)} \\
&\geq \int_z q(z) \log \frac{p(x,z)}{q(z)} = L(x;\theta,\phi) \qquad \text{(by Jensons inequality)} \\
&= \int_z q(z) \log p(x,z) - \int_z q(z) \log q(z) \\
&= \underbrace{\mathbb{E}_{q(z)}[\log p(x,z)]}_{\text{Expectation of joint distribution}} + \underbrace{\mathrm{H}(q(z))}_{\text{Entropy}}
\end{aligned}
$$

Bound is tight when variational approximation matches true posterior:

$$\log p(x) - \underbrace{L(x;\theta,\phi)}_{\substack{\text{Evidence Lower} \\ \text{BOund (ELBO)}}} = \log p(x) - \int_z q(z) \log \frac{p(x,z)}{q(z)}$$

$$= \int_z q(z) \log p(x) - \int_z q(z) \log \frac{p(x,z)}{q(z)}$$

$$= \int_z q(z) \log \frac{q(z)p(x)}{p(x,z)}$$

$$= \int_z q(z) \log \frac{q(z)}{p(z|x)}$$

$$= D_{KL}(q(z;\phi)||p(z|x))$$

Learning directed graphical models

- Maximize bound on likelihood of data:

$$\max_{\theta} \sum_{i=1}^{N} \log p(x_i; \theta) \geq \max_{\theta, \phi_1, \ldots, \phi_N} \sum_{i=1}^{N} L(x_i; \theta, \phi_i)$$

- Historically, used different ϕ_i for every data point
  - But we'll move away from this soon..
- Can still use EM style algorithm to iteratively optimize
- For more info see Blei *et al.* (2003)

New method of learning: approximate inference model

- Instead of having different variational parameters for each data point, fit a conditional parametric function
- The output of this function will be the parameters of the variational distribution $q(z|x)$
- Instead of q(z) we have $q_\phi(z|x)$

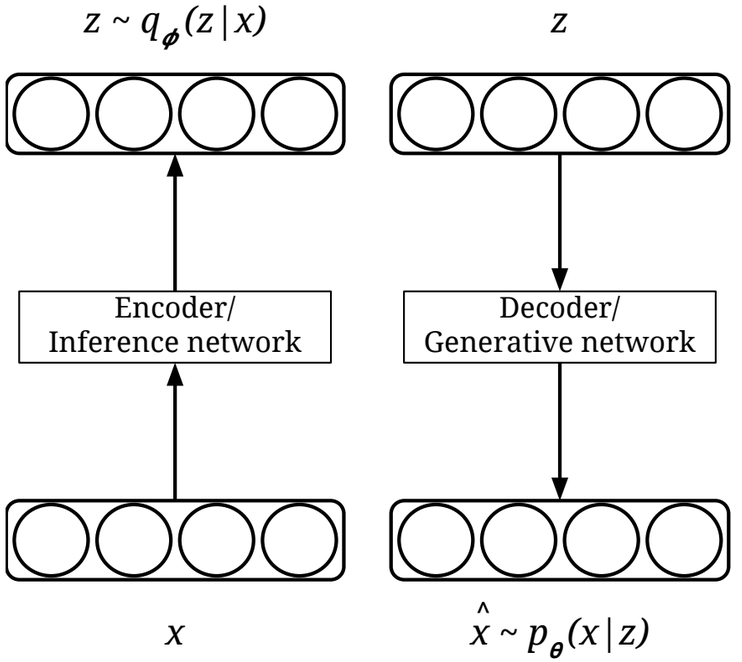
Evidence Lower BOund (ELBO)

- ELBO becomes:

$$L(x;\theta,\phi) = \underbrace{\mathbb{E}_{q_\phi(z|x)}[\log p_\theta(x,z)]}_{\text{Expectation of joint distribution}} + \underbrace{\mathrm{H}(q_\phi(z|x))}_{\text{Entropy}}$$

Variational autoencoder

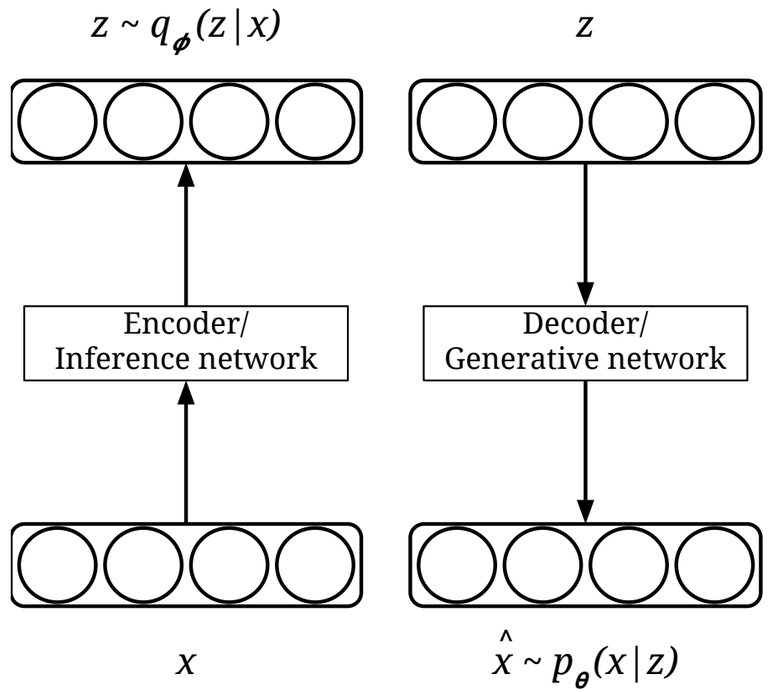
- *Encoder* network maps from image space to latent space
  - Outputs parameters of $q_\phi(z|x)$
- *Decoder* maps from latent space back into image space
  - Outputs parameters of $p_\theta(x|z)$



[Kingma & Welling (2013)]

Example

- *Encoder* network outputs mean and variance of Normal distribution
  - $q_\phi(z|x) = \mathcal{N}(\mu_\phi(x), \sigma_\phi(x))$
- *Decoder* network outputs mean (and optionally variance) of Normal distribution
  - $p_\theta(x|z) = \mathcal{N}(\mu_\theta(z), \mathbf{I})$



[Kingma & Welling (2013)]

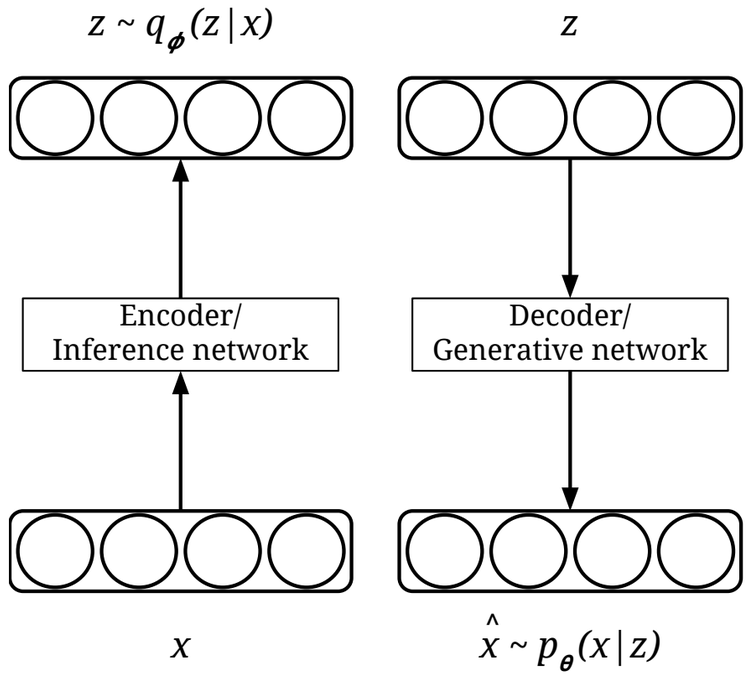
Variational autoencoder

- Rearranging the ELBO:

$$
\begin{aligned}
L(x;\theta,\phi) &= \int_z q(z|x)\log\frac{p(x,z)}{q(z|x)} \\
&= \int_z q(z|x)\log\frac{p(x|z)p(z)}{q(z|x)} \\
&= \int_z q(z|x)\log p(x|z) + \int_z q(z|x)\log\frac{p(z)}{q(z|x)} \\
&= \mathbb{E}_{q(z|x)}\log p(x|z) - \mathbb{E}_{q(z|x)}\log\frac{q(z|x)}{p(z)} \\
&= \underbrace{\mathbb{E}_{q(z|x)}\log p(x|z)}_{\text{Reconstruction term}} - \underbrace{D_{KL}(q(z|x)||p(z))}_{\text{Prior term}}
\end{aligned}
$$

Variational autoencoder

- Inference network outputs parameters of $q_\phi(z|x)$
- Generative network outputs parameters of $p_\theta(x|z)$
- Optimize θ and ϕ jointly by maximizing ELBO:



$$L(x;\theta,\phi) = \underbrace{\mathbb{E}_{q(z|x)} \log p(x|z)}_{\text{Reconstruction term}} - \underbrace{D_{KL}(q(z|x)||p(z))}_{\text{Prior term}}$$

Stochastic gradient variation bayes (SGVB) estimator

- Reparameterization trick : re-parameterize $z \sim q_\phi(z|x)$ as

$$z = g_\phi(x, \epsilon) \text{ with } \epsilon \sim p(\epsilon)$$

- For example, with a Gaussian can write $z \sim \mathcal{N}(\mu, \sigma^2)$ as

$$z = \mu + \epsilon\sigma^2 \text{ with } \epsilon \sim \mathcal{N}(0, 1)$$

[Kingma & Welling (2013); Rezende *et al.* (2014)]

Stochastic gradient variation bayes (SGVB) estimator

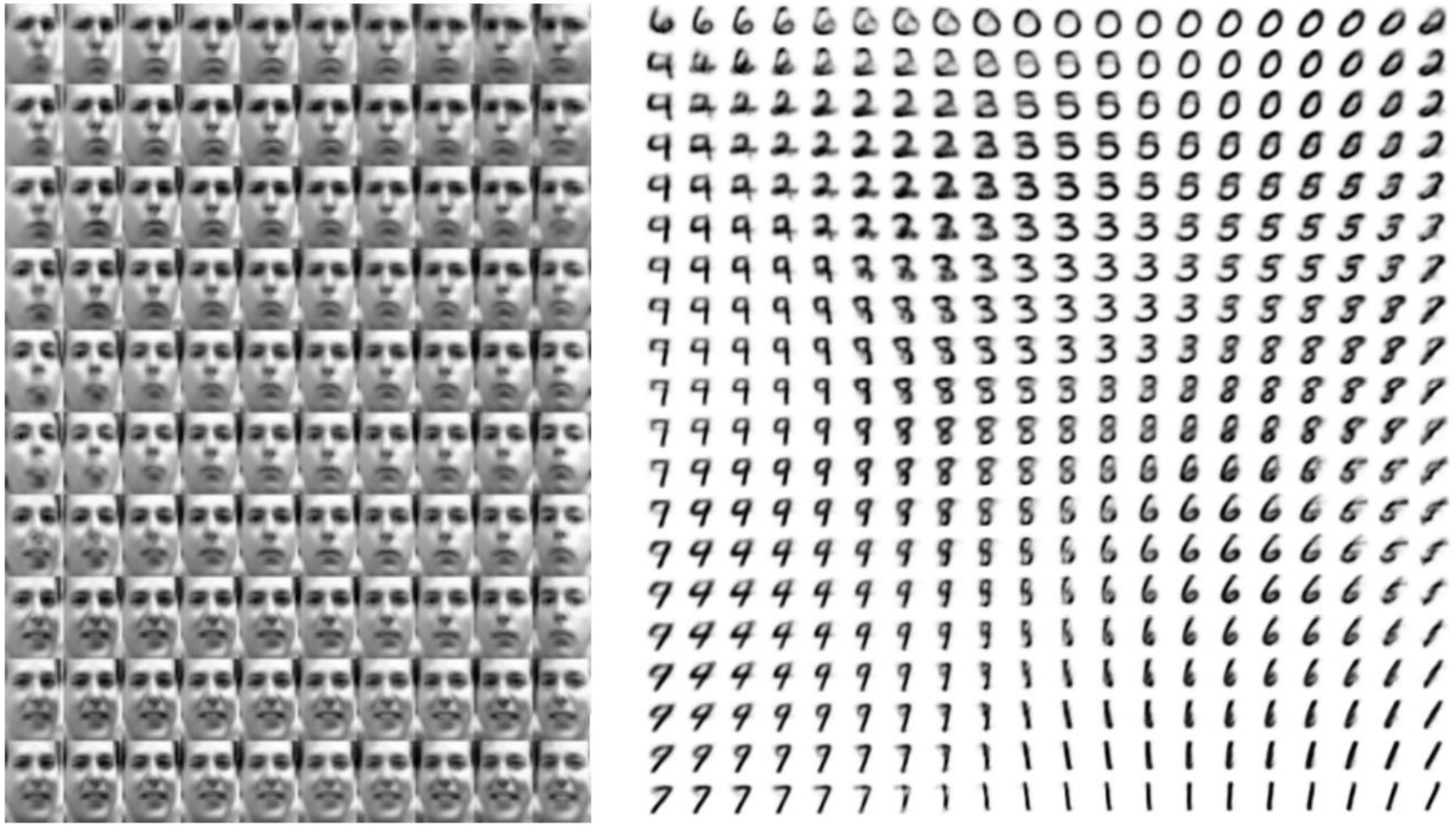
$$L(x;\theta,\phi) = \underbrace{\mathbb{E}_{q(z|x)} \log p(x|z)}_{\text{Reconstruction term}} - \underbrace{D_{KL}(q(z|x)||p(z))}_{\text{Prior term}}$$

- Using reparameterization trick we form Monte Carlo estimate of reconstruction term:

$$\begin{aligned}\mathbb{E}_{q_\phi(z|x)} \log p_\theta(x|z) &= \mathbb{E}_{p(\epsilon)} \log p_\theta(x|g_\phi(x,\epsilon)) \\ &\simeq \frac{1}{L}\sum_{i=1}^{L} \log p_\theta(x|g_\phi(x,\epsilon)) \qquad \text{where } \epsilon \sim p(\epsilon)\end{aligned}$$

- KL divergence term can often be computed analytically (eg. Gaussian)

VAE learned manifold



[Kingma & Welling (2013)]

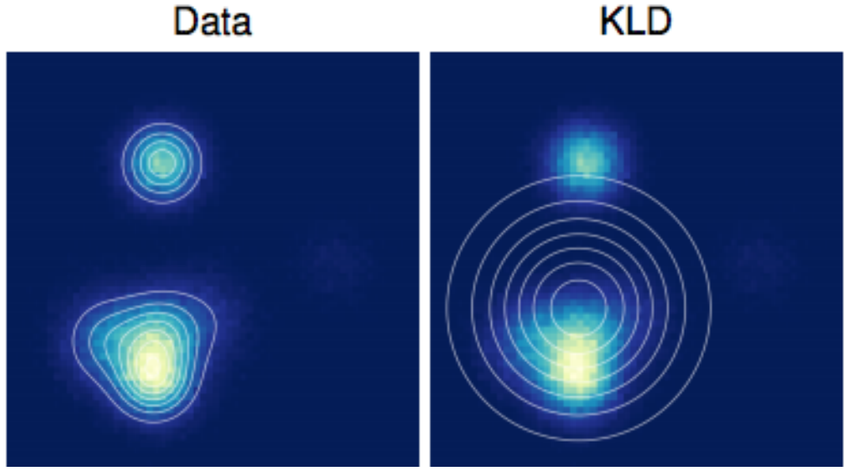
VAE samples

(a) 2-D latent space (b) 5-D latent space (c) 10-D latent space (d) 20-D latent space

[Kingma & Welling (2013)]

VAE tradeoffs

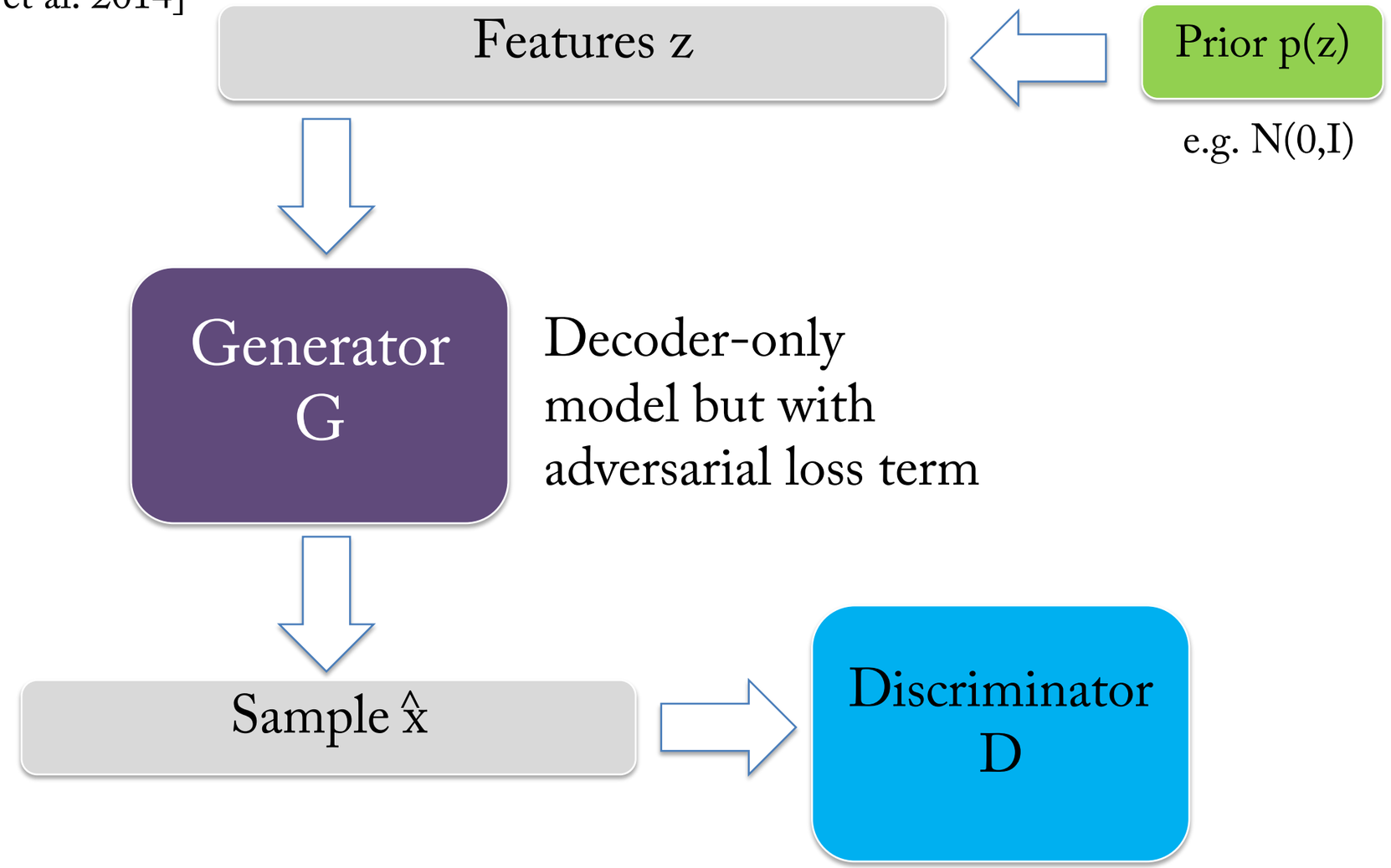
- Pros:
  - Theoretically pleasing
  - Optimizes bound on likelihood
  - Easy to implement
- Cons:
  - Samples tend to be blurry
    - Maximum likelihood minimizes $D_{KL}(p_{data}||p_{model})$



[Theis *et al.* (2016)]

Generative Adversarial Networks

[Goodfellow et al. 2014]



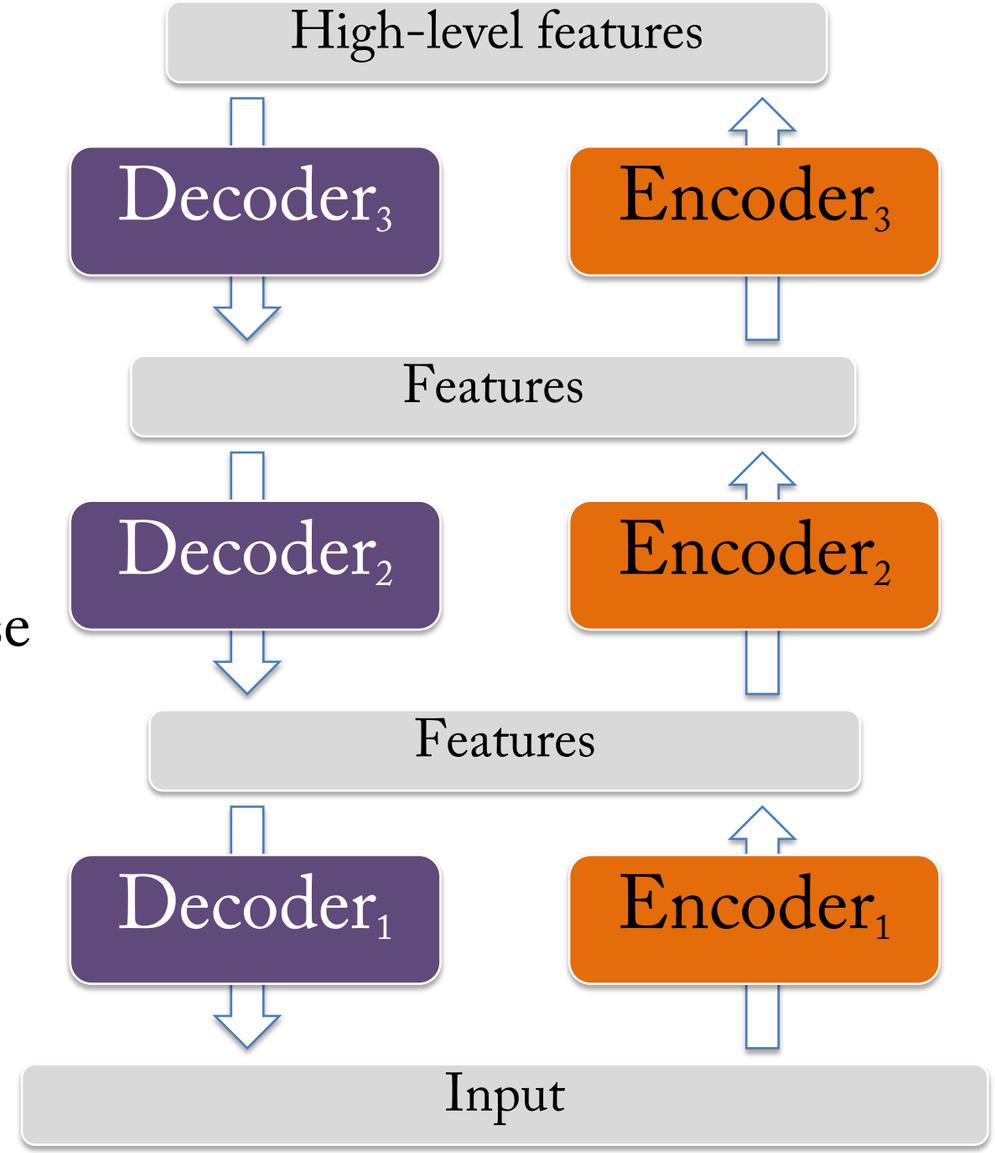
- Mini—max game between G and D

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

Stacked Auto-Encoders

- Ladder Networks
  [Rasmus et al. 2015]
  - Reconstruction constraint at each layer
  - Trained end-to-end

- Can be trained layer-wise
  - Stacked RBMs
  [Hinton & Salakhutdinov 2006]



Many Others Approaches

- Autoencoder (most unsupervised Deep Learning methods)
  - Restricted / Deep Boltzmann Machines
  - Denoising autoencoders
  - Predictive sparse decomposition
- Decoder-only
  - Sparse coding & hierarchical variants

Autoregressive models

- Tractably model a joint distribution of the pixels in the image
- Learn to predict the next pixel given all the previously generated pixels
- Joint distribution of all pixels just product of conditionals:

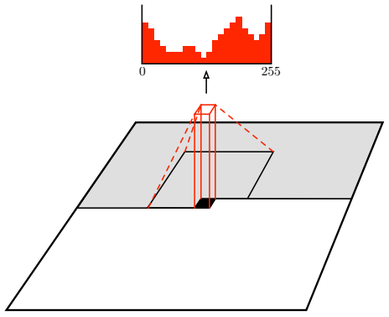
$$p(\mathbf{x}) = \prod_{i=1}^{n^2} p(x_i | x_1, ..., x_{i-1})$$

Pixel-CNN

[van den Oord et al., arXiv 1606.05328, 2016]

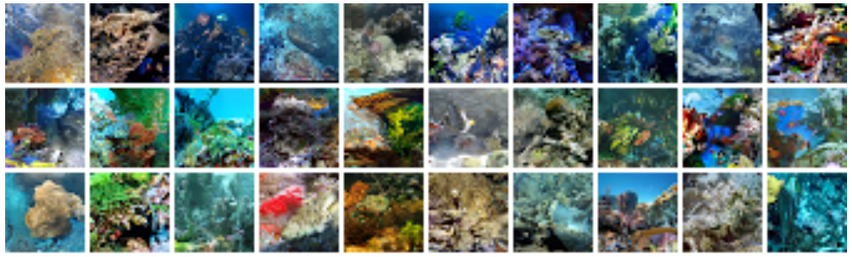
- Conditional generative model of images
- Generate each pixel, in raster-scan order
- Just predict distribution over a single pixel (can be multi-modal)
- See also Video Pixel Networks [Kalchbrenner et al., 2016],
- NADE [Larochelle & Murray 2011] & RIDE [Theis and Bethge, NIPS 2015].

$$p(\mathbf{x}) = \prod_{i=1}^{n^2} p(x_i | x_1, ..., x_{i-1}).$$



1	1	1	1	1
1	1	1	1	1
1	1	0	0	0
0	0	0	0	0
0	0	0	0	0

African elephant



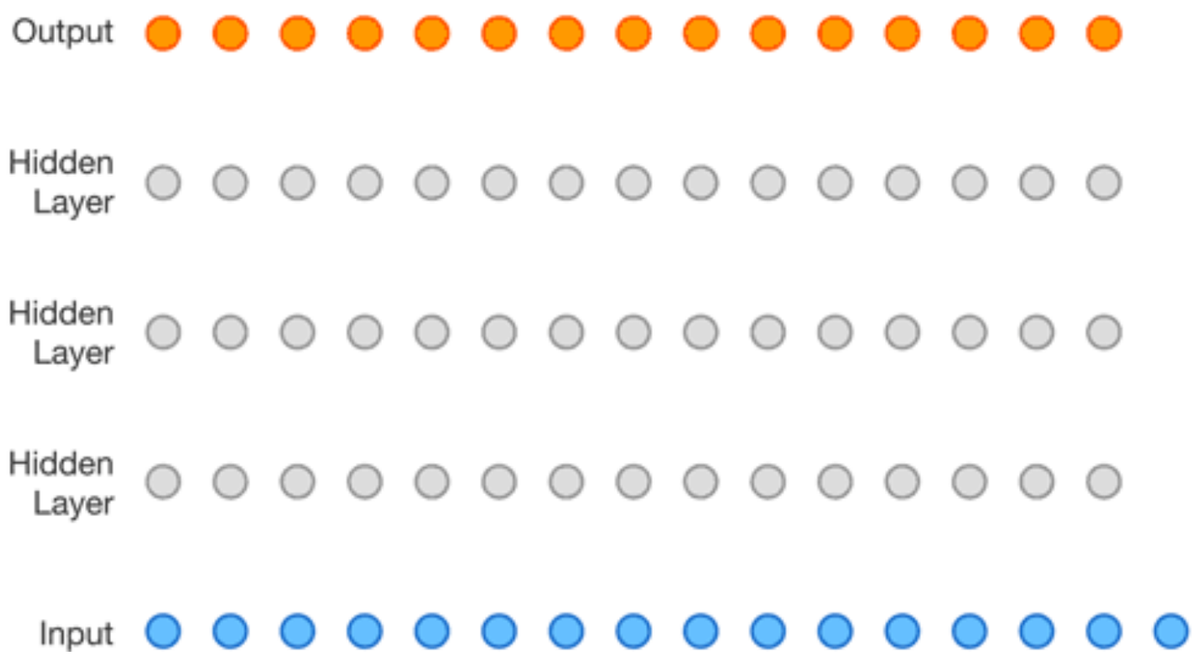
Coral Reef

Wavenet

[van den Oord et al., arXiv 1609.03499, 2016]

- Generative model of raw speech waveform
- Condition on previous parts of waveform
- Dilated causal convolution layers
- Discrete output distribution (use softmax)

$$p(\mathbf{x}) = \prod_{t=1}^{T} p(x_t \mid x_1, \ldots, x_{t-1})$$



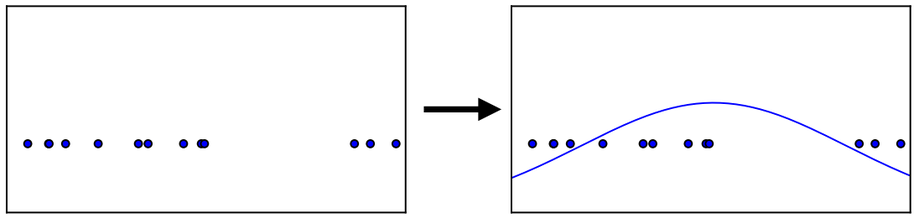
Generative Adversarial Networks

Slides from: Emily Denton, Ian Goodfellow, Soumith Chintala

Generative Adversarial Networks

- [Generative Adversarial Nets, Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, Yoshua Bengio, NIPS 2014]
- Focus on sample generation

Generative Modeling: Density Estimation



Training Data | Density Function

Generative Modeling: Sample Generation

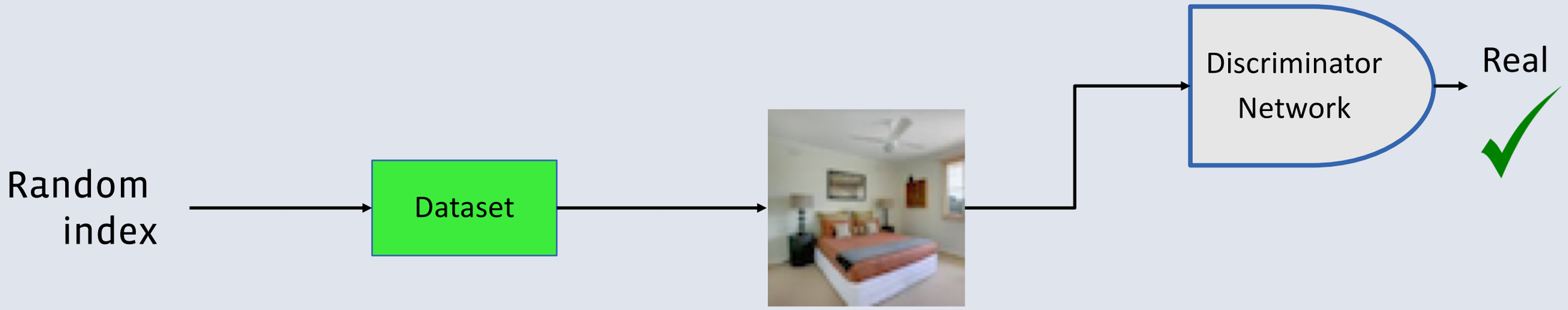
Training Data (CelebA) | Sample Generator (Karras et al, 2017)

(Goodfellow 2018)

Generative Adversarial Network

[Goodfellow et al. NIPS 2014]

- Initial application to still images
- Way to train generative model to match **distribution** of data
- Discriminator network predicts if input image is from data (real) or model (fake)



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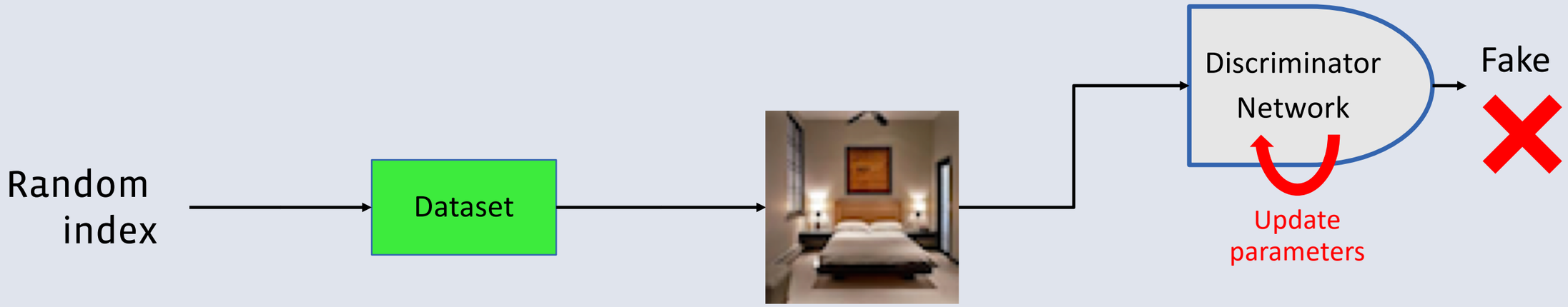

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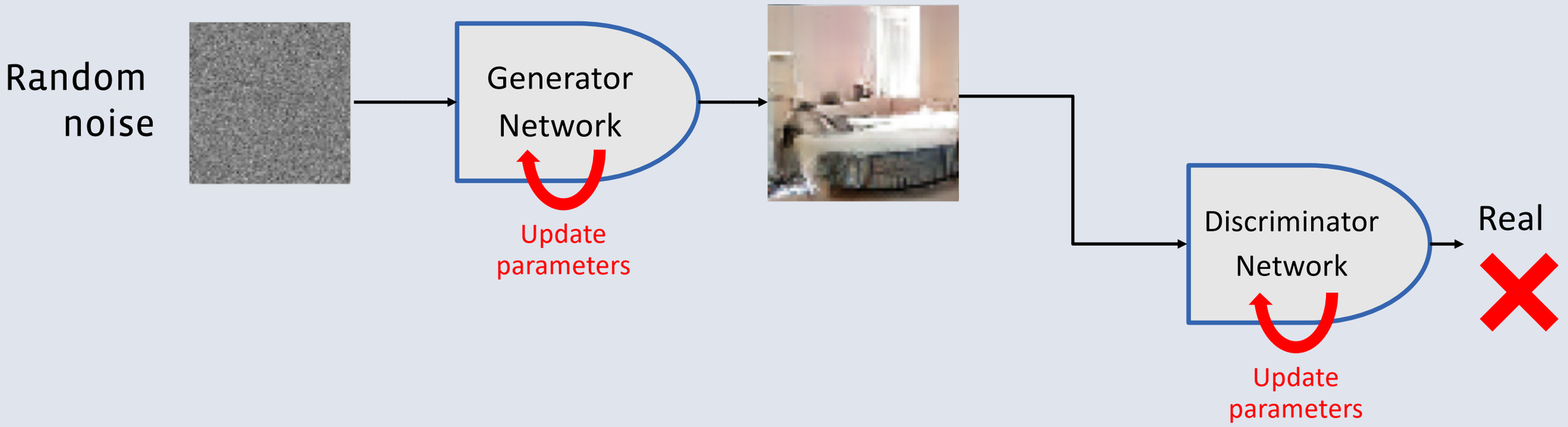

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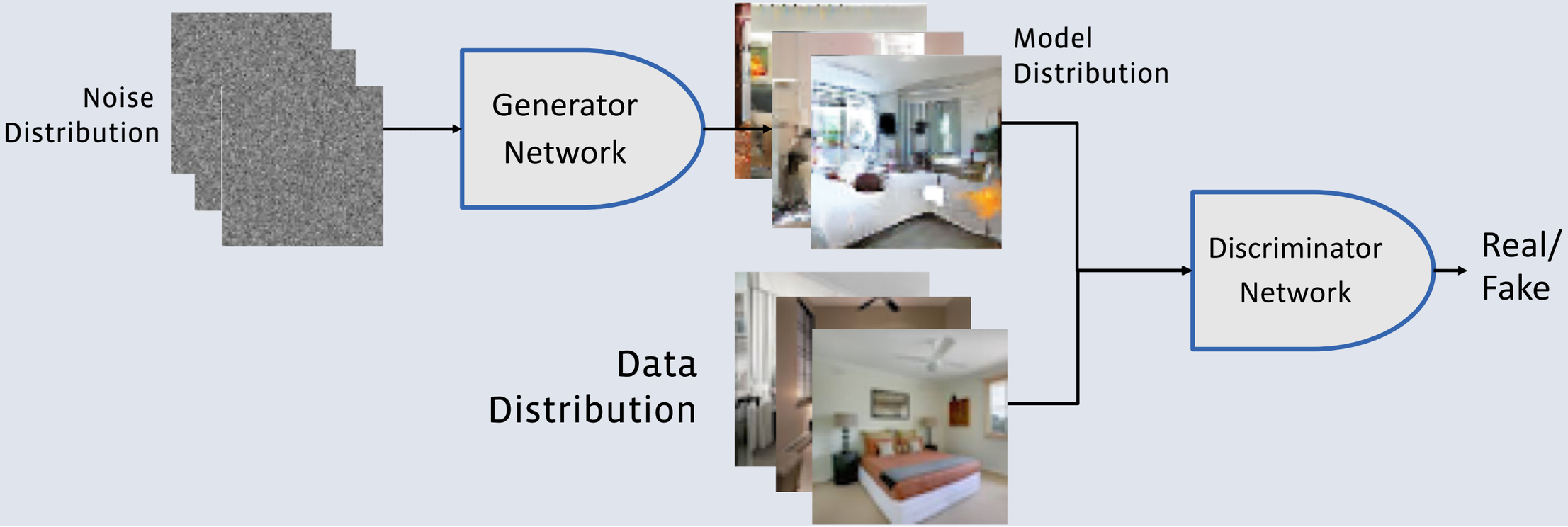


Generative Adversarial Networks

D(x) tries to be near 1

Differentiable function D

x sampled from data

D tries to make $D(G(z))$ near 0, G tries to make $D(G(z))$ near 1

D

x sampled from model

Differentiable function G

Input noise z

(Goodfellow et al., 2014)

Generative Adversarial Networks

[Generative Adversarial Nets, Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, Yoshua Bengio, NIPS 2014]

- Minimax value function:

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

Generator pushes down

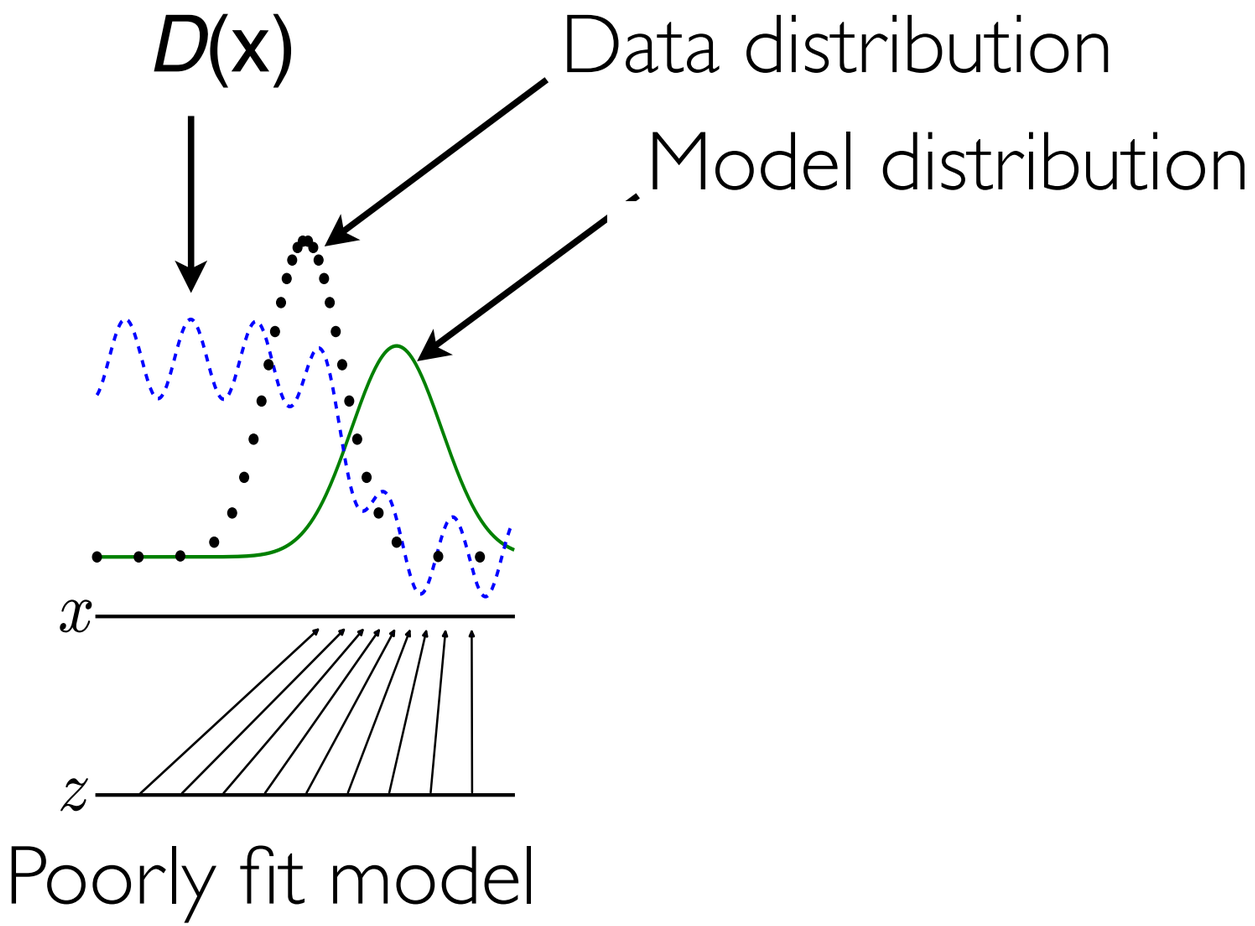
Discriminator pushes up

Discriminator's ability to recognize data as being real

Discriminator's ability to recognize generator samples as being fake

[Slide: Ian Goodfellow, Deep Learning workshop, ICML 2015]

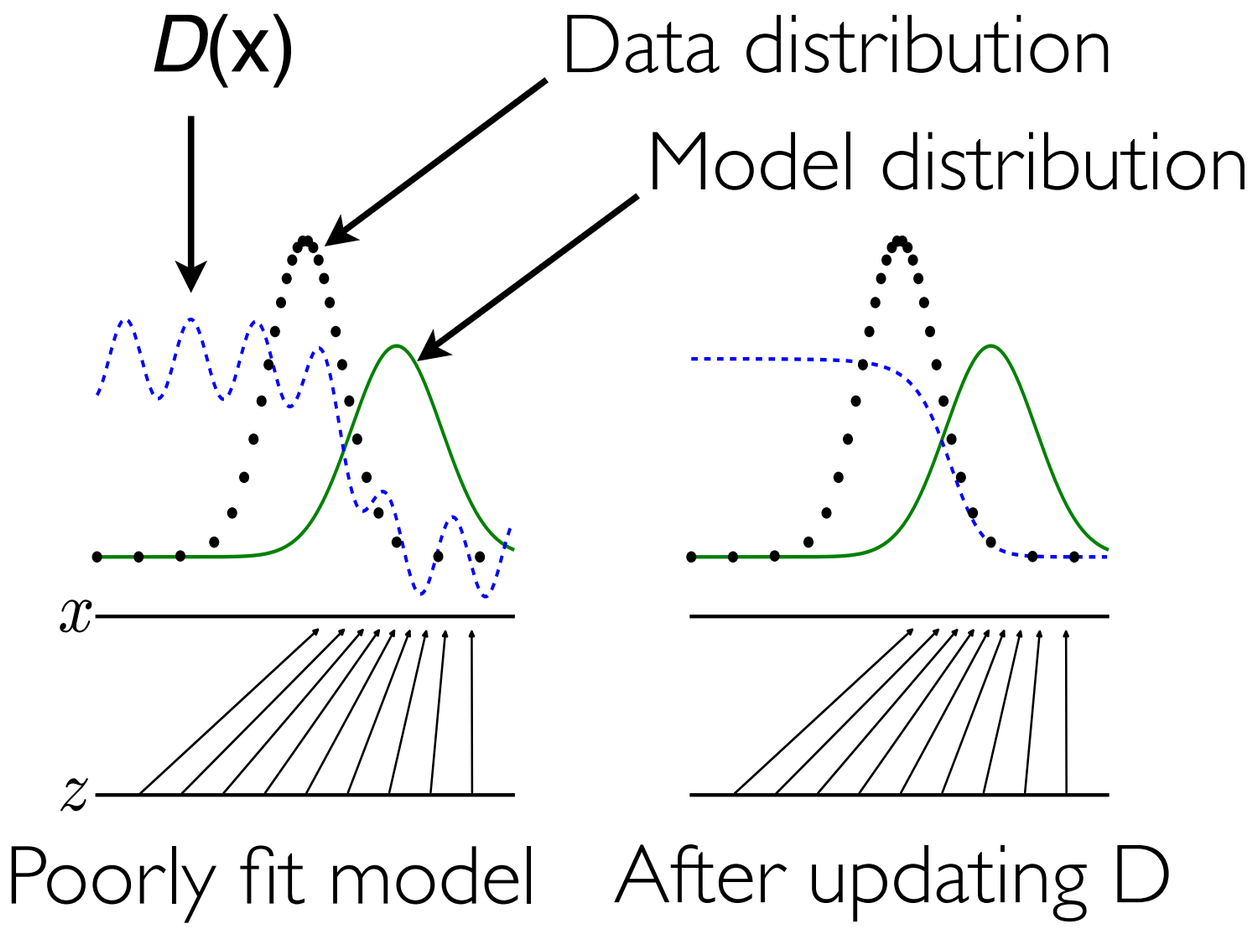
Generative Adversarial Networks



Poorly fit model

[Slide: Ian Goodfellow, Deep Learning workshop, ICML 2015]

Generative Adversarial Networks



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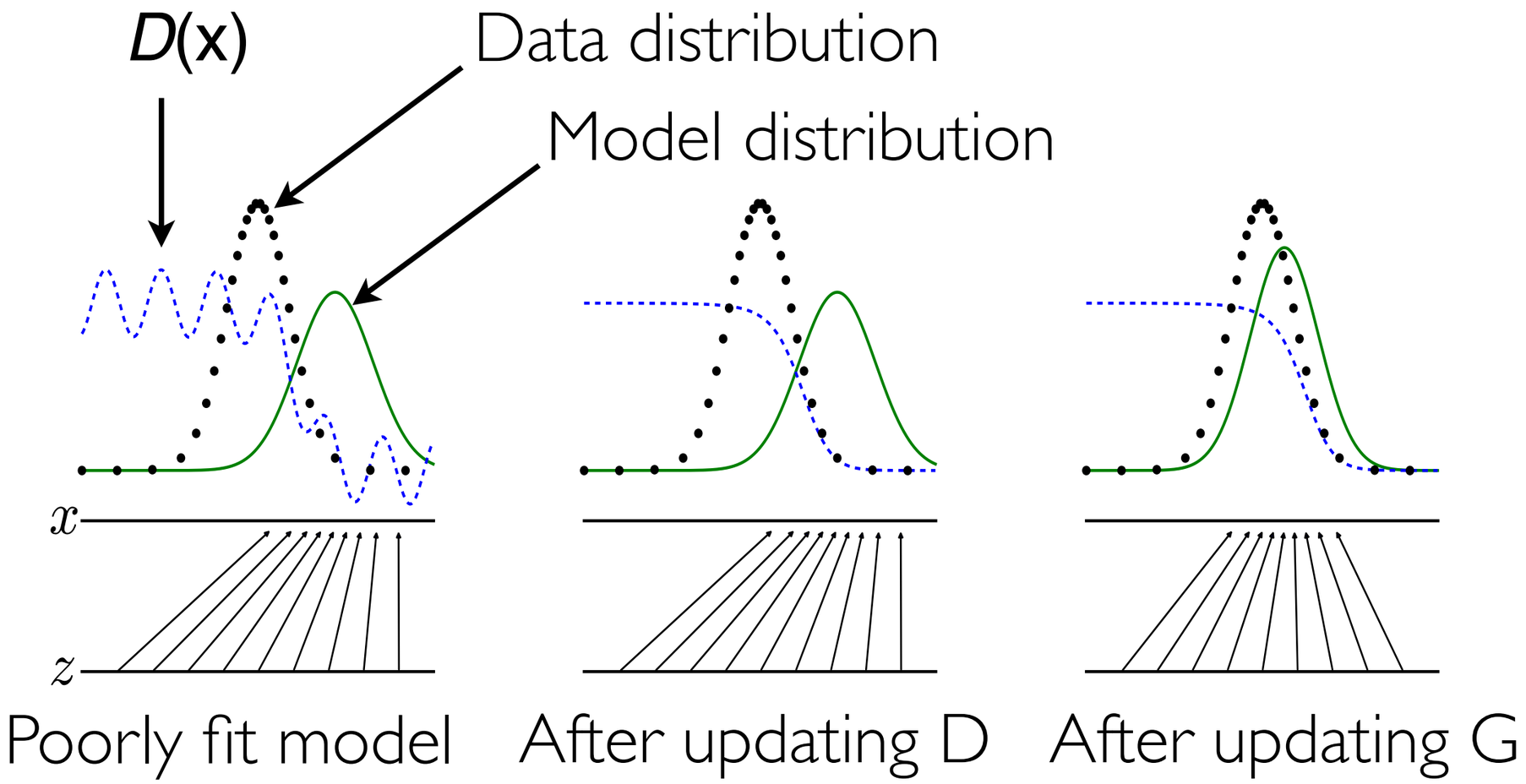
Generative Adversarial Networks



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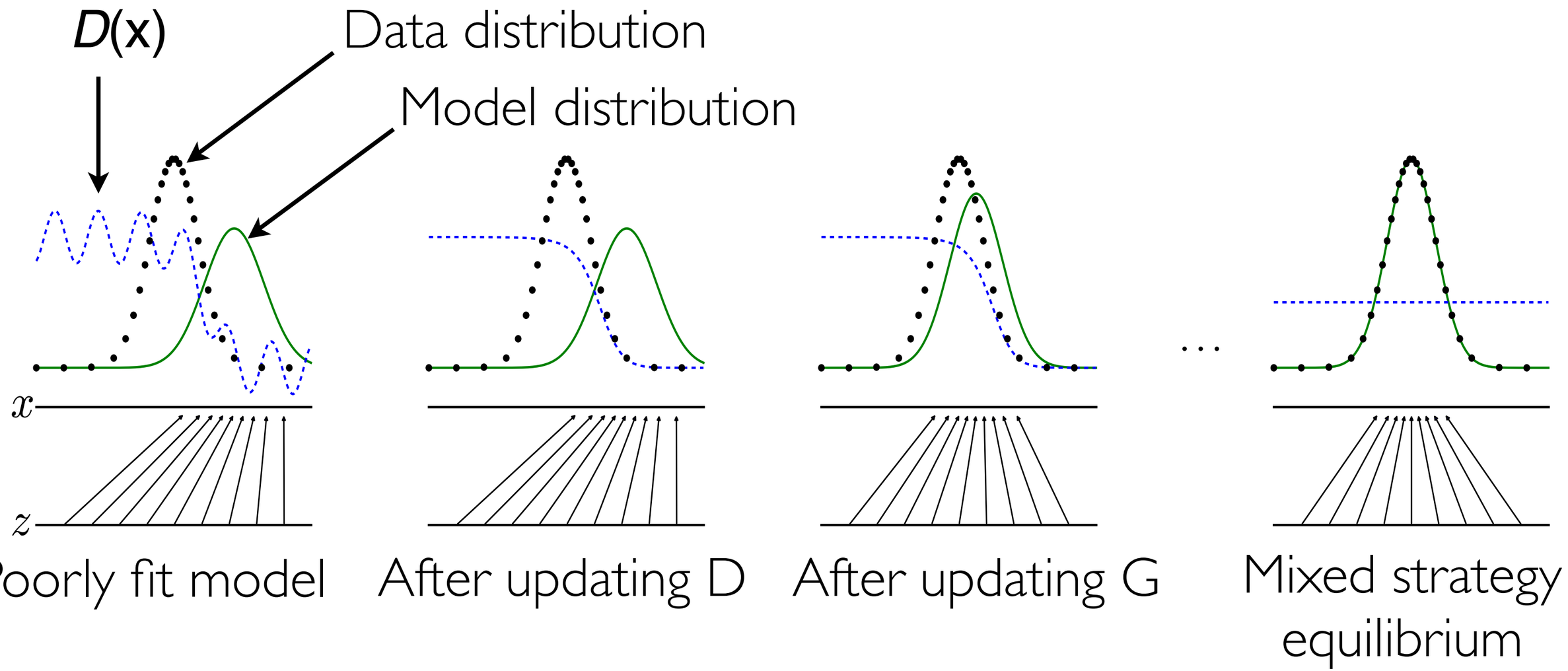
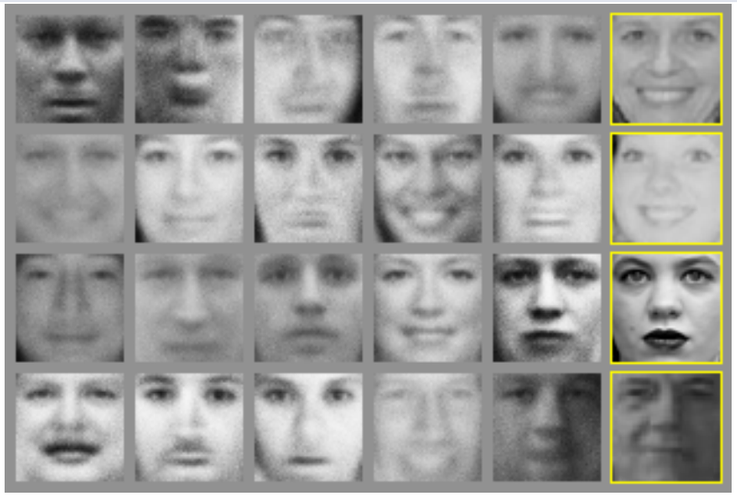
Generative Adversarial Networks



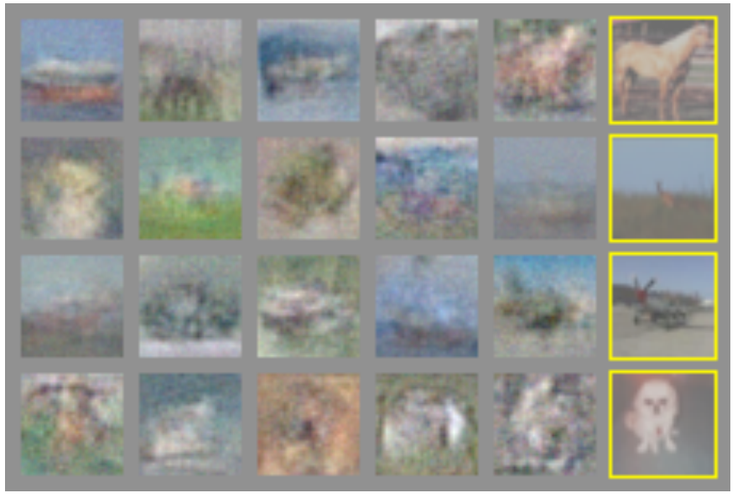
[Slide: Ian Goodfellow, Deep Learning workshop, ICML 2015]

Adversarial Network Samples

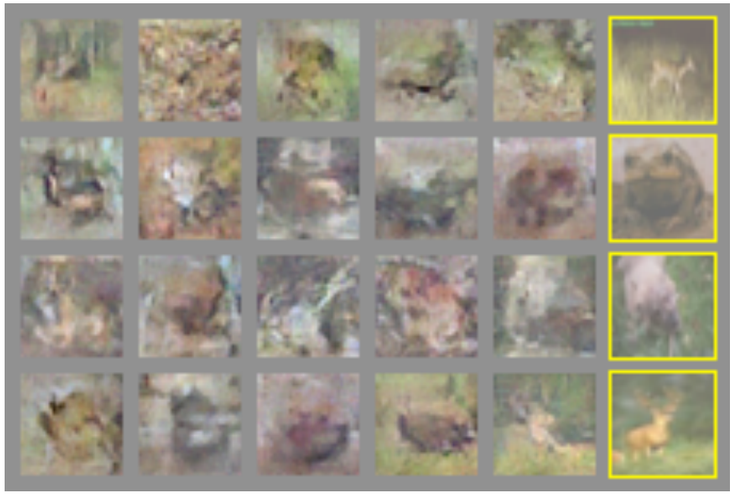
MNIST



TFD



CIFAR-10 (fully connected)



CIFAR-10 (convolutional)

[Slide: Ian Goodfellow, Deep Learning workshop, ICML 2015]

DCGAN

UNSUPERVISED REPRESENTATION LEARNING WITH DEEP CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORKS

Alec Radford & Luke Metz
indico Research
Boston, MA
{alec,luke}@indico.io

Soumith Chintala
Facebook AI Research
New York, NY
soumith@fb.com

ICLR 2016

- First to generate plausible results at 64x64.
- Improved architectures for generator/discriminator
- Most GAN architectures used now are similar

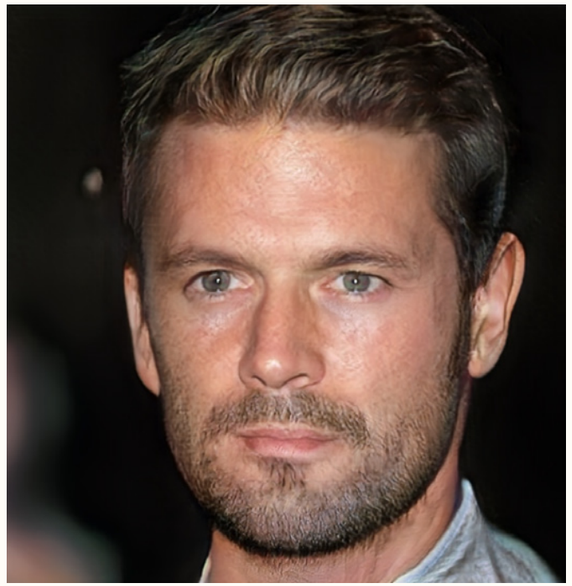
- Lots of tricks to get GANs to train well

3.5 Years of Progress on Faces

2014

2015

2016



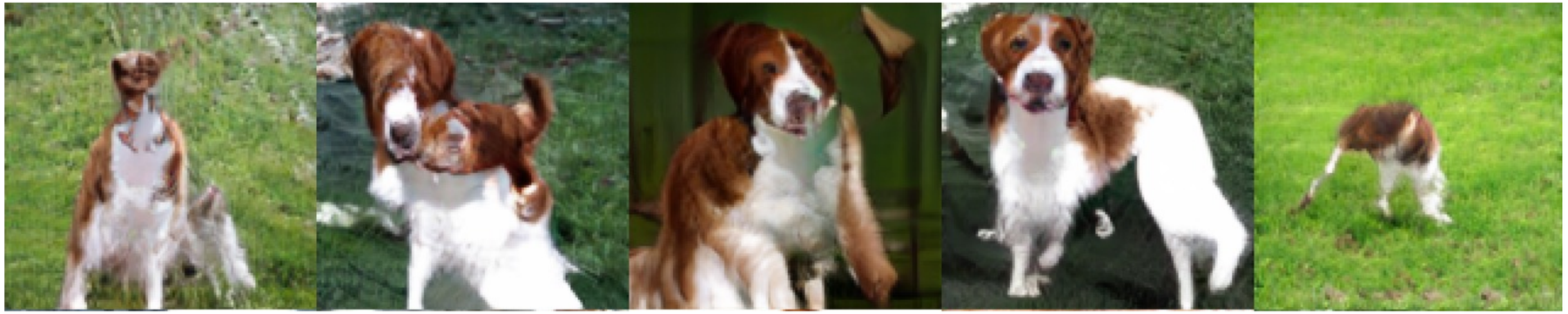
2017

(Brundage et al, 2018)

<2 Years of Progress on ImageNet

Odena et al 2016

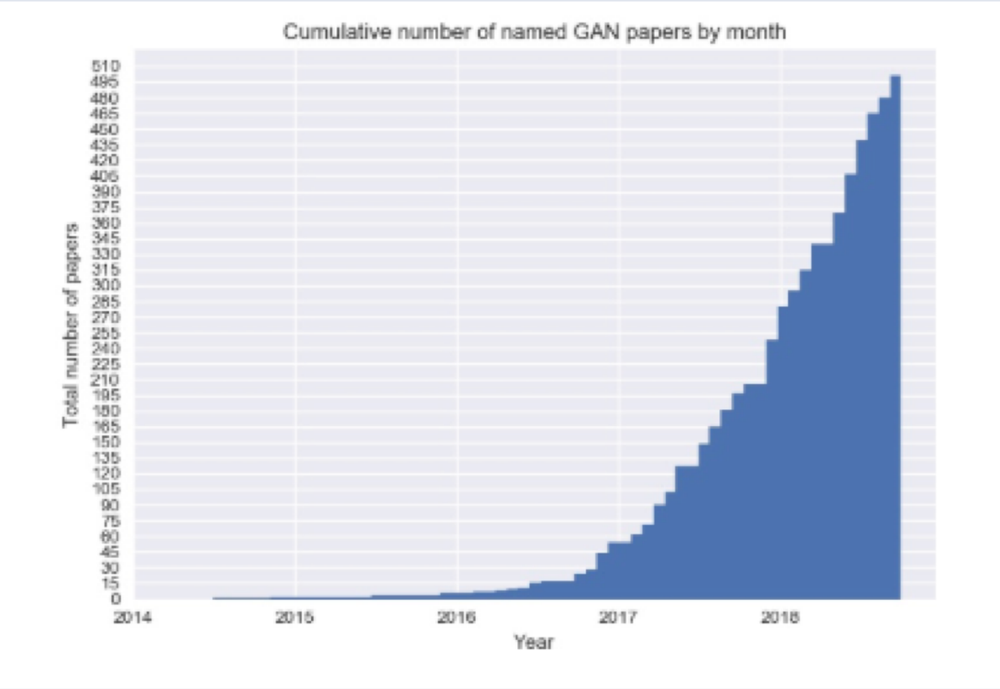
Miyato et al 2017



Zhang et al 2018

The GAN Zoo

https://github.com/hindupuravinash/the-gan-zoo



- 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)

Evaluation of GANs

- Short answer: hard; look at quality of samples
- Computing log-likelihood not directly possible

  LLH is problematic.

  See [A note on the evaluation of generative models, Lucas Theis, Aäron van den Oord, Matthias Bethge, ICLR 2016]

- Inception score
- User-study: can humans tell fake from real?

Inception Score

Proposed in 2016

Improved Techniques for Training GANs

Tim Salimans tim@openai.com
Ian Goodfellow ian@openai.com
Wojciech Zaremba woj@openai.com
Vicki Cheung vicki@openai.com
Alec Radford alec.radford@gmail.com
Xi Chen peter@openai.com

Abstract

Inception Score

- Send generated image through Inception model (trained on Imagenet)

generated image to get the conditional label distribution $p(y|\boldsymbol{x})$. Images that contain meaningful objects should have a conditional label distribution $p(y|\boldsymbol{x})$ with low entropy. Moreover, we expect the model to generate varied images, so the marginal $\int p(y|\boldsymbol{x} = G(z))dz$ should have high entropy. Combining these two requirements, the metric that we propose is: $\exp(\mathbb{E}_{\boldsymbol{x}}\mathrm{KL}(p(y|\boldsymbol{x})||p(y)))$, where

Inception Score

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How to Train a GAN

Emily Denton, Martin Arjovsky, Michael Mathieu
New York University

Ian Goodfellow
Google

Soumith Chintala
Facebook AI Research

The stability of GANs

Timeline - the stability of GANs

Goodfellow et. al. “Generative Adversarial Networks”

2014

Timeline - the stability of GANs

model architecture generator

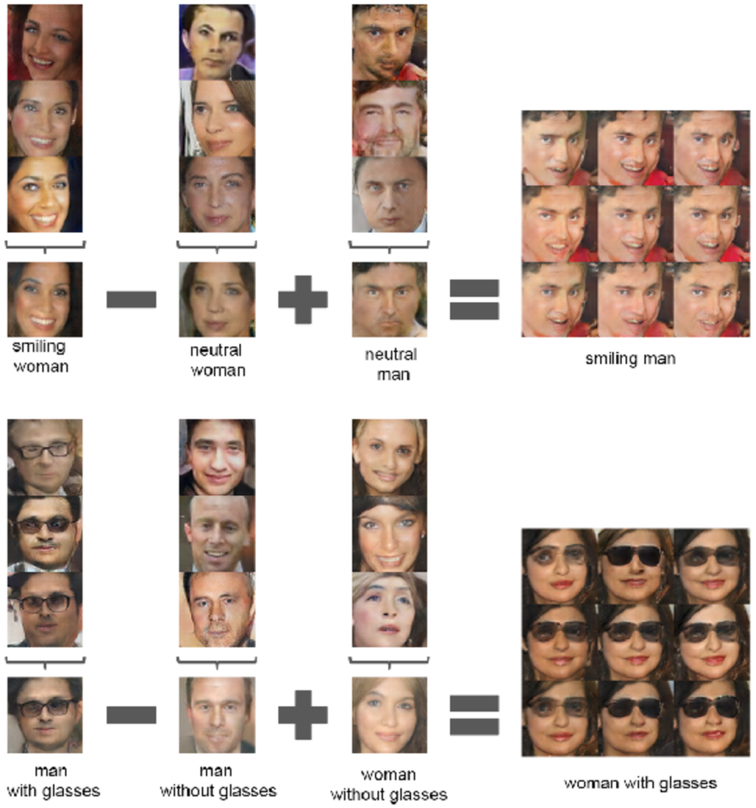
visual inspection

countless failed stability hacks

Denton et. al. “Deep Generative Image Models using a Laplacian Pyramid of Adversarial Networks”

2015

Timeline - the stability of GANs



countless hours finding stable models

stable upto 64x64

mode dropping

underfitting

Radford et. al. “Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks”

2015

Timeline - the stability of GANs

more heuristics

more stability

Salimans et. al. “Improved Techniques for Training GANs”

2015

Timeline - the stability of GANs

gradient norm regularization

Least-Squares
Boundary Equilibrium

Gulrajani et. al. "Improved Training of Wasserstein GANs"

Xudong et al. "Least squares generative adversarial networks."

Berthelot et. al. "Began: Boundary equilibrium generative adversarial networks."

2016-2017

Timeline - the stability of GANs

https://github.com/khanrc/tf.gans-comparison
by Junbum Cha

GANs comparison without cherry-picking

Implementations of some theoretical generative adversarial nets: DCGAN, EBGAN, LSGAN, WGAN, WGAN-GP, BEGAN, DRAGAN and CoulombGAN.

I implemented the structure of model equal to the structure in paper and compared it on the CelebA dataset and LSUN dataset without cherry-picking.

Comparison to Classification ConvNets

- Throw things at the wall and see what sticks
- Intuition is poorer
- Theoretical work is somewhat improving but still far away
- Objective validation metrics are not there yet

#1: Normalize the inputs

- normalize the images between -1 and 1
- Tanh as the last layer of the generator output
  - or some kind of bounds normalization

#2: Modified loss function (classic GAN)

- In papers people write min (log 1-D), but in practice folks practically use max log D
  - because the first formulation has vanishing gradients early on
  - Goodfellow et. al (2014)
- In practice:
  - Flip labels when training generator: real = fake, fake = real

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LOT OF NEW LOSS FORMULATIONS

#2: Modified loss function (classic GAN)

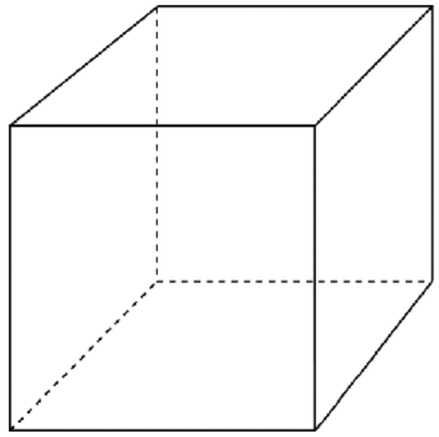
https://github.com/hwalsuklee/tensorflow-generative-model-collections

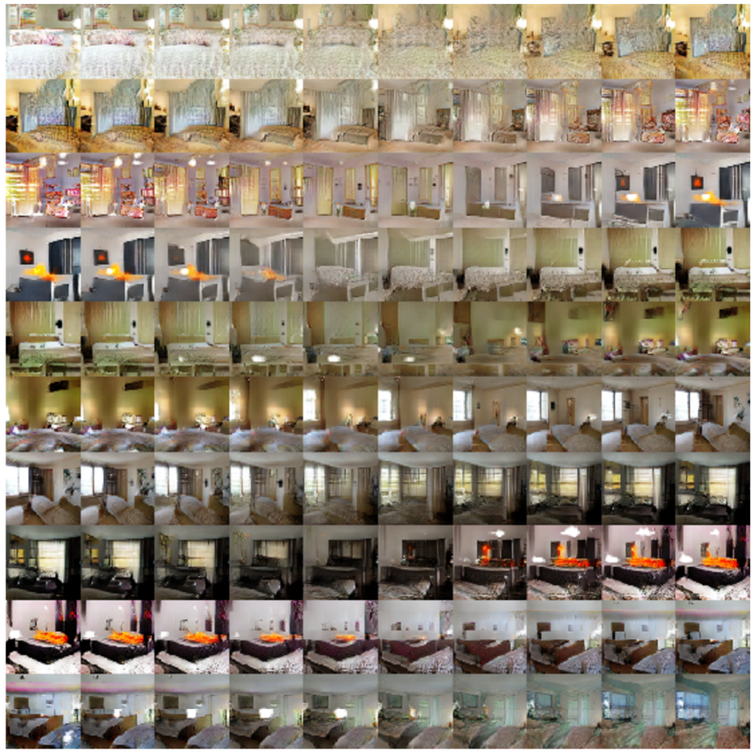
https://github.com/znxlwm/pytorch-generative-model-collections

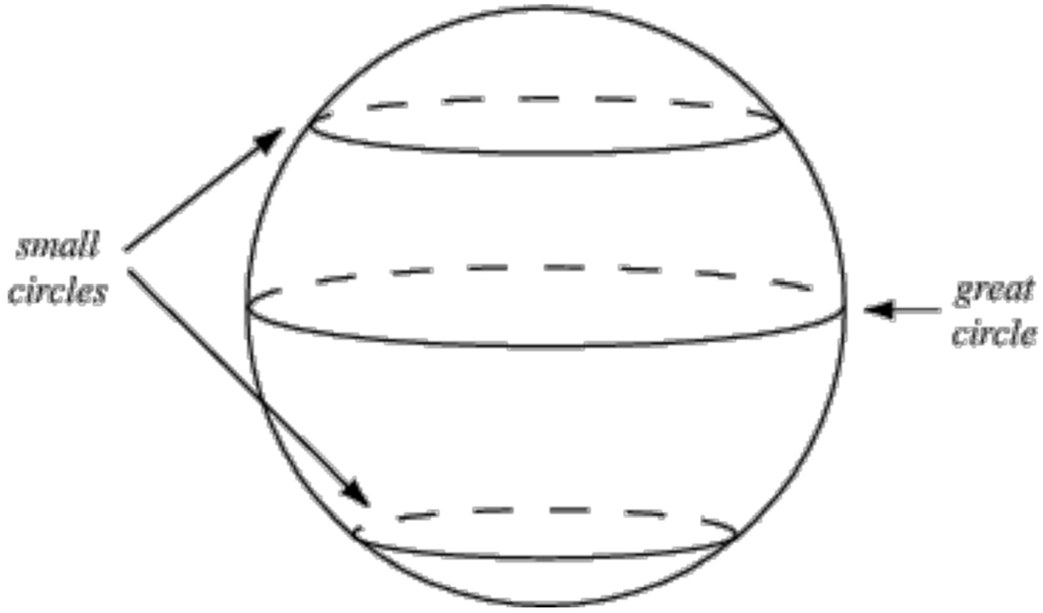
Name	Paper Link	Value Function
GAN	Arxiv	$L_D^{GAN} = E\left[\log\left(D(x)\right)\right] + E\left[\log\left(1 - D(G(z))\right)\right]$ $L_G^{GAN} = E\left[\log\left(D(G(z))\right)\right]$
LSGAN	Arxiv	$L_D^{LSGAN} = E[(D(x) - 1)^2] + E[D(G(z))^2]$ $L_G^{LSGAN} = E[(D(G(z)) - 1)^2]$
WGAN	Arxiv	$L_D^{WGAN} = E[D(x)] - E[D(G(z))]$ $L_G^{WGAN} = E[D(G(z))]$ $W_D \leftarrow clip\_by\_value(W_D, -0.01, 0.01)$
WGAN-GP	Arxiv	$L_D^{WGAN\_GP} = L_D^{WGAN} + \lambda E[(\lvert\nabla D(\alpha x - (1 - \alpha G(z)))\rvert - 1)^2]$ $L_G^{WGAN\_GP} = L_G^{WGAN}$
DRAGAN	Arxiv	$L_D^{DRAGAN} = L_D^{GAN} + \lambda E[\left(\lvert\nabla D(\alpha x - (1 - \alpha x_p))\rvert - 1\right)^2]$ $L_G^{DRAGAN} = L_G^{GAN}$
CGAN	Arxiv	$L_D^{CGAN} = E\left[\log\left(D(x, c)\right)\right] + E\left[\log\left(1 - D(G(z), c)\right)\right]$ $L_G^{CGAN} = E\left[\log\left(D(G(z), c)\right)\right]$
infoGAN	Arxiv	$L_{D,Q}^{infoGAN} = L_D^{GAN} - \lambda L_I(c, c')$ $L_G^{infoGAN} = L_G^{GAN} - \lambda L_I(c, c')$
ACGAN	Arxiv	$L_{D,Q}^{ACGAN} = L_D^{GAN} + E[P(class = c\lvert x)] + E[P(class = c\lvert G(z))]$ $L_G^{ACGAN} = L_G^{GAN} + E[P(class = c\lvert G(z))]$
EBGAN	Arxiv	$L_D^{EBGAN} = D_{AE}(x) + \max(0, m - D_{AE}(G(z)))$ $L_G^{EBGAN} = D_{AE}(G(z)) + \lambda \cdot PT$
BEGAN	Arxiv	$L_D^{BEGAN} = D_{AE}(x) - k_t D_{AE}(G(z))$ $L_G^{BEGAN} = D_{AE}(G(z))$ $k_{t+1} = k_t + \lambda(\gamma D_{AE}(x) - D_{AE}(G(z)))$

#3: Use spherical z

- interpolation via great circle
- Tom White “Sampling Generative Networks”
  - https://arxiv.org/abs/1609.04468

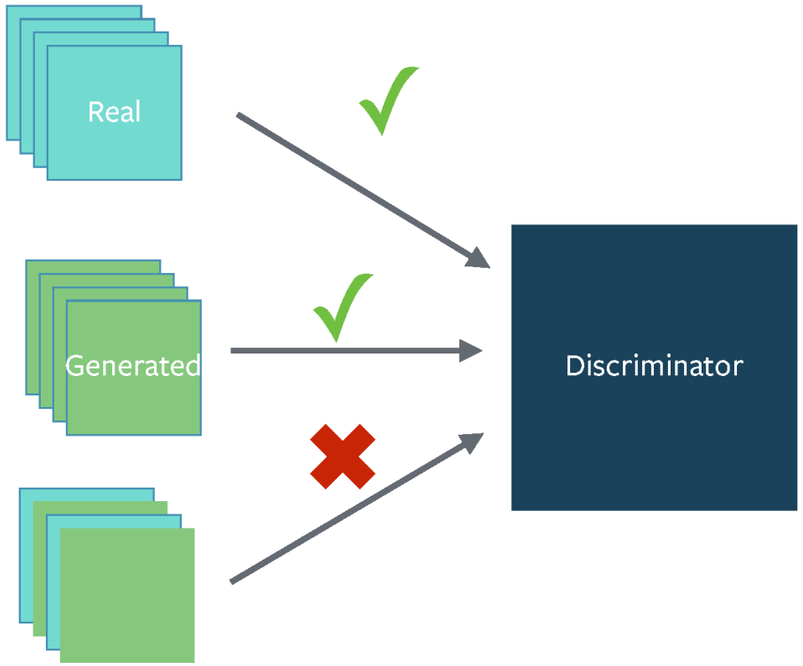






#4: BatchNorm

- different batches for real and fake
- when batchnorm is not an option use instance norm



#5: Avoid Sparse Gradients: ReLU, MaxPool

- the stability of the GAN game suffers
- LeakyReLU (both G and D)
- Downsampling: Average Pooling, Conv2d + stride
- Upsampling: PixelShuffle, ConvTranspose2d + stride
  - PixelShuffle: https://arxiv.org/abs/1609.05158

#6: Soft and Noisy Labels

- Label Smoothing
- making the labels the noisy a bit for the discriminator, sometimes

-Salimans et. al. 2016

#7: Architectures: DCGANs / Hybrids

- DCGAN when you can

- if you cant use DCGANs and no model is stable,
- use a hybrid model : KL + GAN or VAE + GAN

- ResNets from WGAN-gp also work pretty well (but are very slow)
  - https://github.com/igul222/improved_wgan_training

- Width matters more than Depth

#8: Stability tricks from RL

- Experience replay
- Things that work for deep deterministic policy gradients
- See Pfau & Vinyals (2016)

#9: Optimizer: ADAM

- optim.Adam rules!
  - See Radford et. al. 2015
- [MMathieu] Use SGD for discriminator and ADAM for generator

#10: Use Gradient Penalty

- Regularize the norm of the gradients
  - multiple theories on why this is useful (WGAN-GP, DRAGAN, Stabilizing GANs by Regularization etc.)

#11: Dont balance via loss statistics (classic GAN)

- Dont try to find a (number of G / number of D) schedule to uncollapse training

- while lossD > X:
  - train D
- while lossG > X:
  - train G

#12: If you have labels, use them

- if you have labels available, training the discriminator to also classify the samples: auxillary GANs

#13: Add noise to inputs, decay over time

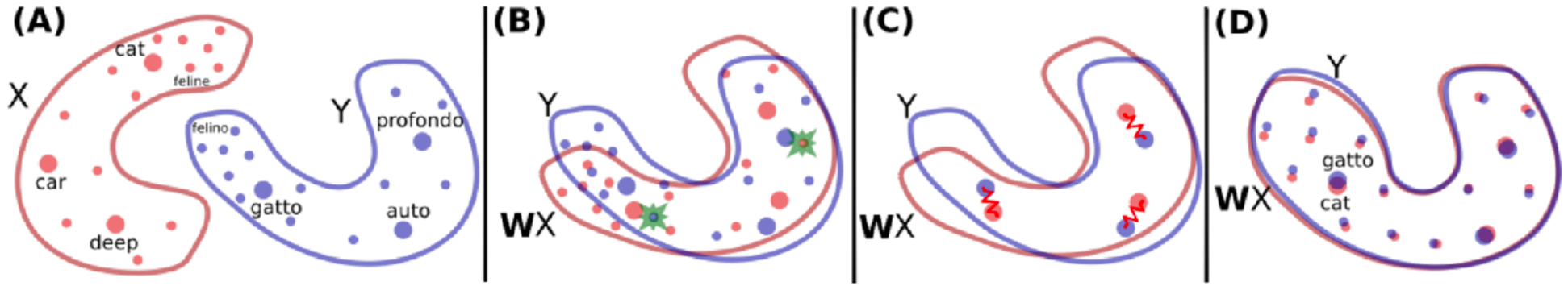
- Add some artificial noise to inputs to D (Arjovsky et. al., Huszar, 2016)
  - http://www.inference.vc/instance-noise-a-trick-for-stabilising-gan-training/
  - https://openreview.net/forum?id=Hk4_qw5xe
- adding gaussian noise to every layer of generator (Zhao et. al. EBGAN)
- Improved GANs: OpenAI code also has it (commented out)

#14: Train discriminator more

- especially when you have noise
- hard to find a schedule of number of D iterations vs G iterations
- WGAN/WGAN-gp papers suggest 5x D iterations per G iteration

#15: Avoid discrete spaces

- Pose the generation as a continuous prediction

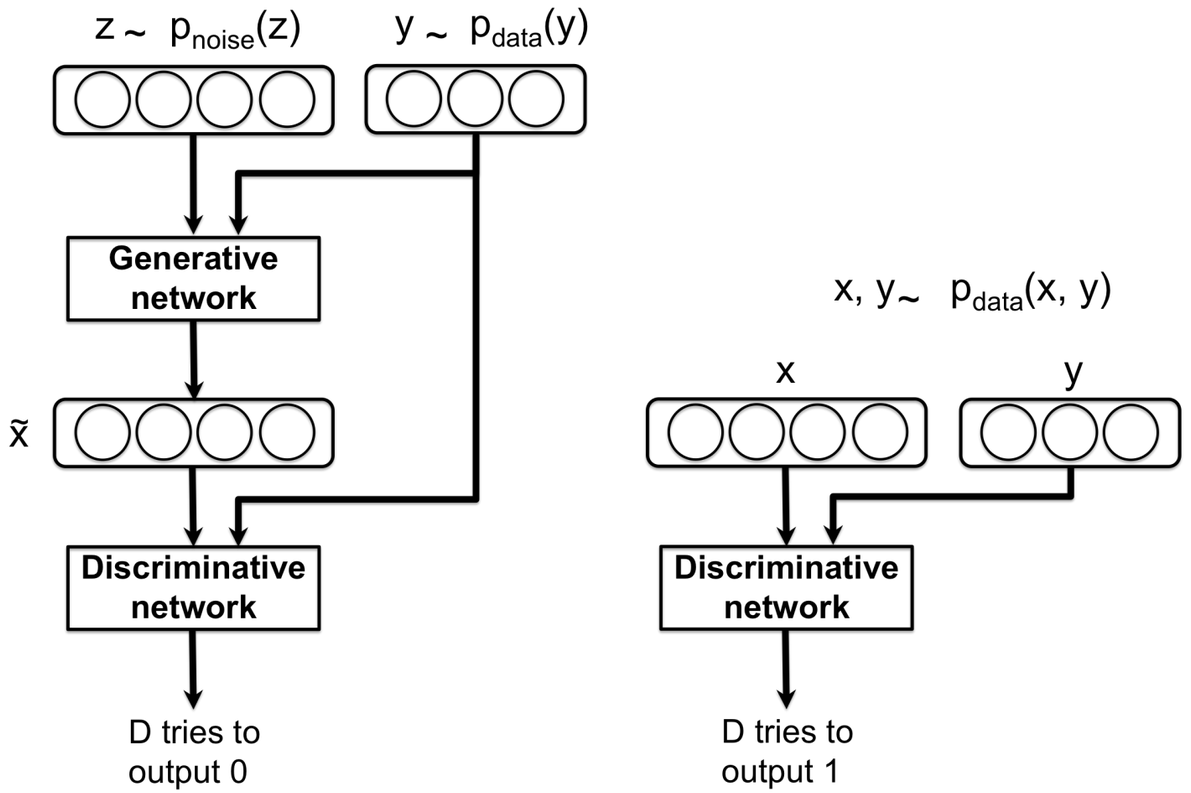


Conneau, Lample et. al. "Word Translation Without Parallel Data"

Conditional GANs

Conditional generative adversarial networks (CGAN)

- Condition generation on additional info **y** (e.g. class label, another image)
- D has to determine if samples are realistic given **y**



[Mirza and Osindero (2014); Gauthier (2014)]

#16: Discrete Variables

- Use an Embedding layer
- Add as additional channels to images
- Keep embedding dimensionality low and upsample to match image channel size

Conclusion

- Model stability is improving
- Theory is improving
- Hacks are a stop-gap

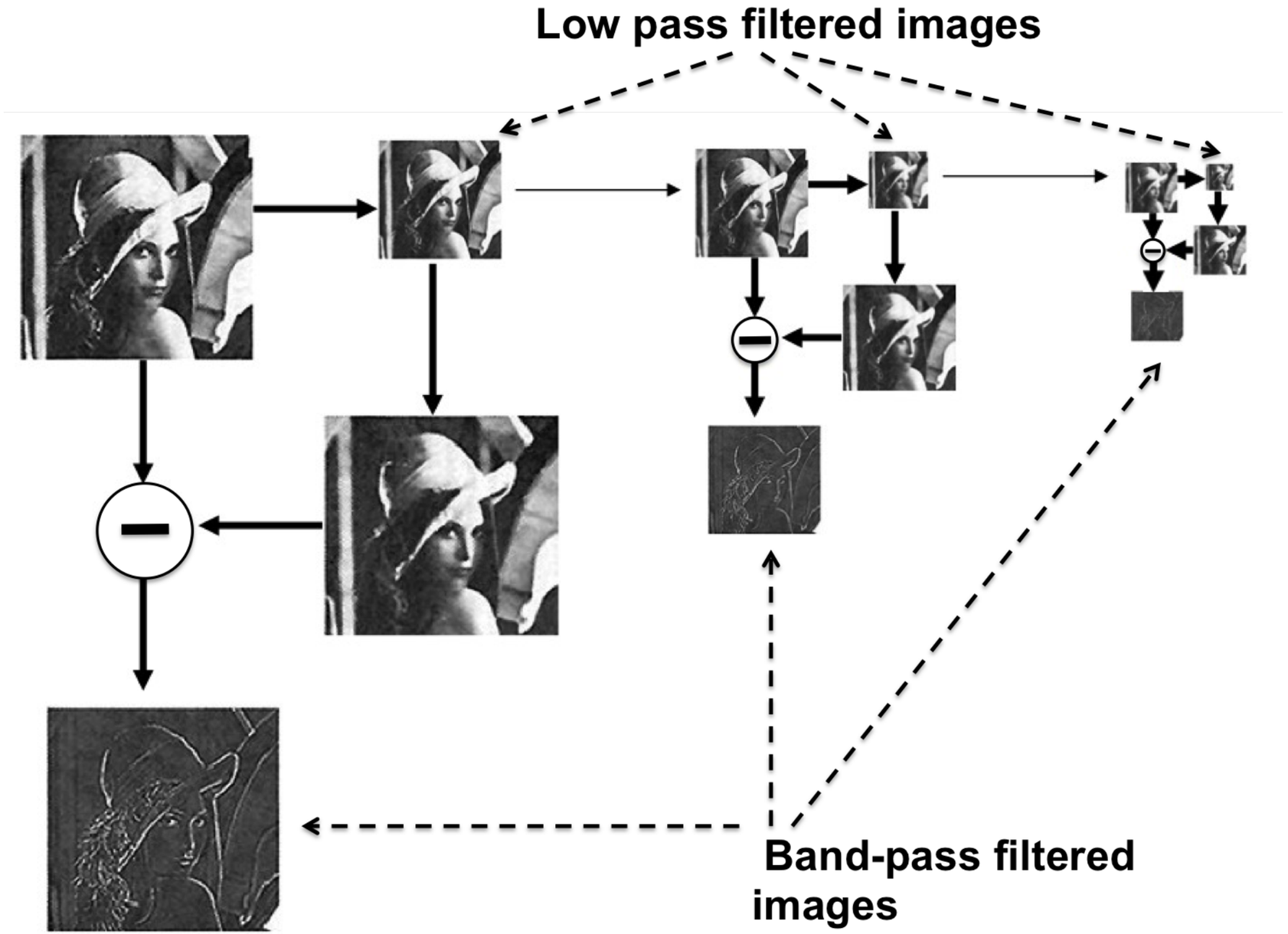
Deep Generative Image Models using a Laplacian Pyramid of Adversarial Networks

Emily Denton[1*], Soumith Chintala[2*],
Arthur Szlam[2], Rob Fergus[2]

[1]New York University
[2]Facebook AI Research
[*]Denotes equal contribution

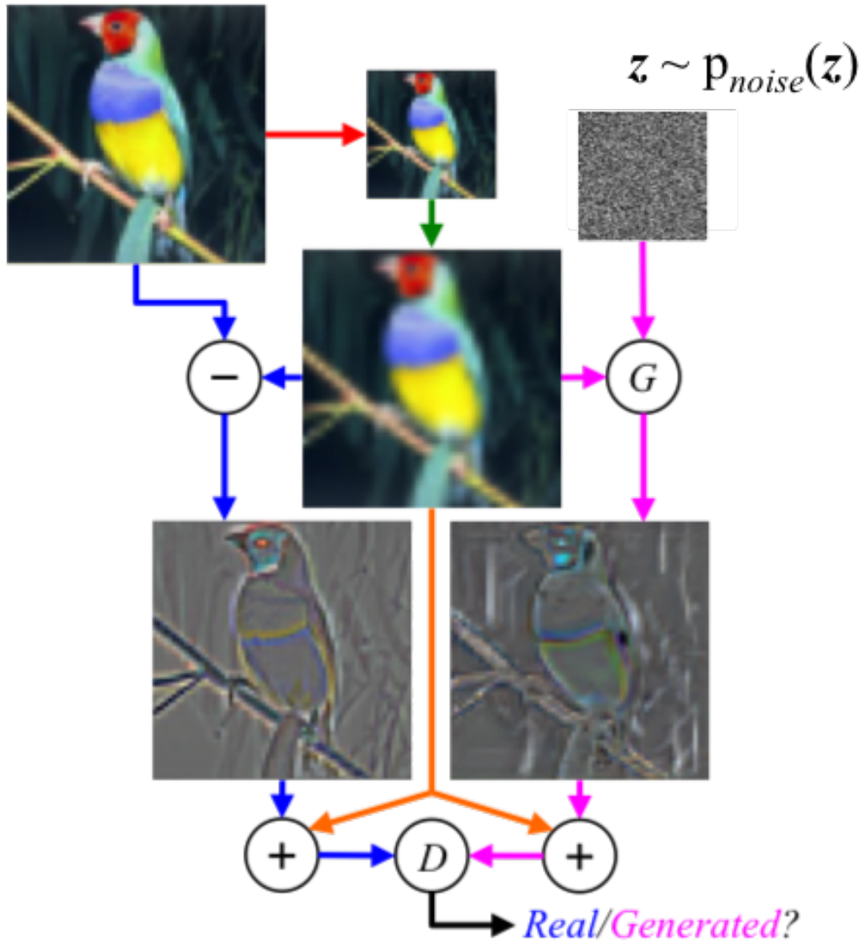
December 16, 2015

Laplacian pyramid (Burt & Adelson, 1983)



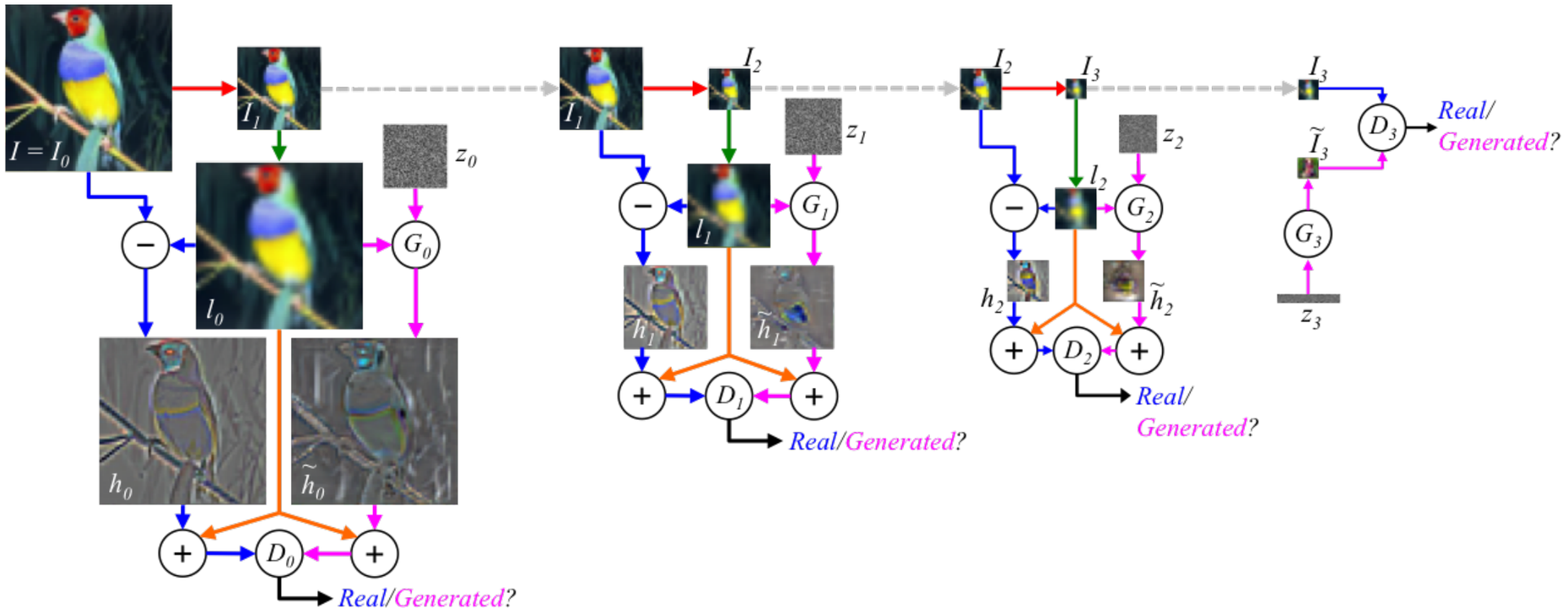
Training procedure

- Train conditional GAN for each level of Laplacian pyramid
- G learns to generate high frequency structure consistent with low frequency image

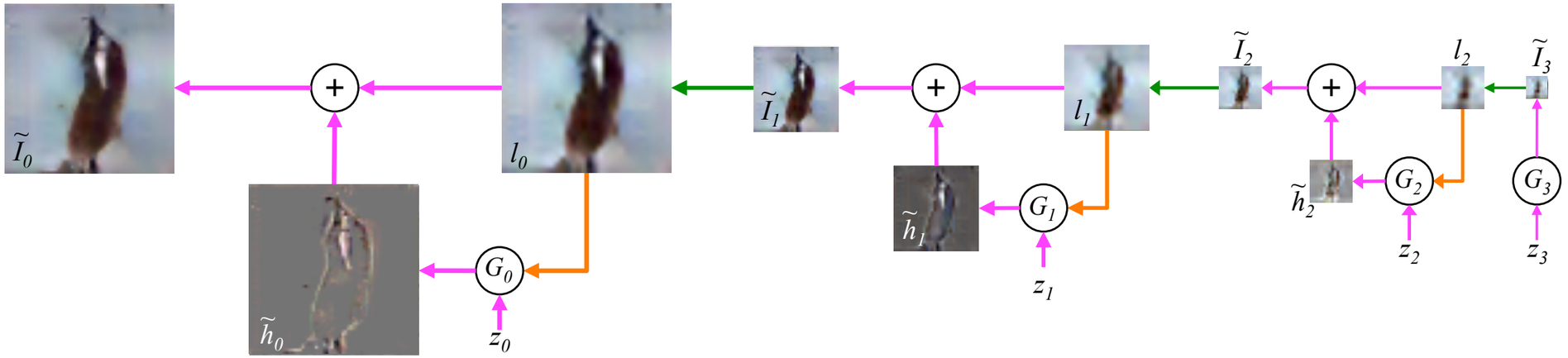


Training procedure

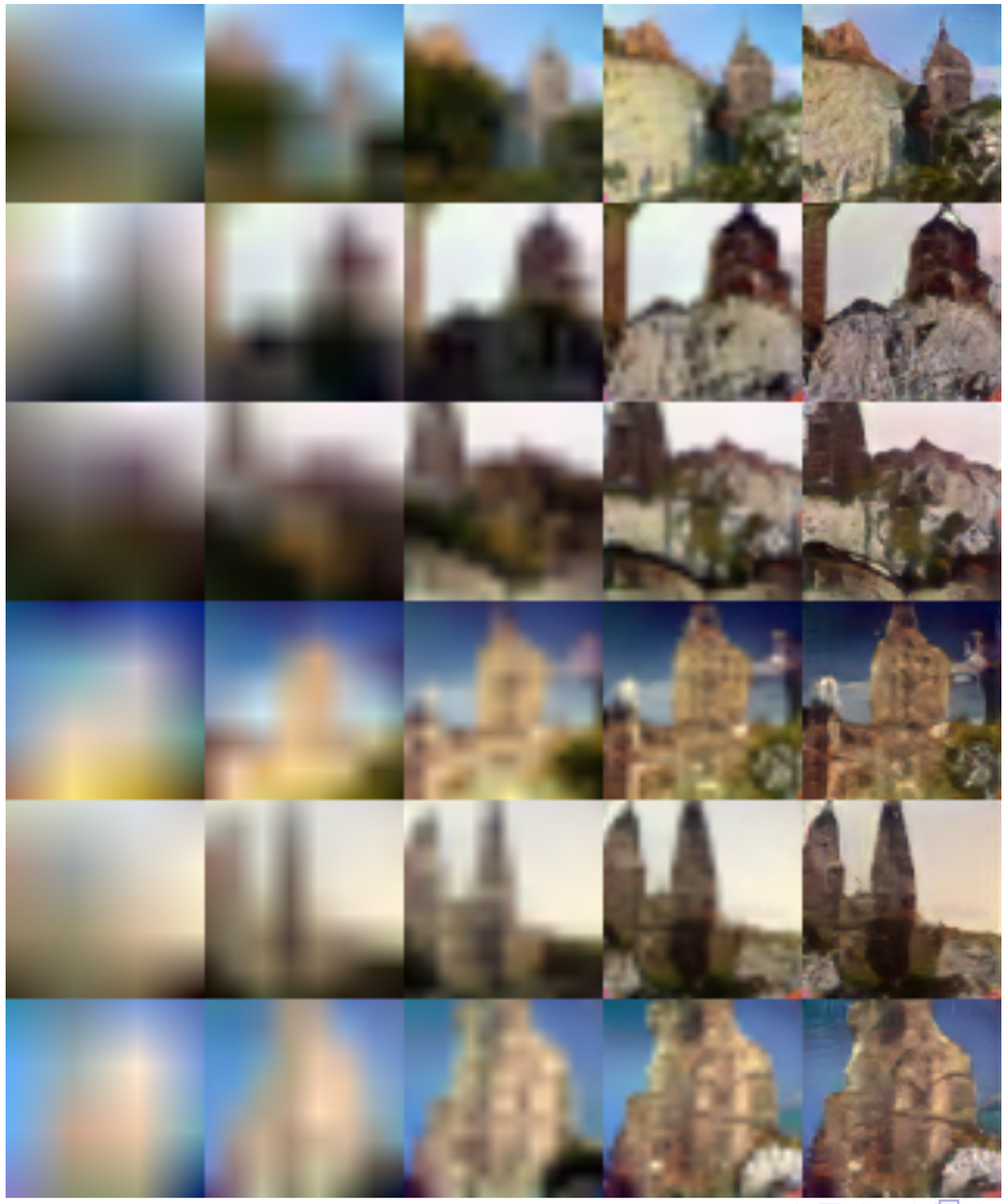
Each level of Laplacian pyramid trained independently



Sampling procedure



LSUN coarse-to-fine chain



LSUN church samples

PROGRESSIVE GROWING OF GANS FOR IMPROVED QUALITY, STABILITY, AND VARIATION

Tero Karras NVIDIA
Timo Aila NVIDIA
Samuli Laine NVIDIA
Jaakko Lehtinen NVIDIA and Aalto University
{tkarras,taila,slaine,jlehtinen}@nvidia.com

ICLR 2018

(Probably) current state-of-art generations

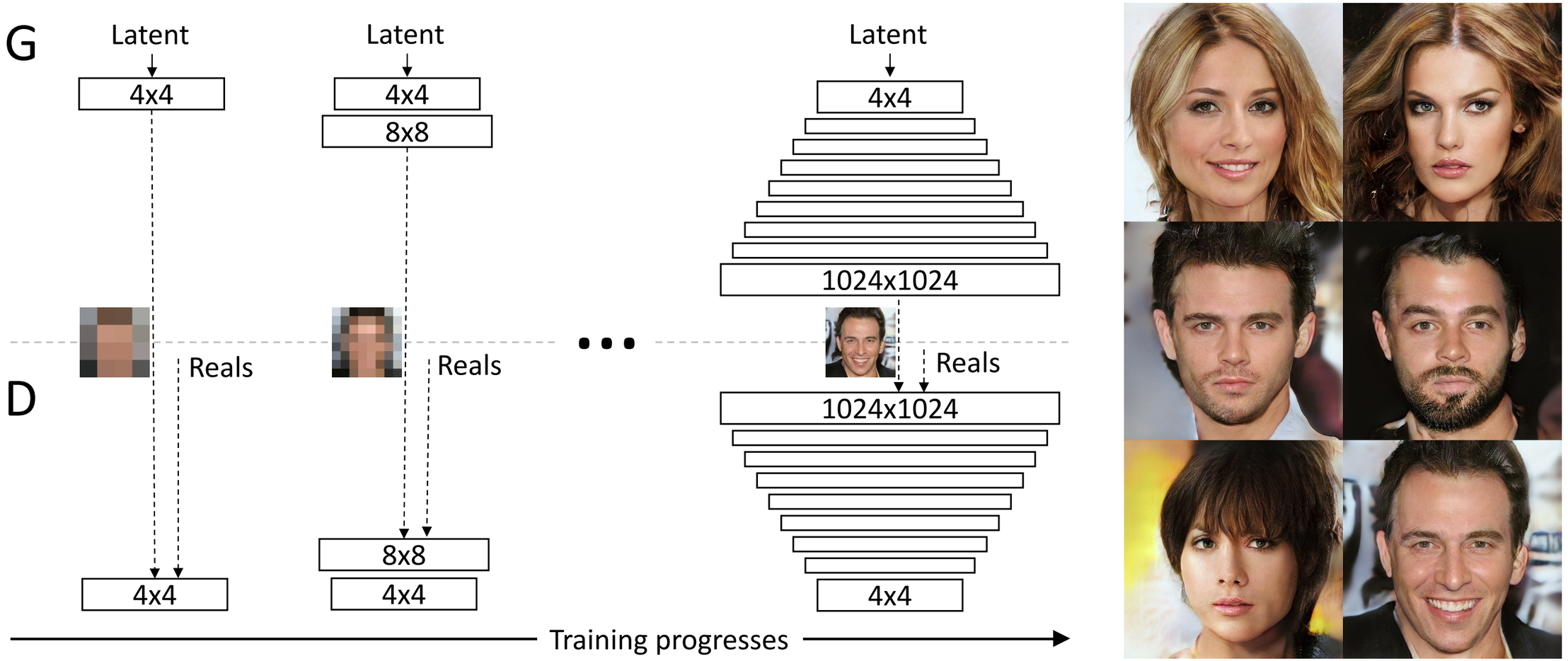
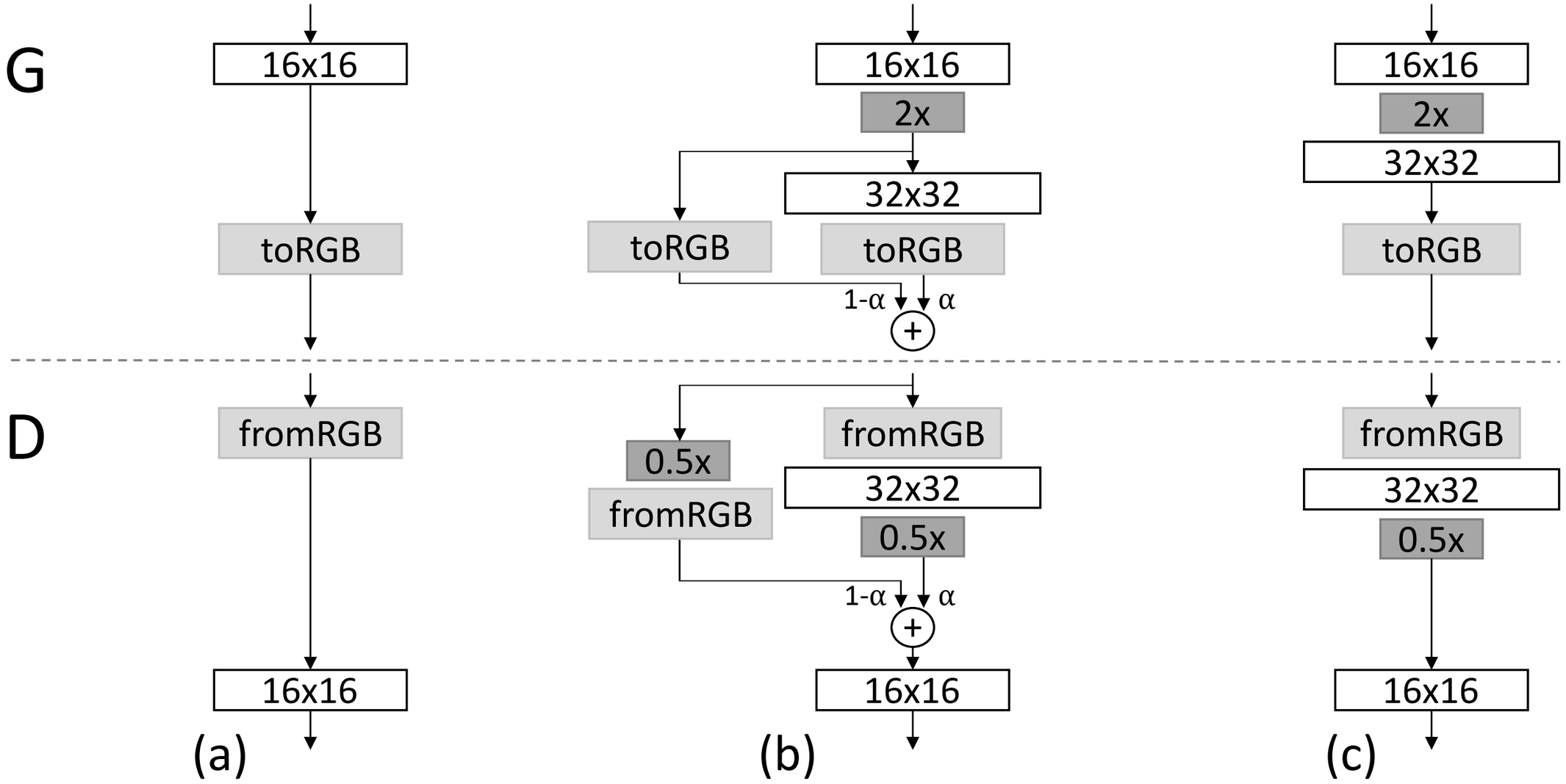


Figure 1: Our training starts with both the generator (G) and discriminator (D) having a low spatial resolution of 4×4 pixels. As the training advances, we incrementally add layers to G and D, thus increasing the spatial resolution of the generated images. All existing layers remain trainable throughout the process. Here $\boxed{N \times N}$ refers to convolutional layers operating on $N \times N$ spatial resolution. This allows stable synthesis in high resolutions and also speeds up training considerably. One the right we show six example images generated using progressive growing at 1024×1024.

Smooth blending with scale increase



Training configuration	CELEBA						LSUN BEDROOM					
	Sliced Wasserstein distance $\times 10^3$					MS-SSIM	Sliced Wasserstein distance $\times 10^3$					MS-SSIM
	128	64	32	16	Avg		128	64	32	16	Avg	
(a) Gulrajani et al. (2017)	12.99	7.79	7.62	8.73	9.28	0.2854	11.97	10.51	8.03	14.48	11.25	**0.0587**
(b) + Progressive growing	4.62	**2.64**	3.78	6.06	4.28	**0.2838**	7.09	6.27	7.40	9.64	7.60	0.0615
(c) + Small minibatch	75.42	41.33	41.62	26.57	46.23	0.4065	72.73	40.16	42.75	42.46	49.52	0.1061
(d) + Revised training parameters	9.20	6.53	4.71	11.84	8.07	0.3027	7.39	5.51	3.65	9.63	6.54	0.0662
(e*) + Minibatch discrimination	10.76	6.28	6.04	16.29	9.84	0.3057	10.29	6.22	5.32	11.88	8.43	0.0648
(e) Minibatch stddev	13.94	5.67	2.82	5.71	7.04	0.2950	7.77	5.23	3.27	9.64	6.48	0.0671
(f) + Equalized learning rate	4.42	3.28	2.32	7.52	4.39	0.2902	**3.61**	3.32	**2.71**	6.44	4.02	0.0668
(g) + Pixelwise normalization	**4.06**	3.04	**2.02**	**5.13**	**3.56**	0.2845	3.89	**3.05**	3.24	**5.87**	**4.01**	0.0640
(h) Converged	2.42	2.17	2.24	4.99	2.96	0.2828	3.47	2.60	2.30	4.87	3.31	0.0636

Table 1: Sliced Wasserstein distance (SWD) between the generated and training images (Section 5) and multi-scale structural similarity (MS-SSIM) among the generated images for several training setups at 128×128. For SWD, each column represents one level of the Laplacian pyramid, and the last one gives an average of the four distances.

(a) (b) (c) (d) (e∗) (e) (f) (g) (h) Converged

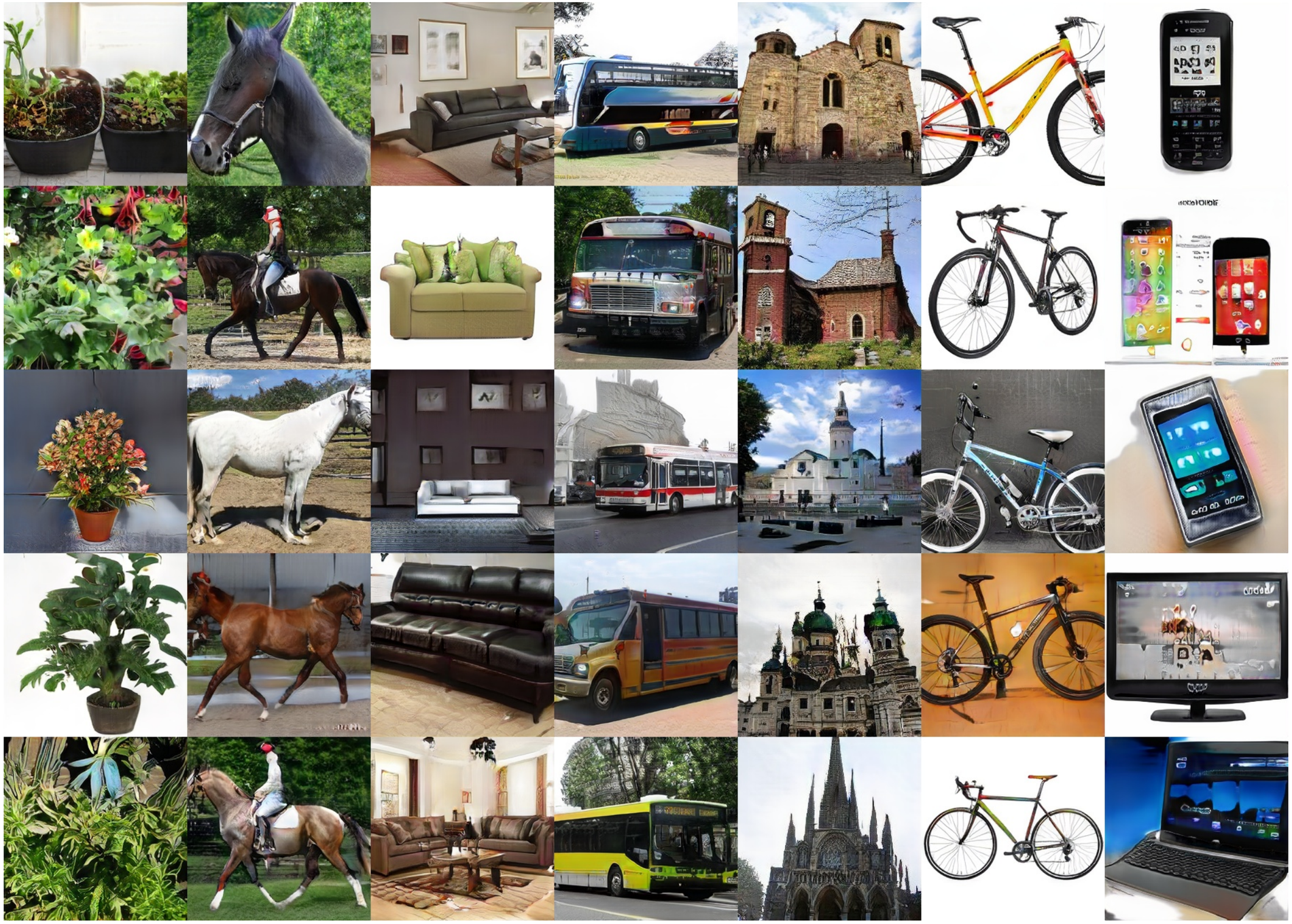
Figure 3: (a) – (g) CELEBA examples corresponding to rows in Table 1. These are intentionally non-converged. (h) Our converged result. Notice that some images show aliasing and some are not sharp – this is a flaw of the dataset, which the model learns to replicate faithfully.

Figure 5: 1024×1024 images generated using the CELEBA-HQ dataset. See Appendix F for a

Mao et al. (2016b) (128 × 128)

Gulrajani et al. (2017) (128 × 128)

Our (256 × 256)



POTTEDPLANT HORSE SOFA BUS CHURCHOUTDOOR BICYCLE TVMONITOR

Nearest-Neighbor Sanity Check

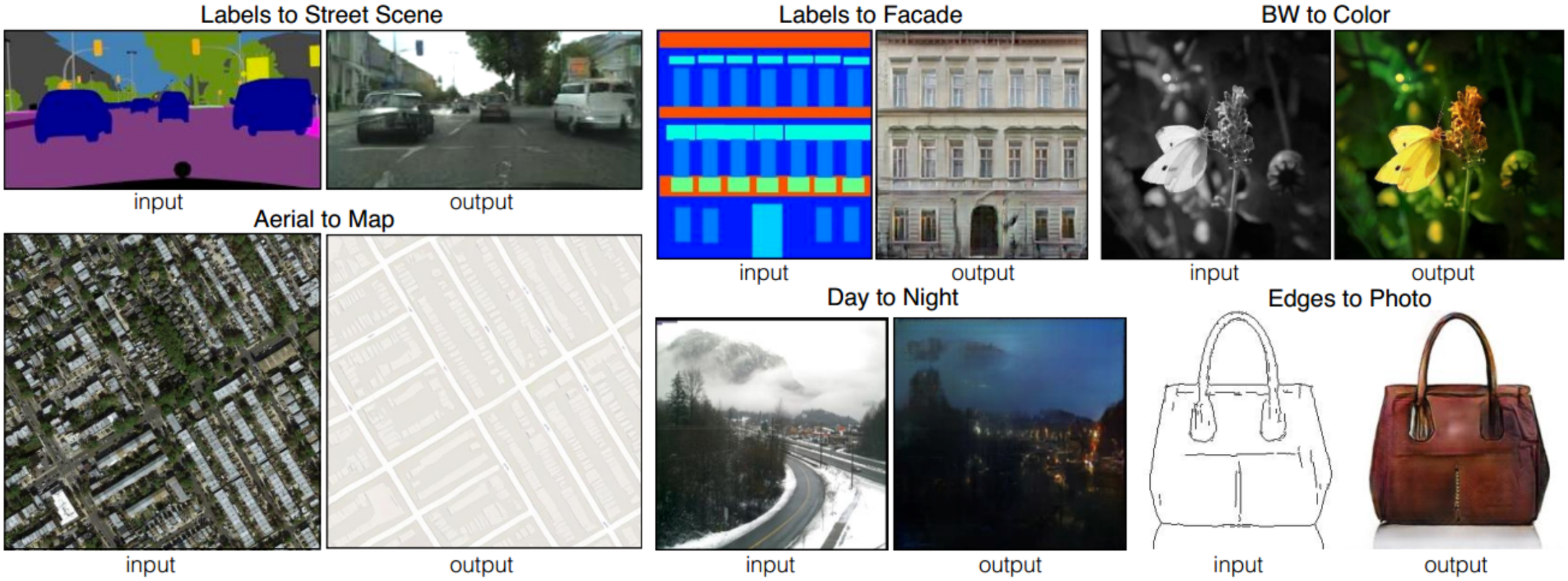
Unpaired Image-to-Image Translation with CycleGAN

Jun-Yan Zhu and Taesung Park
Joint work with Phillip Isola and Alexei A. Efros

BAIR
BERKELEY ARTIFICIAL INTELLIGENCE RESEARCH

CSAIL

Image-to-Image Translation with **pix2pix**



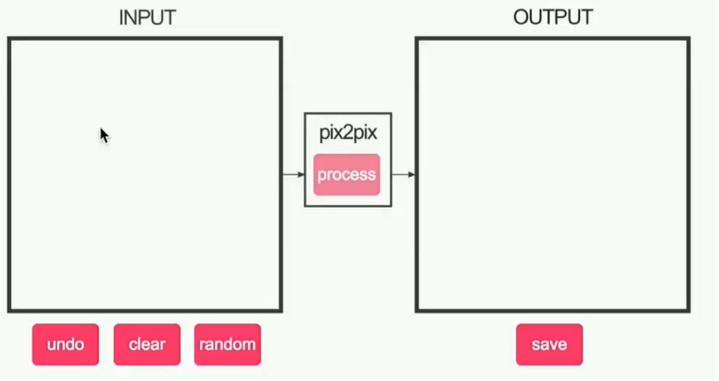
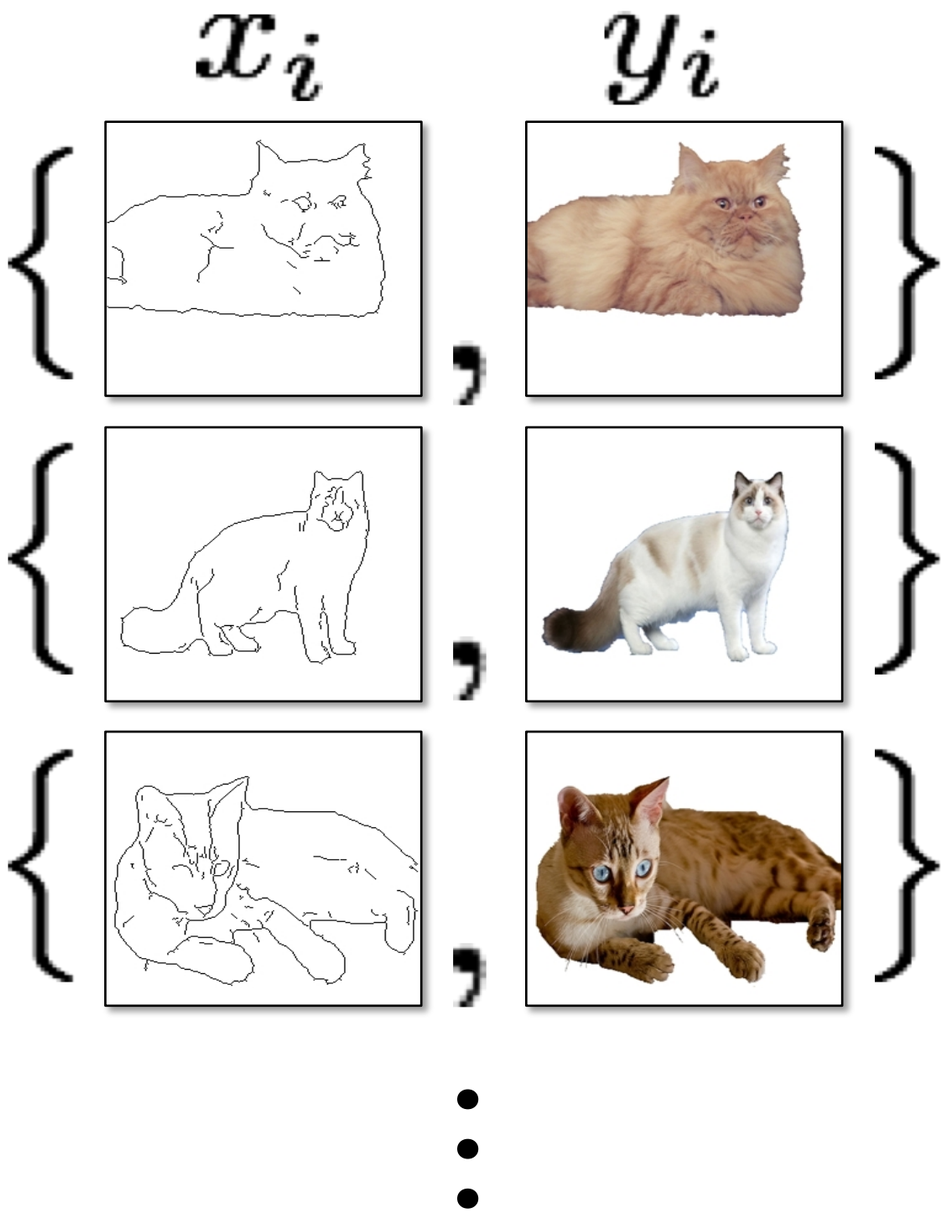
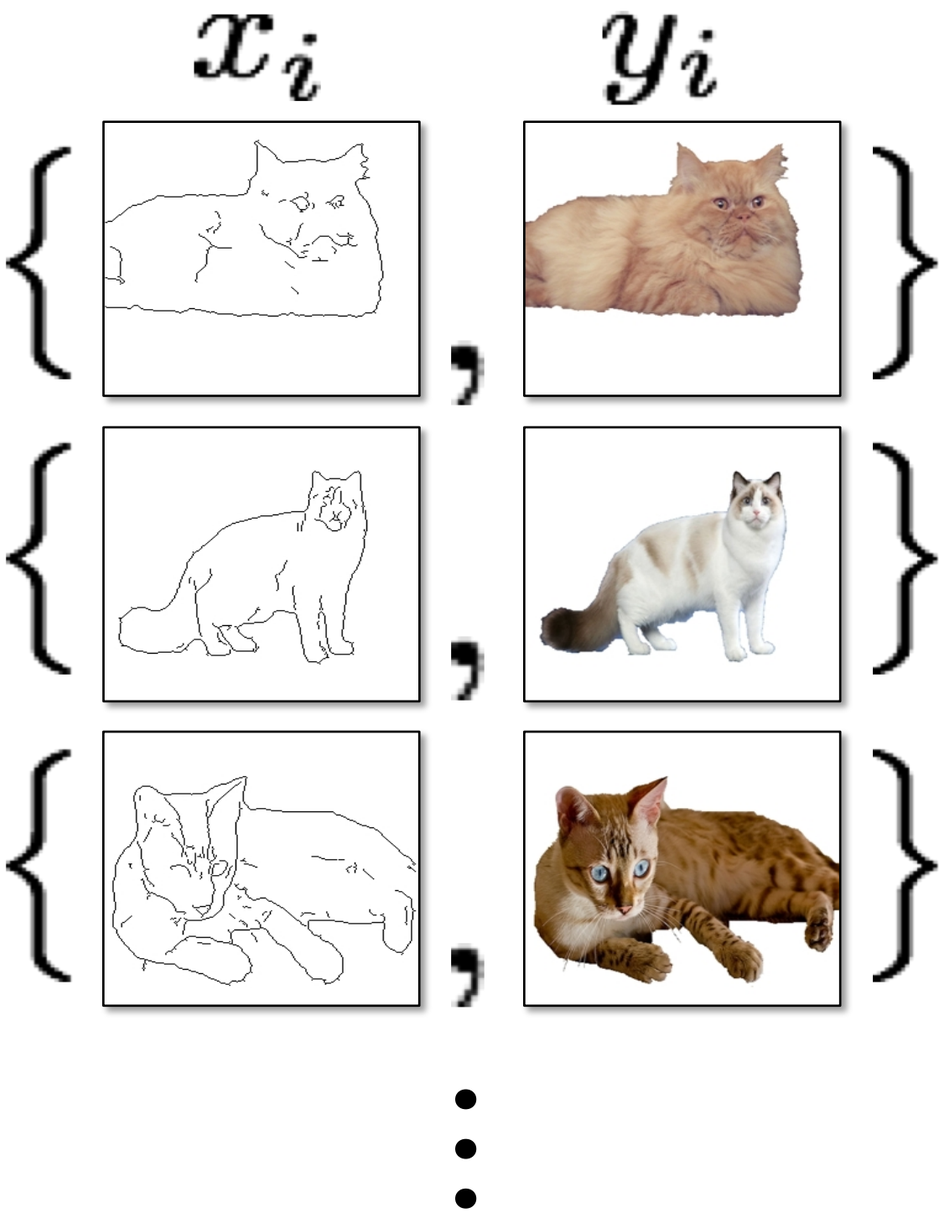


Image-to-image Translation with Conditional Adversarial Nets
Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, Alexei A. Efros. CVPR 2017

Paired



Paired

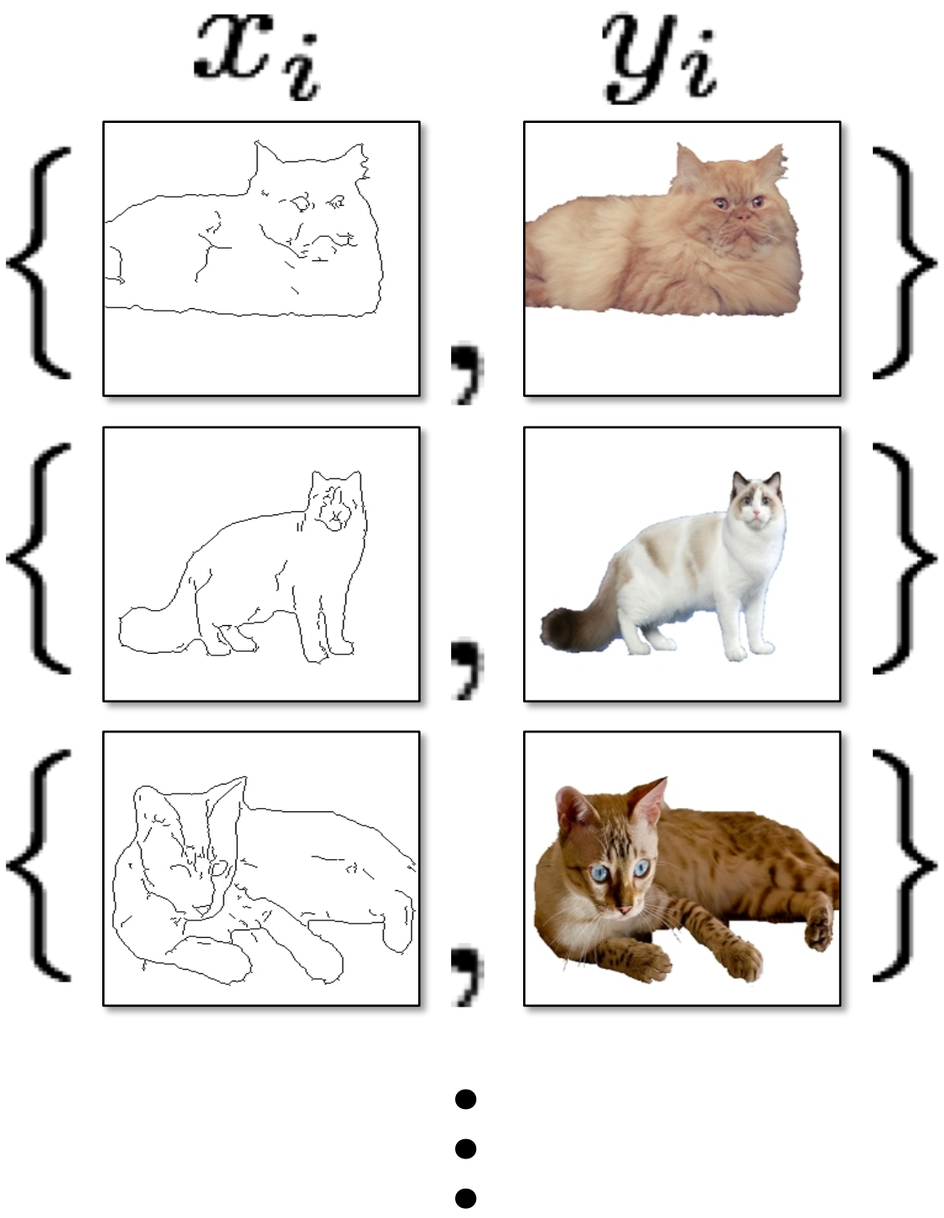


Label ↔ photo: per-pixel labeling

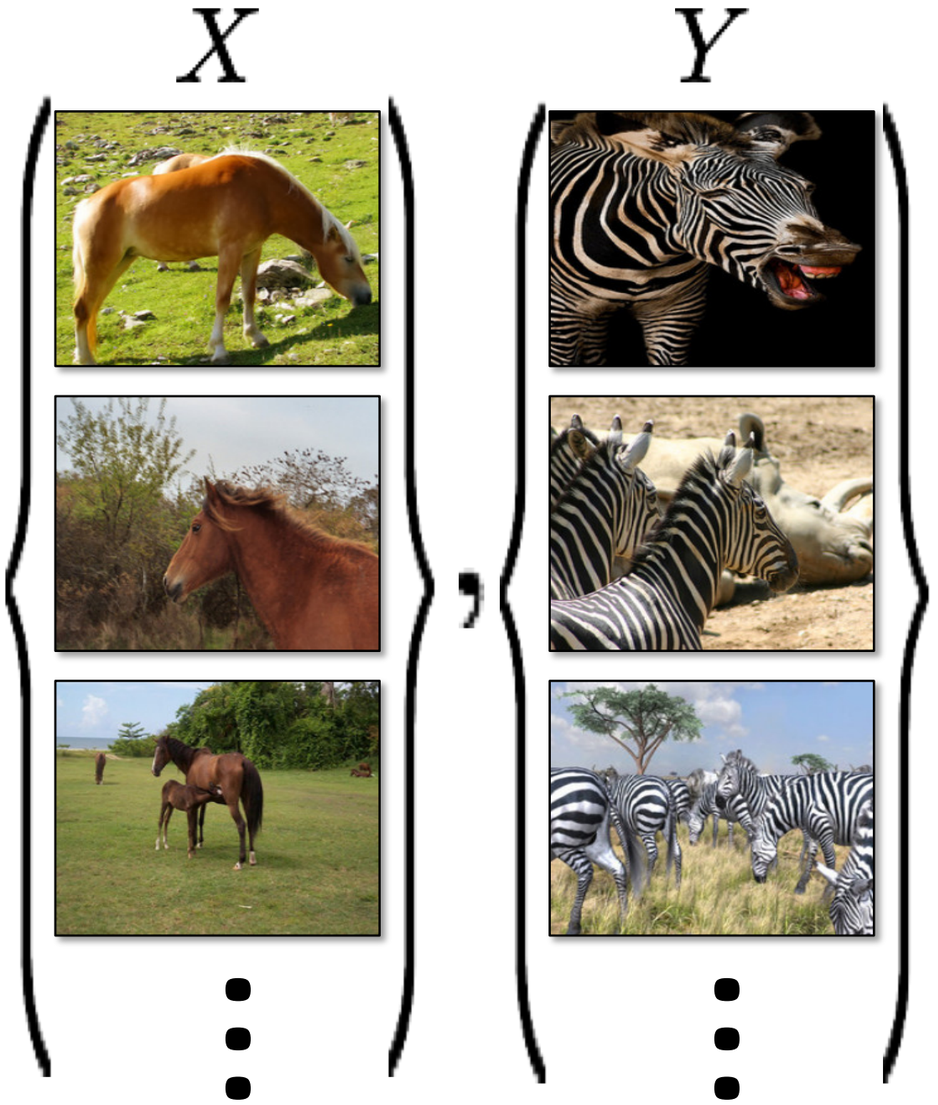
Horse ↔ zebra: how to get zebras?

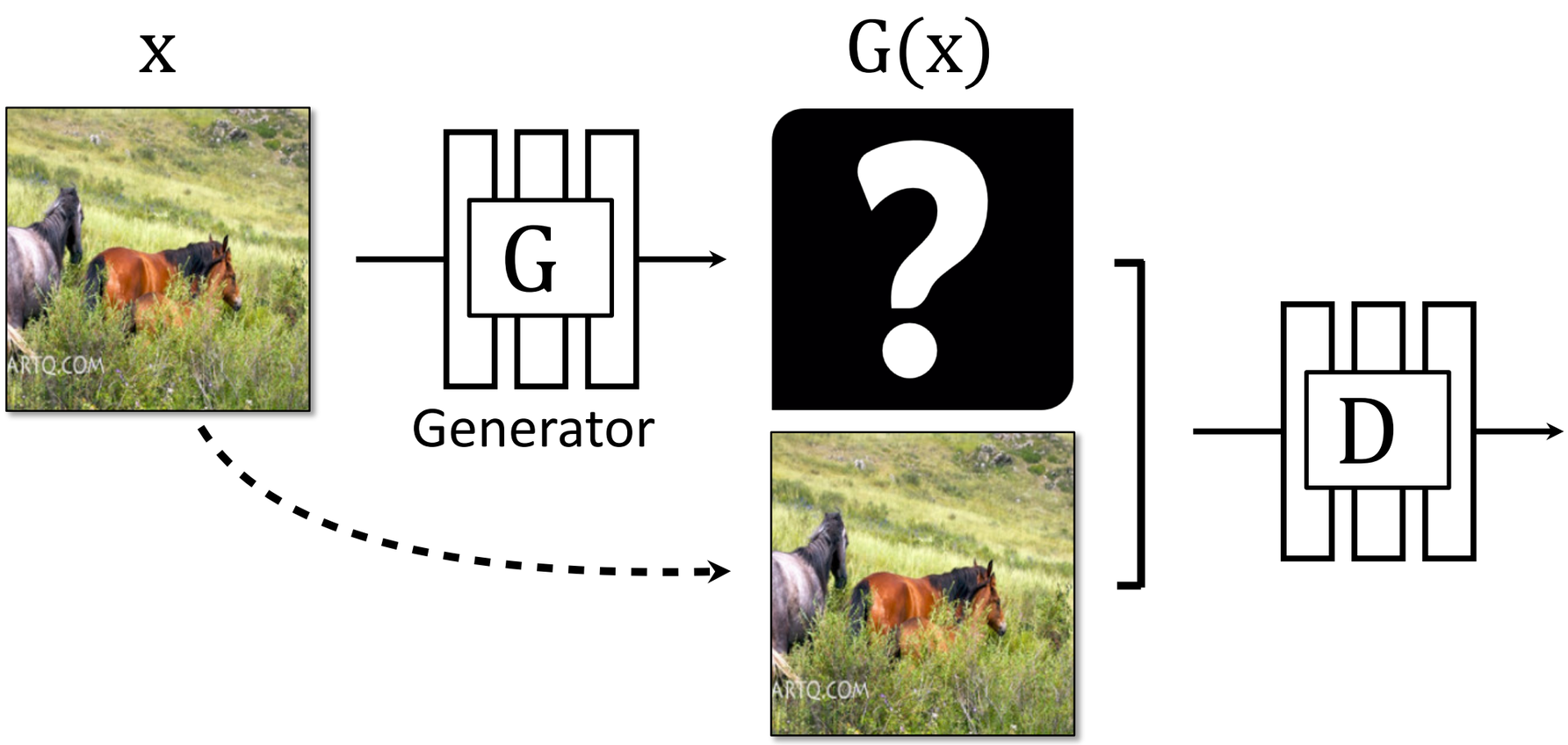
- Expensive to collect pairs.
- Impossible in many scenarios.

Paired



Unpaired





No input-output pairs!

x

G

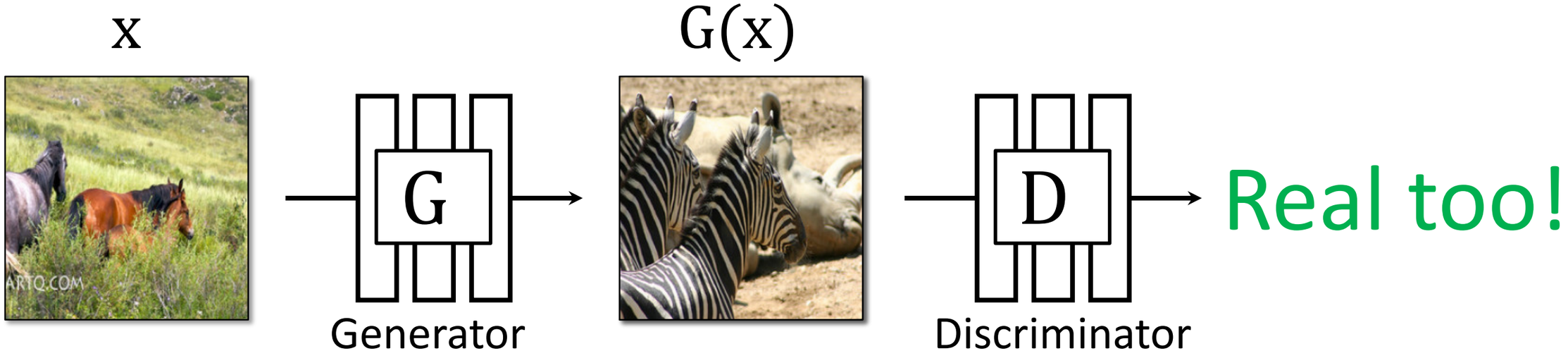
Generator

G(x)

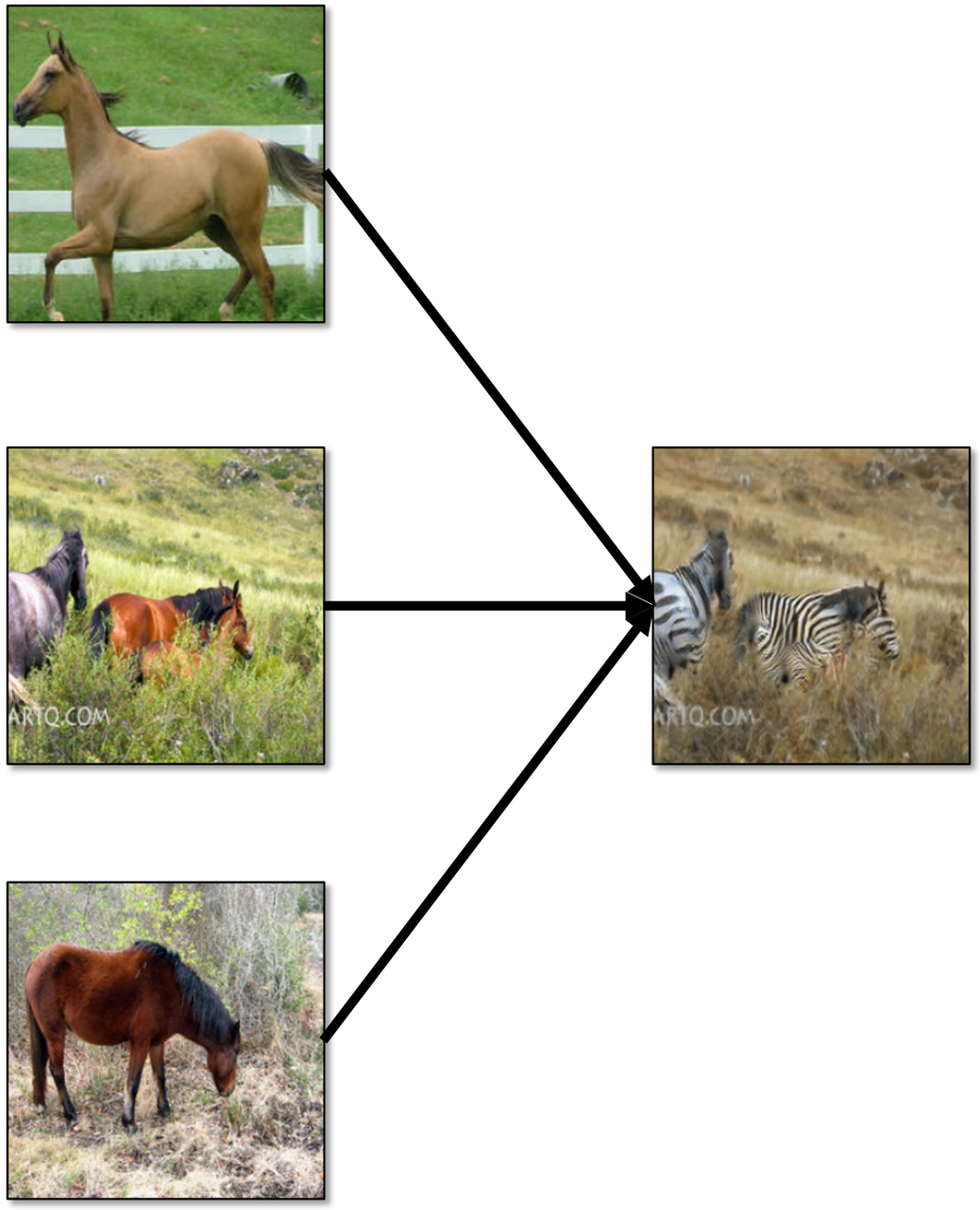
D

Discriminator

Real!

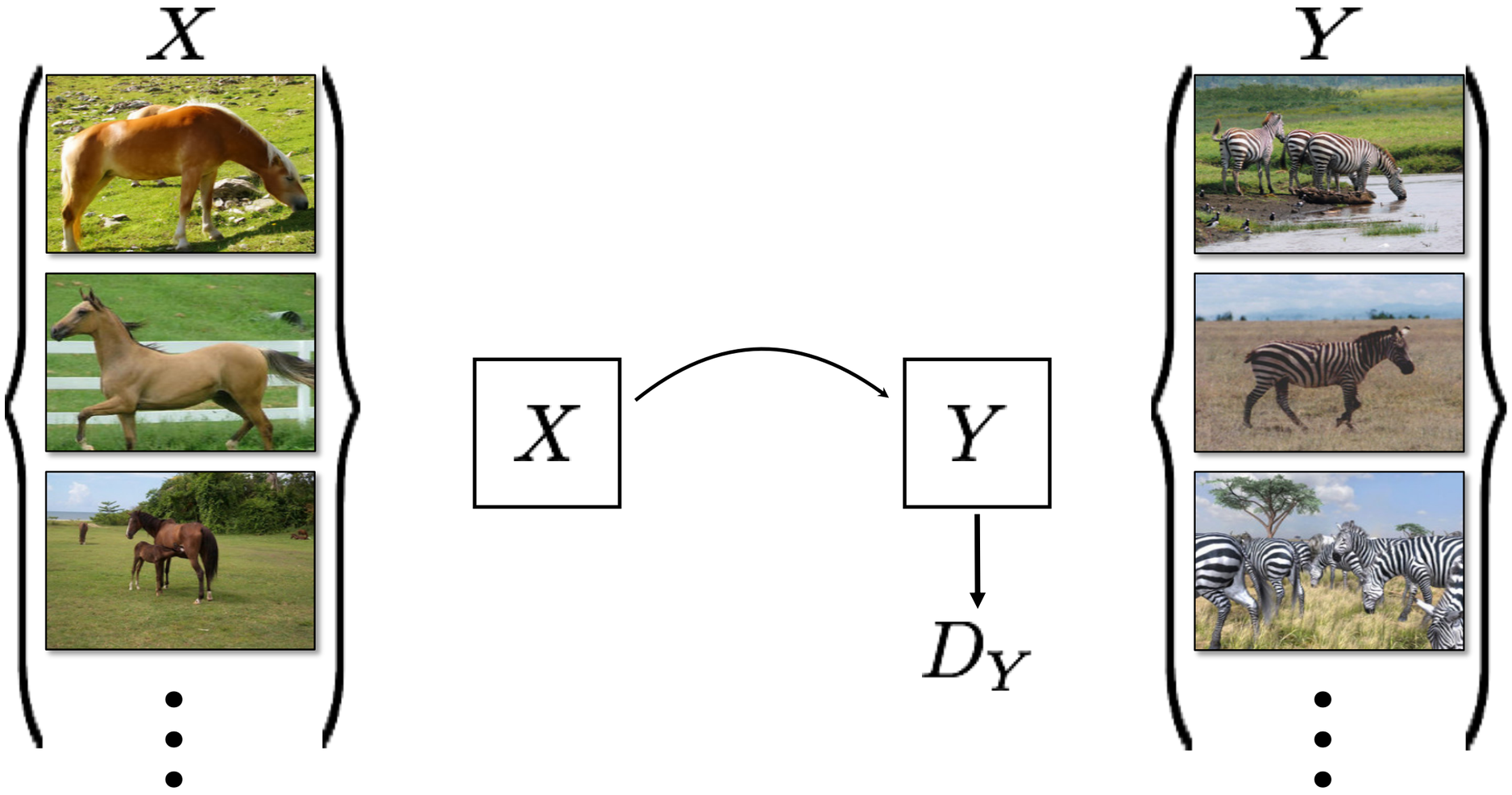


GANs do **not** force output to correspond to input



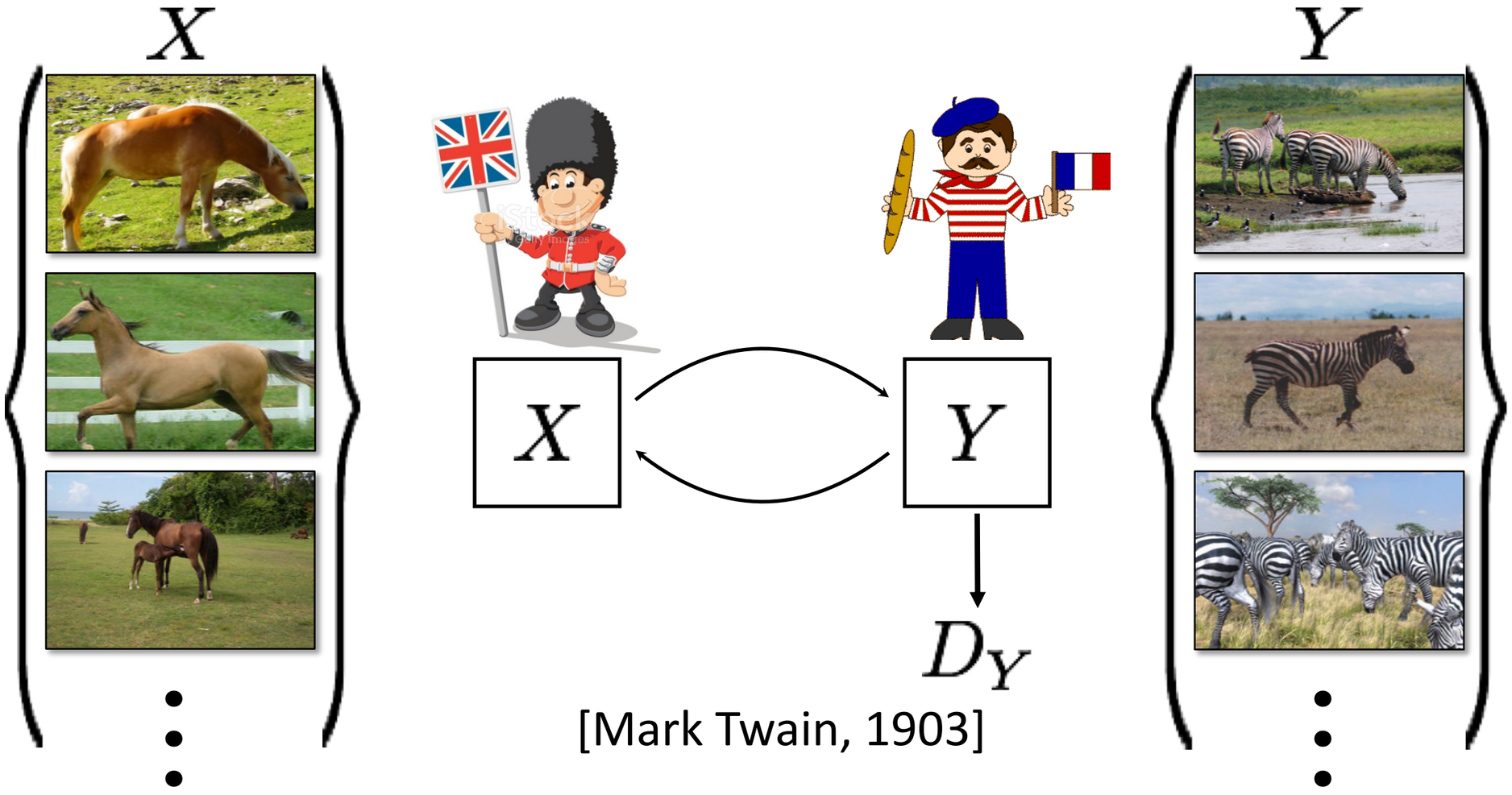
mode collapse!

Cycle-Consistent Adversarial Networks



[Zhu*, Park*, Isola, and Efros, ICCV 2017]

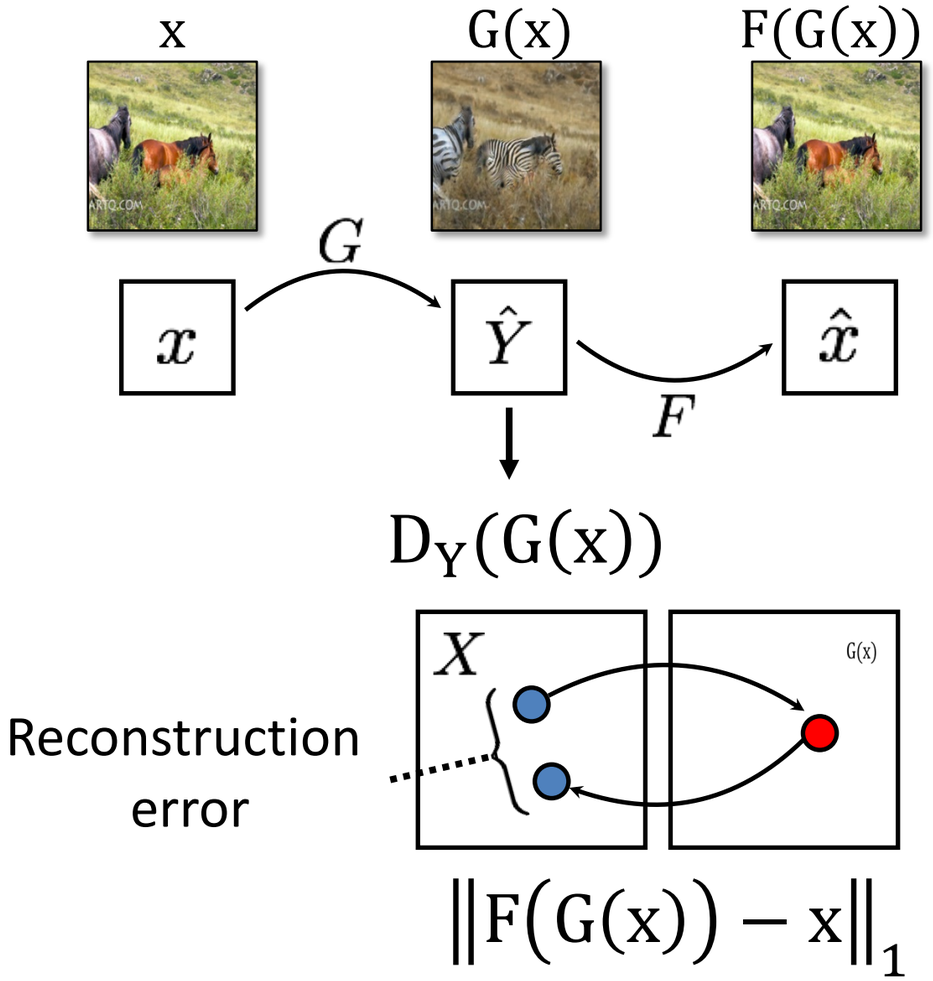
Cycle-Consistent Adversarial Networks



[Mark Twain, 1903]

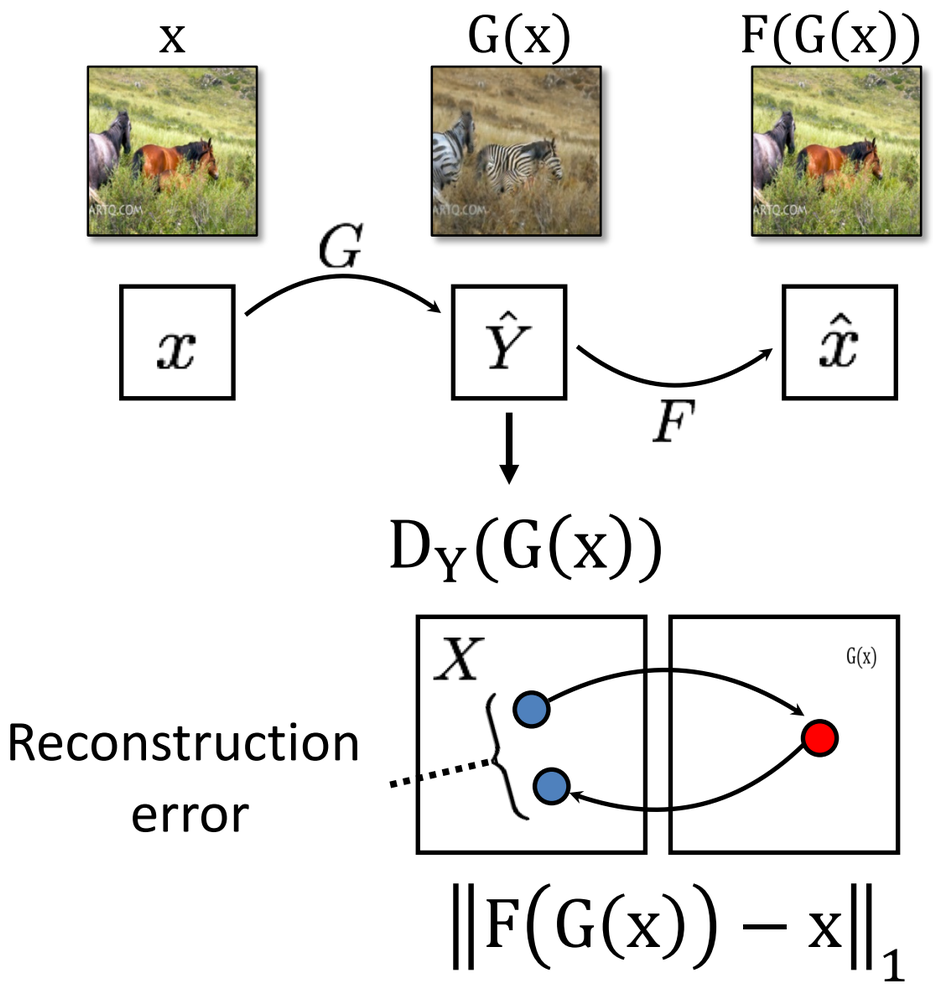
[Zhu*, Park*, Isola, and Efros, ICCV 2017]

Cycle-Consistent Adversarial Networks

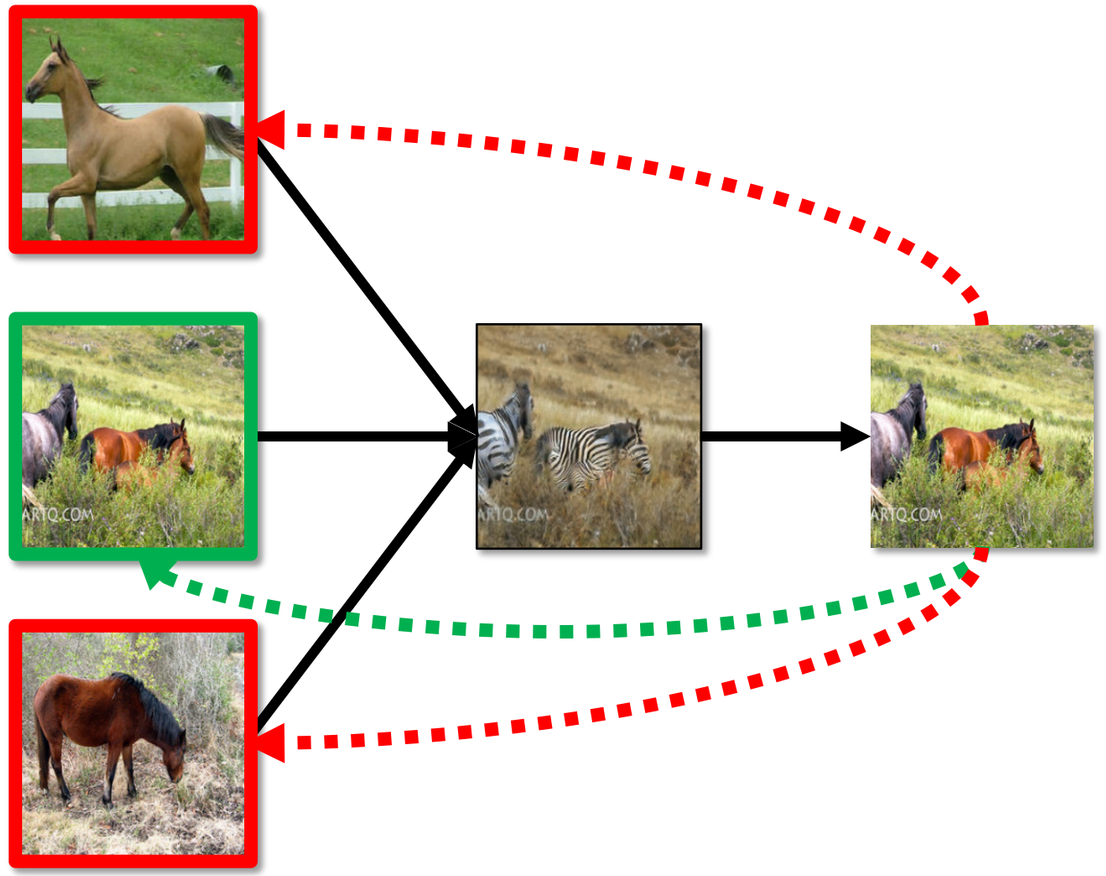


[Zhu*, Park*, Isola, and Efros, ICCV 2017]

Cycle Consistency Loss

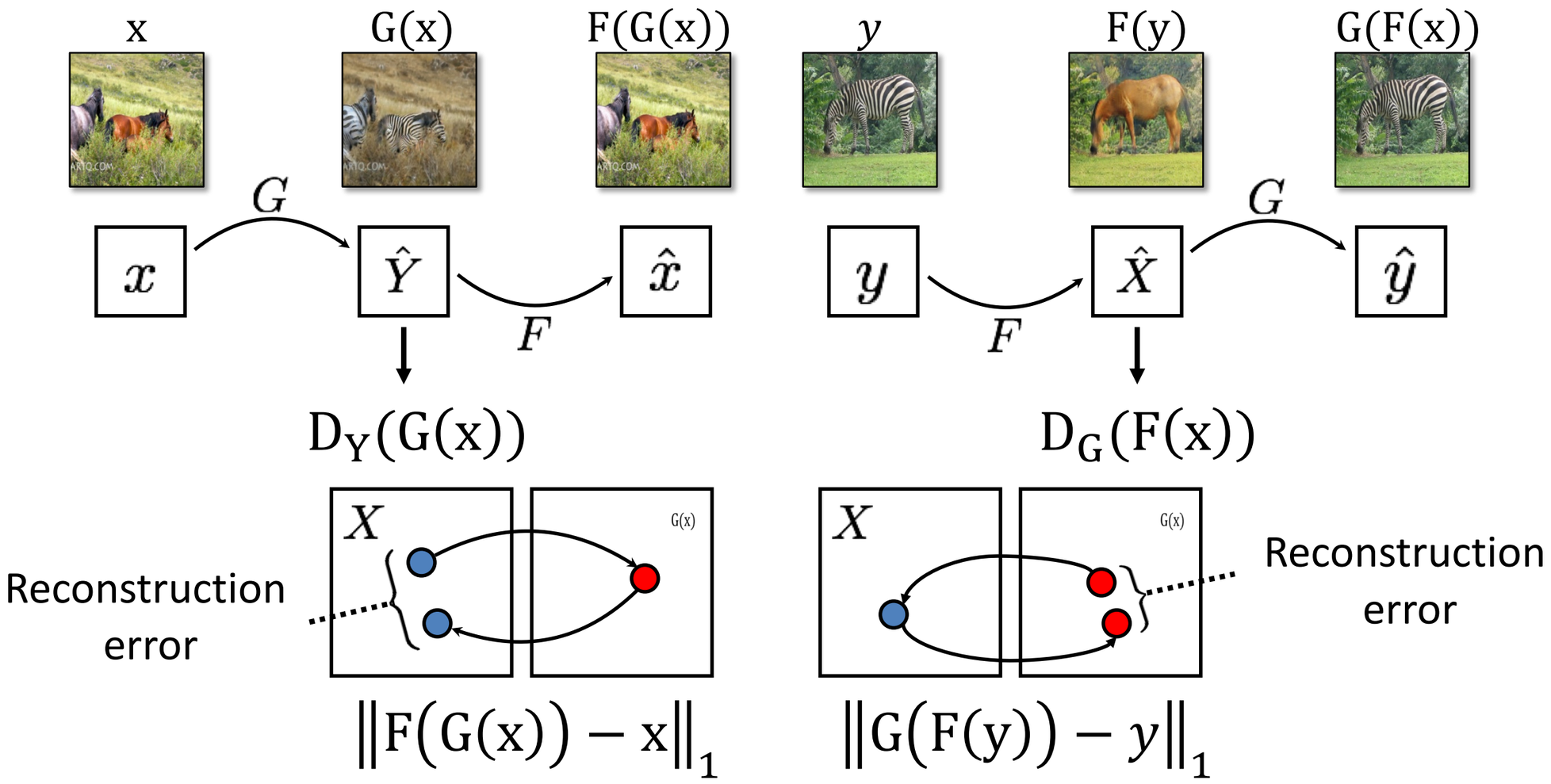


Small cycle loss



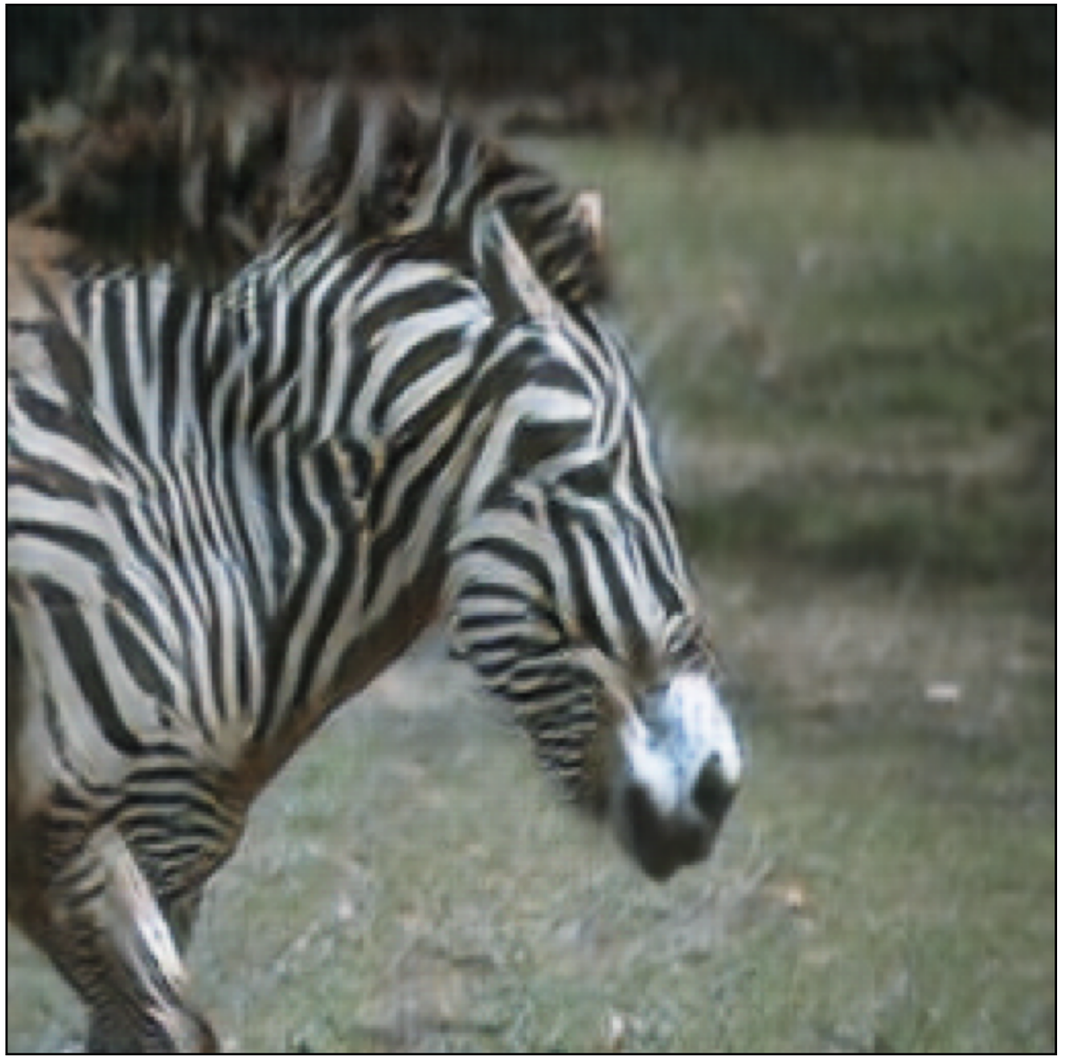
[Zhu*, Park*, Isola, and Efros, ICCV 2017]

Cycle Consistency Loss



See similar formulations [Yi et al. 2017], [Kim et al. 2017] [Zhu*, Park*, Isola, and Efros, ICCV 2017]

Results



Collection Style Transfer

Photograph
@ Alexei Efros

Monet

Van Gogh

Cezanne

Ukiyo-e


Input
Monet
Van Gogh
Cezanne
Ukiyo-e

Monet’s paintings → photos

Monet’s paintings → photos

Loss	Map → Photo % Turkers labeled *real*	Photo → Map % Turkers labeled *real*
CoGAN [30]	0.6% ± 0.5%	0.9% ± 0.5%
BiGAN/ALI [8, 6]	2.1% ± 1.0%	1.9% ± 0.9%
SimGAN [45]	0.7% ± 0.5%	2.6% ± 1.1%
Feature loss + GAN	1.2% ± 0.6%	0.3% ± 0.2%
CycleGAN (ours)	**26.8% ± 2.8%**	**23.2% ± 3.4%**

AMT ‘real vs fake’ test on maps ↔ aerial

Loss	Per-pixel acc.	Per-class acc.	Class IOU
CoGAN [30]	0.40	0.10	0.06
BiGAN/ALI [8, 6]	0.19	0.06	0.02
SimGAN [45]	0.20	0.10	0.04
Feature loss + GAN	0.06	0.04	0.01
CycleGAN (ours)	**0.52**	**0.17**	**0.11**

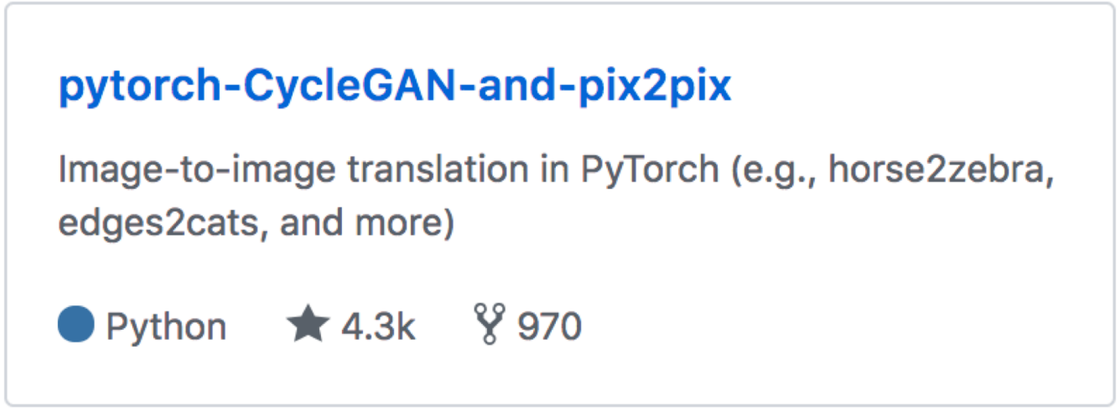
FCN scores on cityscapes labels→ photos

Loss	Per-pixel acc.	Per-class acc.	Class IOU
CoGAN [30]	0.45	0.11	0.08
BiGAN/ALI [8, 6]	0.41	0.13	0.07
SimGAN [45]	0.47	0.11	0.07
Feature loss + GAN	0.50	0.10	0.06
CycleGAN (ours)	**0.58**	**0.22**	**0.16**

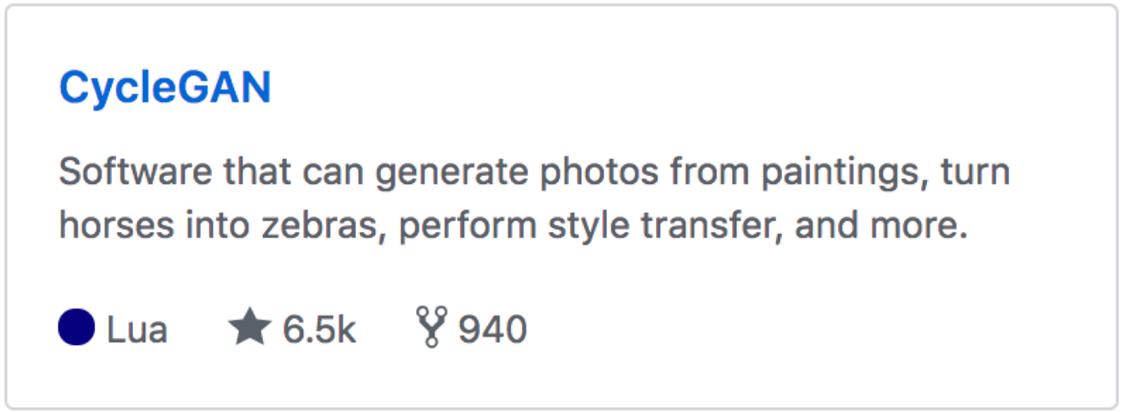
Classification performance of photo→labels

CycleGAN implementations

PyTorch



Torch



20+ implementations by researchers/developers:

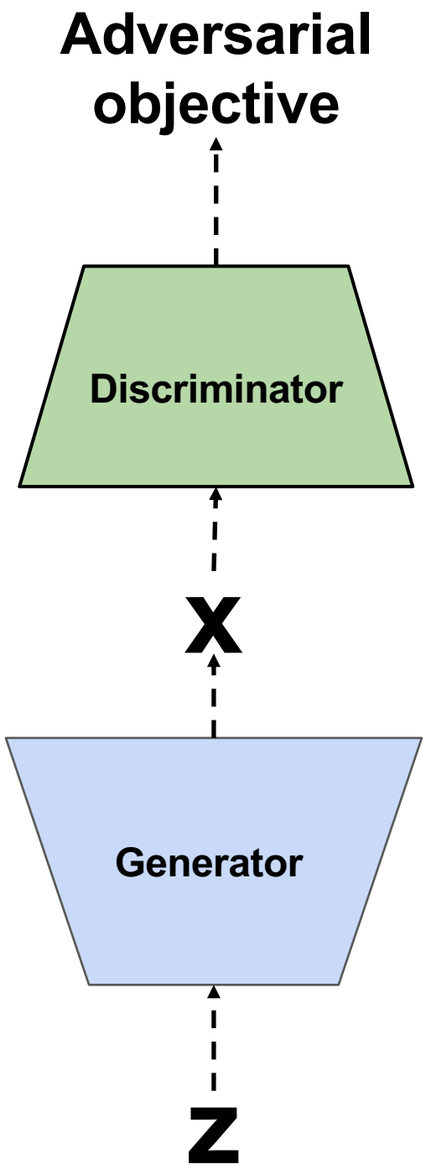
- Tensorflow, Chainer, mxnet, Lasagne, Keras…

Disentangling Content and Pose with an Adversarial loss

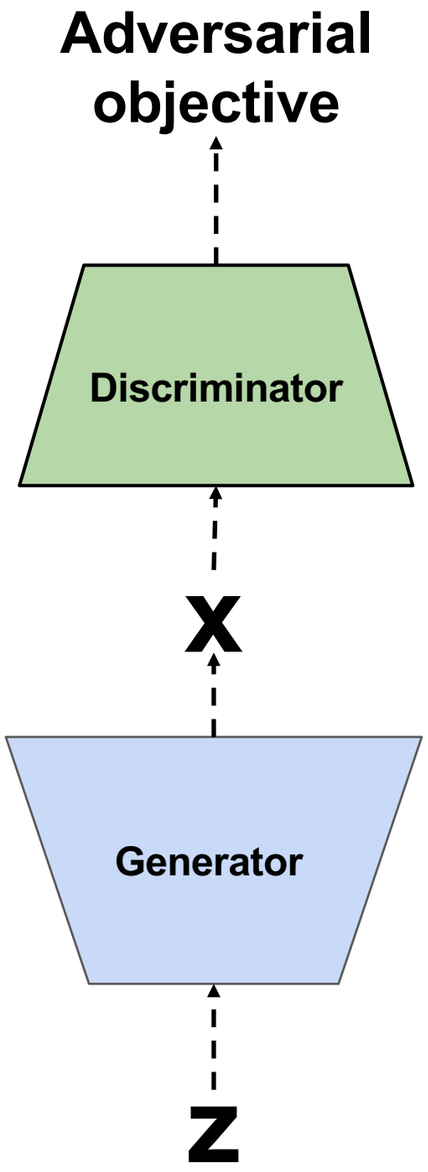
Emily Denton

CVPR GAN Tutorial
June 2018

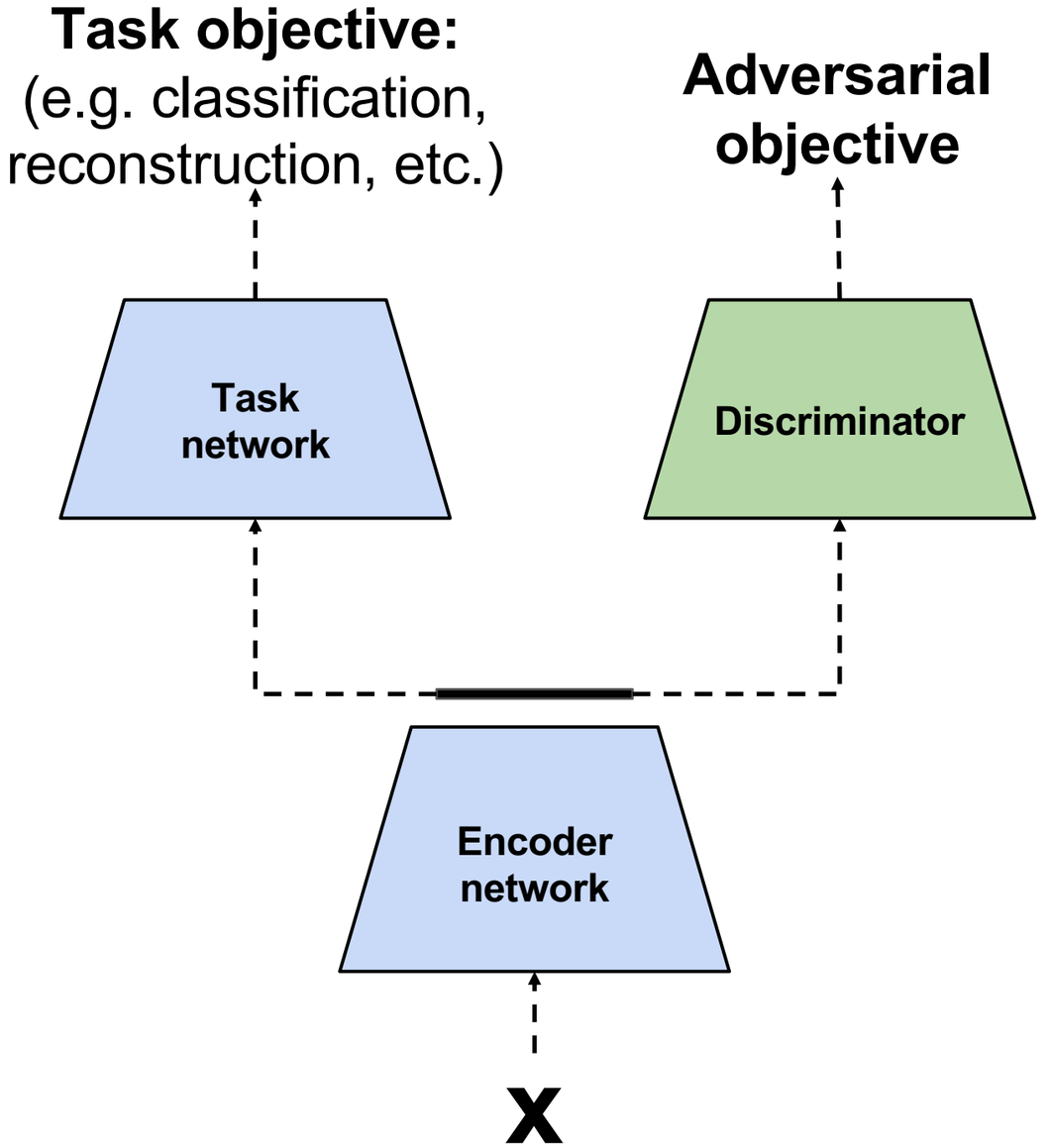
Generative adversarial network framework:



Generative adversarial network framework:

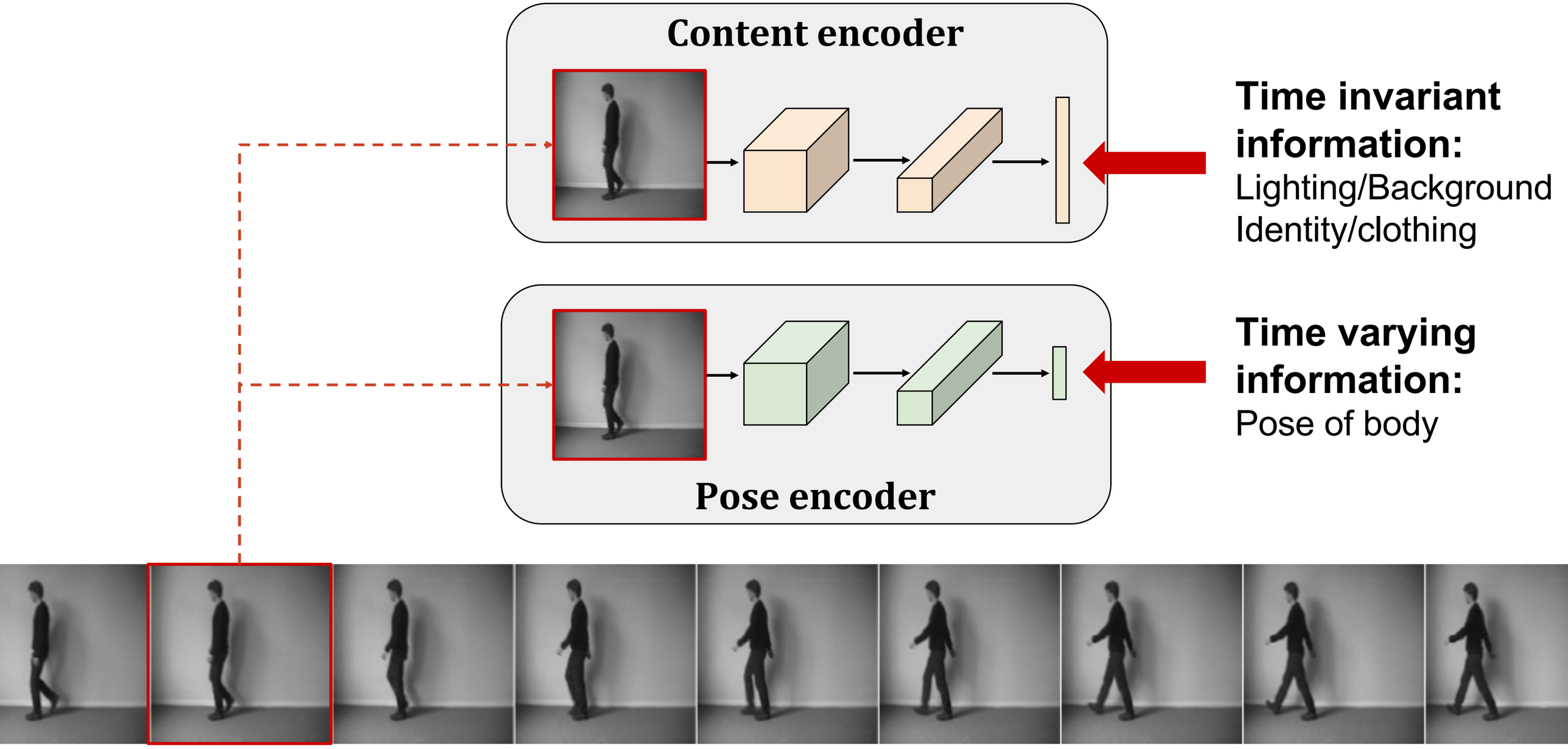


Adversarial losses to shape representations:



DrNet: two seperate encoders

Denton and Birodkar. *Unsupervised Learning of Disentangled Representations from Video*. NIPS, 2017



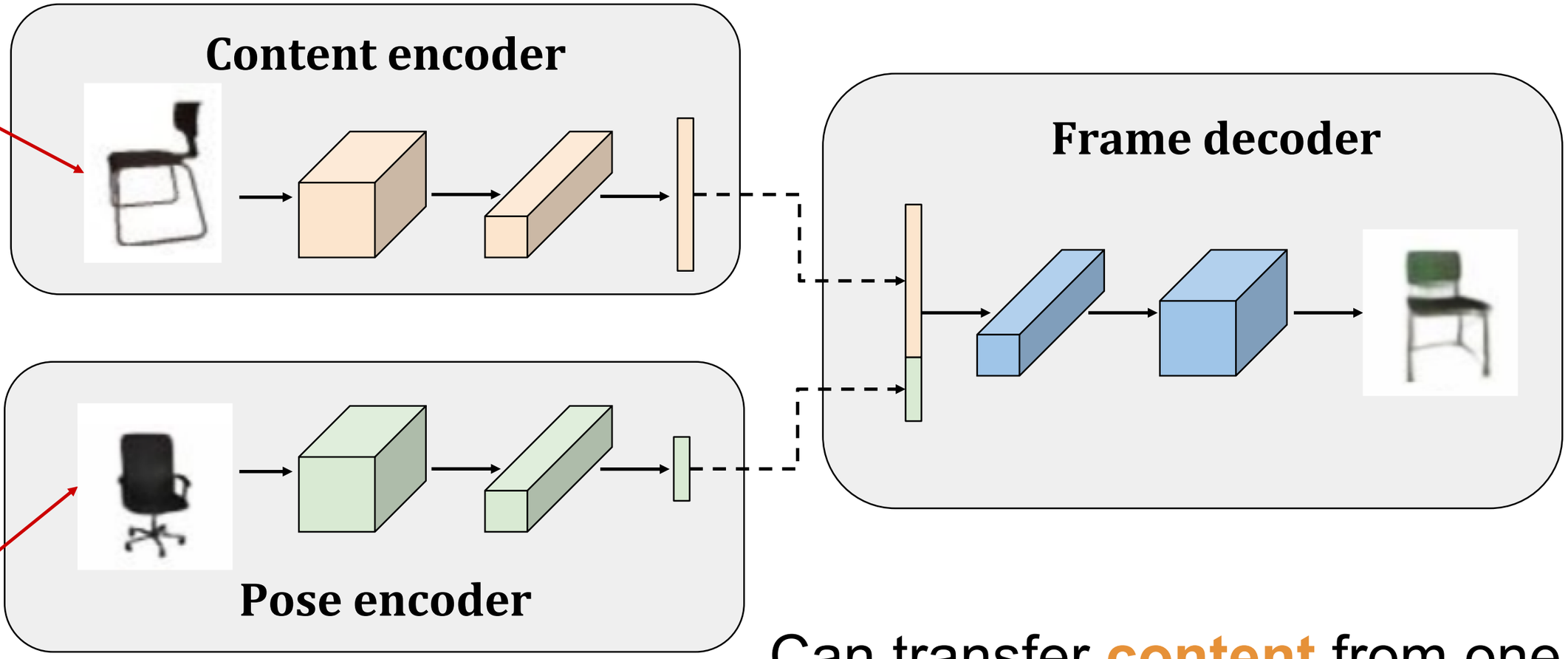
Time invariant information:
Lighting/Background
Identity/clothing

Time varying information:
Pose of body

Image synthesis by analogy

Denton and Birodkar. *Unsupervised Learning of Disentangled Representations from Video*. NIPS, 2017

Content image

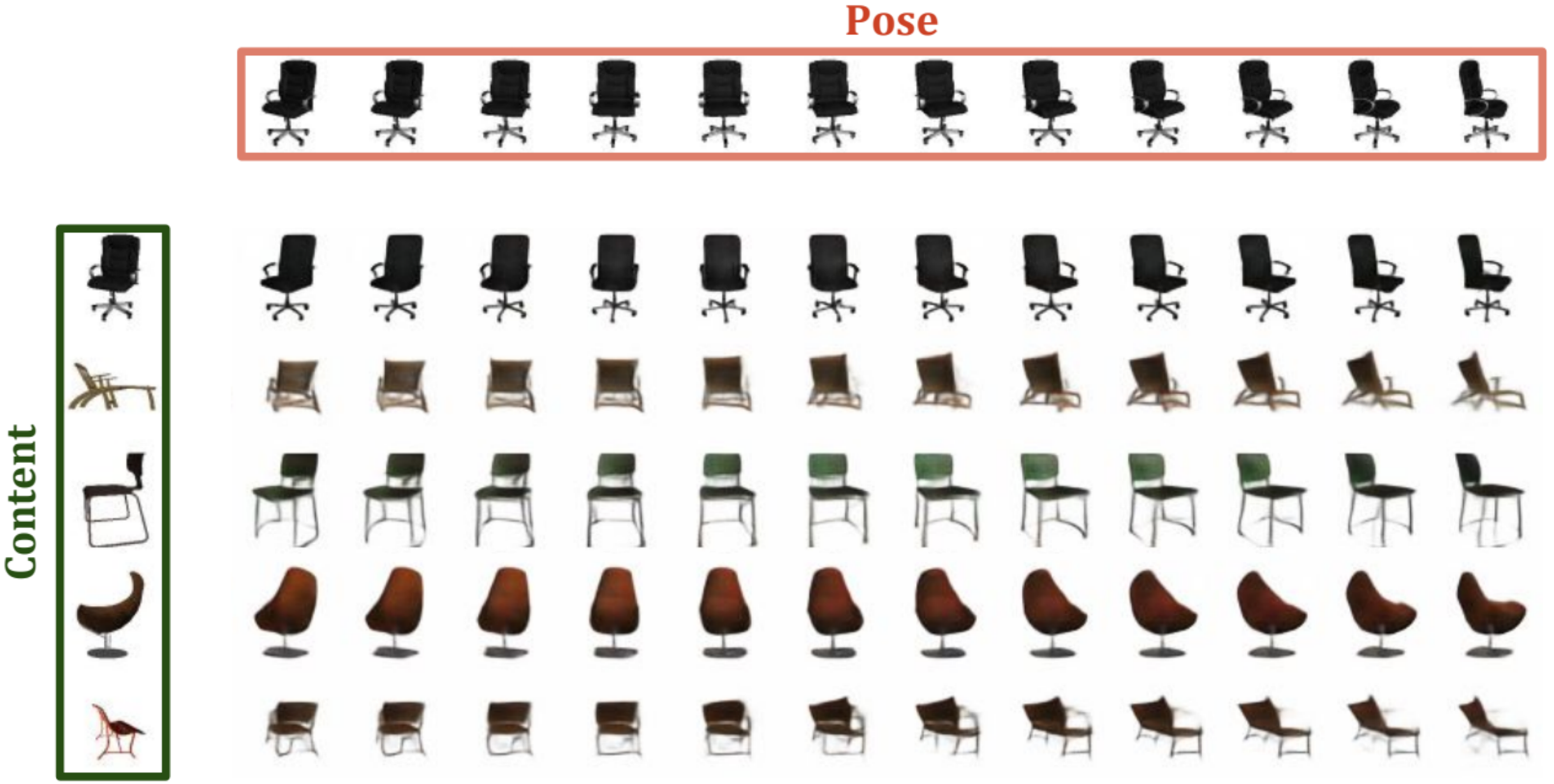


Pose image

Can transfer **content** from one image and **pose** from another to synthesize a **new image**

Image synthesis by analogy

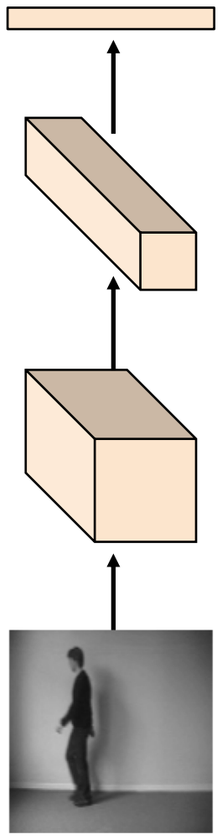
Denton and Birodkar. *Unsupervised Learning of Disentangled Representations from Video*. NIPS, 2017

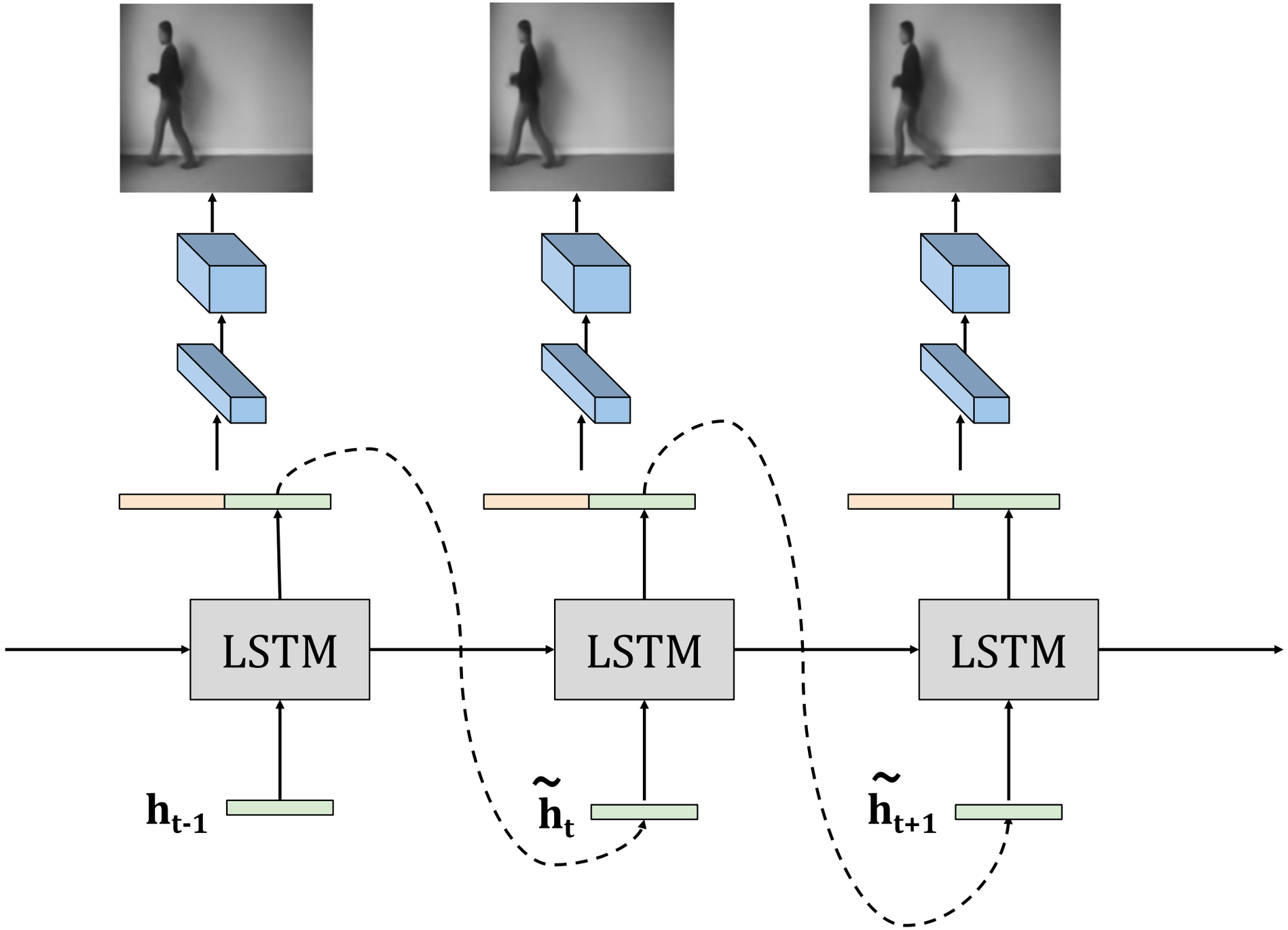


Interpolation in pose space

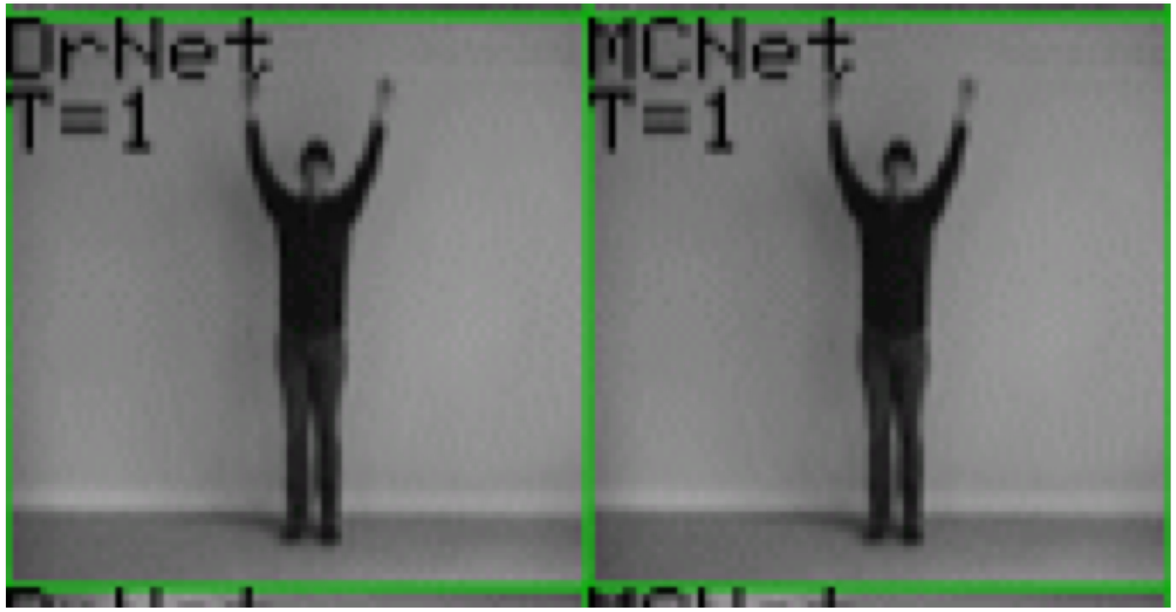
Denton and Birodkar. *Unsupervised Learning of Disentangled Representations from Video*. NIPS, 2017

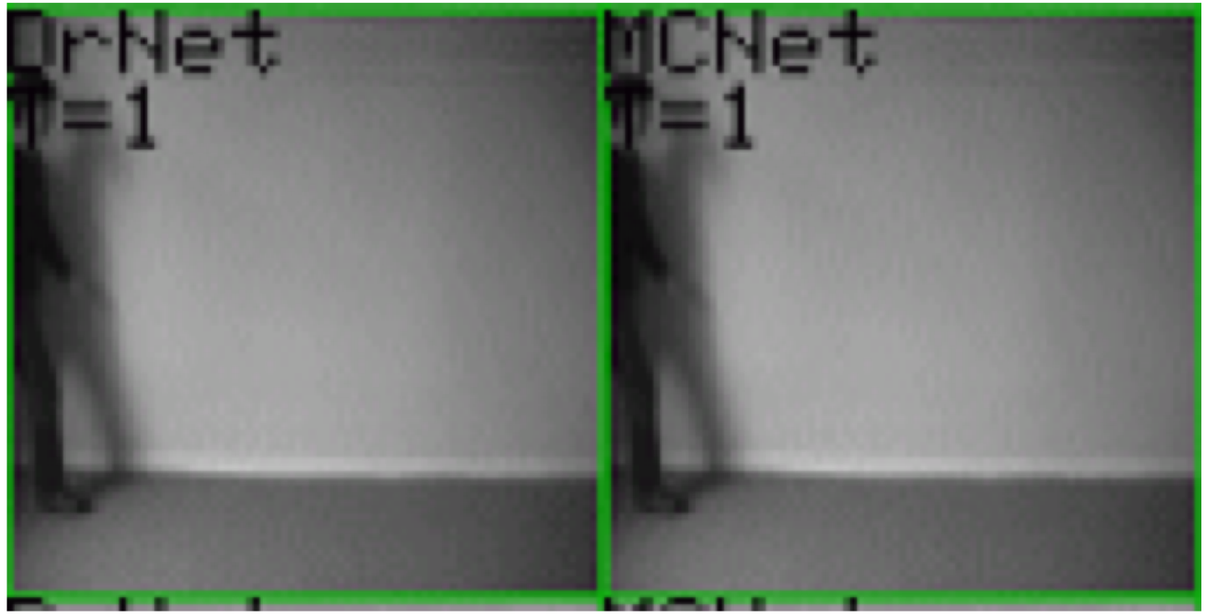
Decoder maps back to pixels:





KTH long term video generation



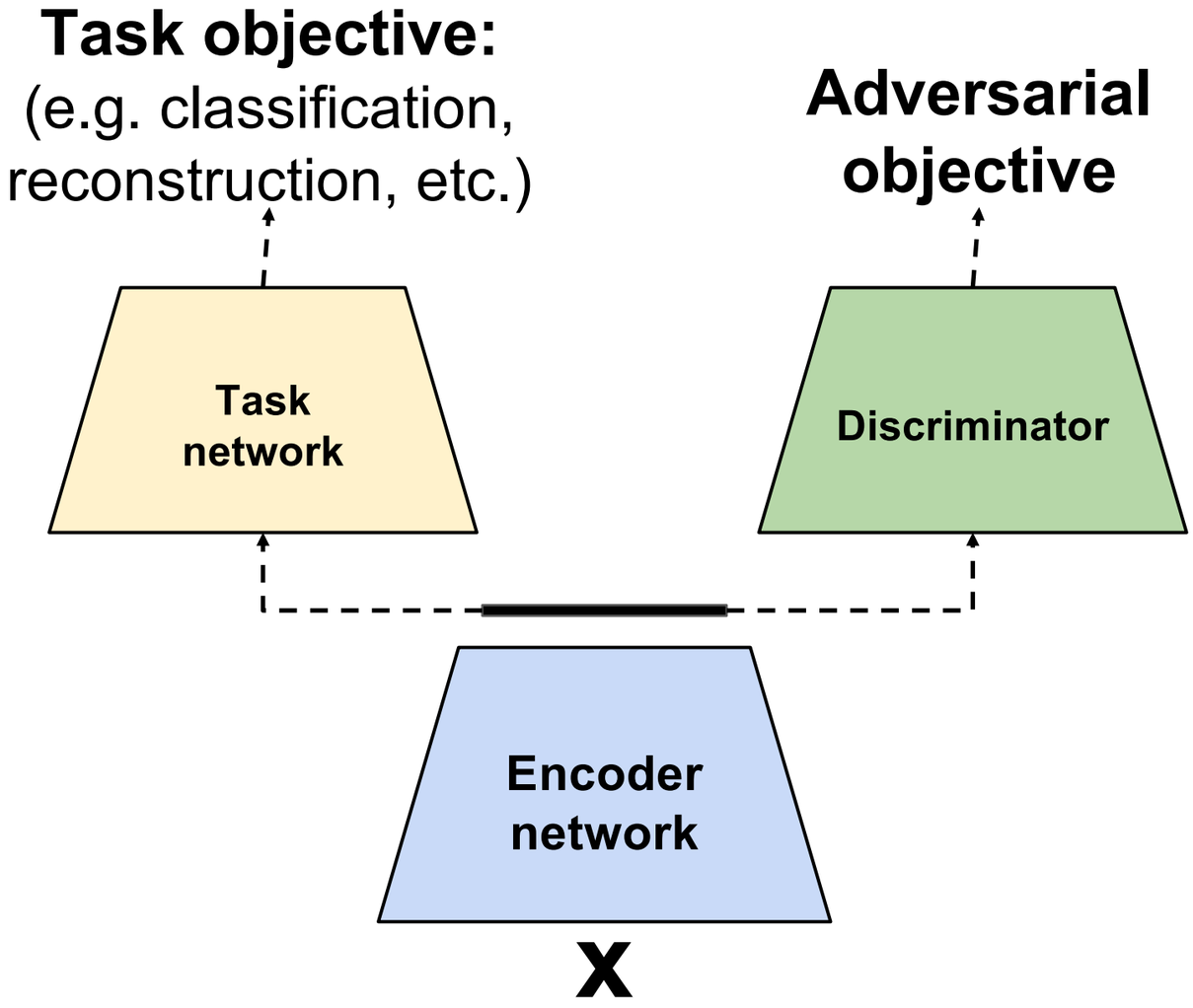


Denton and Birodkar. *Unsupervised Learning of Disentangled Representations from Video*. NIPS, 2017

Part I: Disentangling content and pose with an adversarial loss

Denton and Birodkar. *Unsupervised Learning of Disentangled Representations from Video*. NIPS, 2017

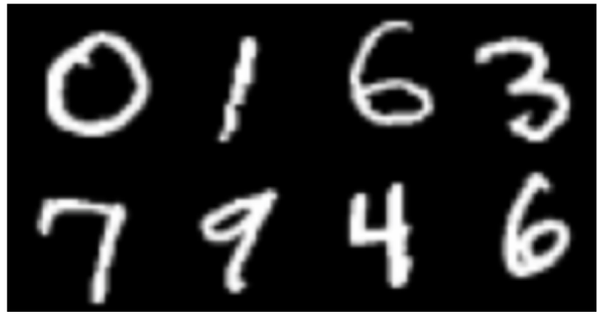
Part II: Survey of adversarial losses in feature space



Domain adaptation

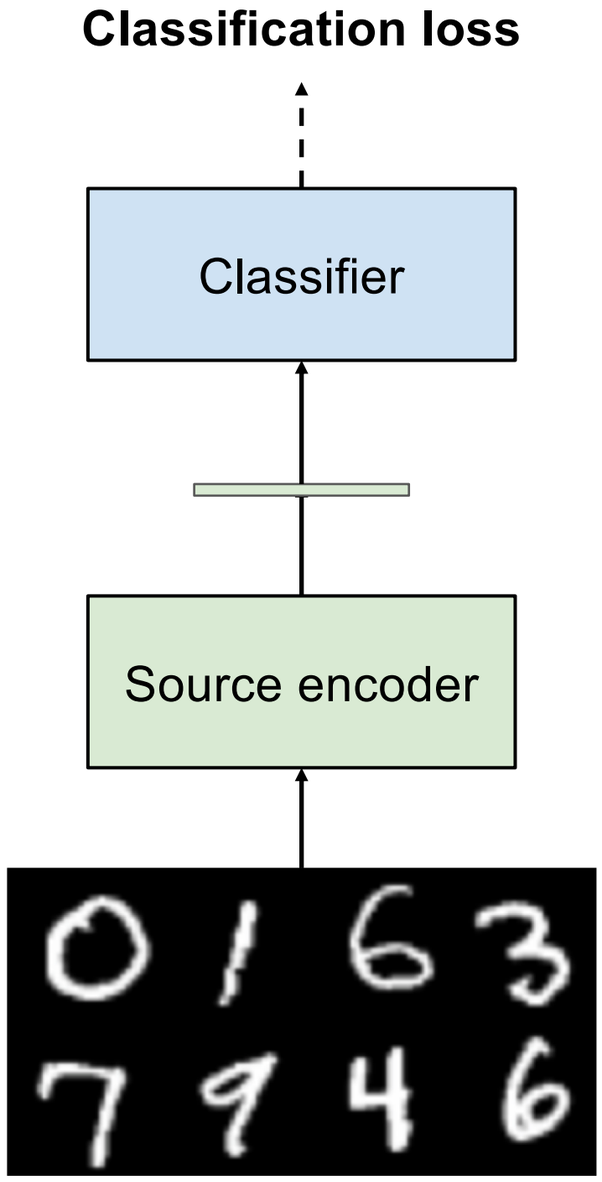
Labelled examples from **source domain**,
few or no labels from **target domain**

Source domain



Target domain

Domain adaptation

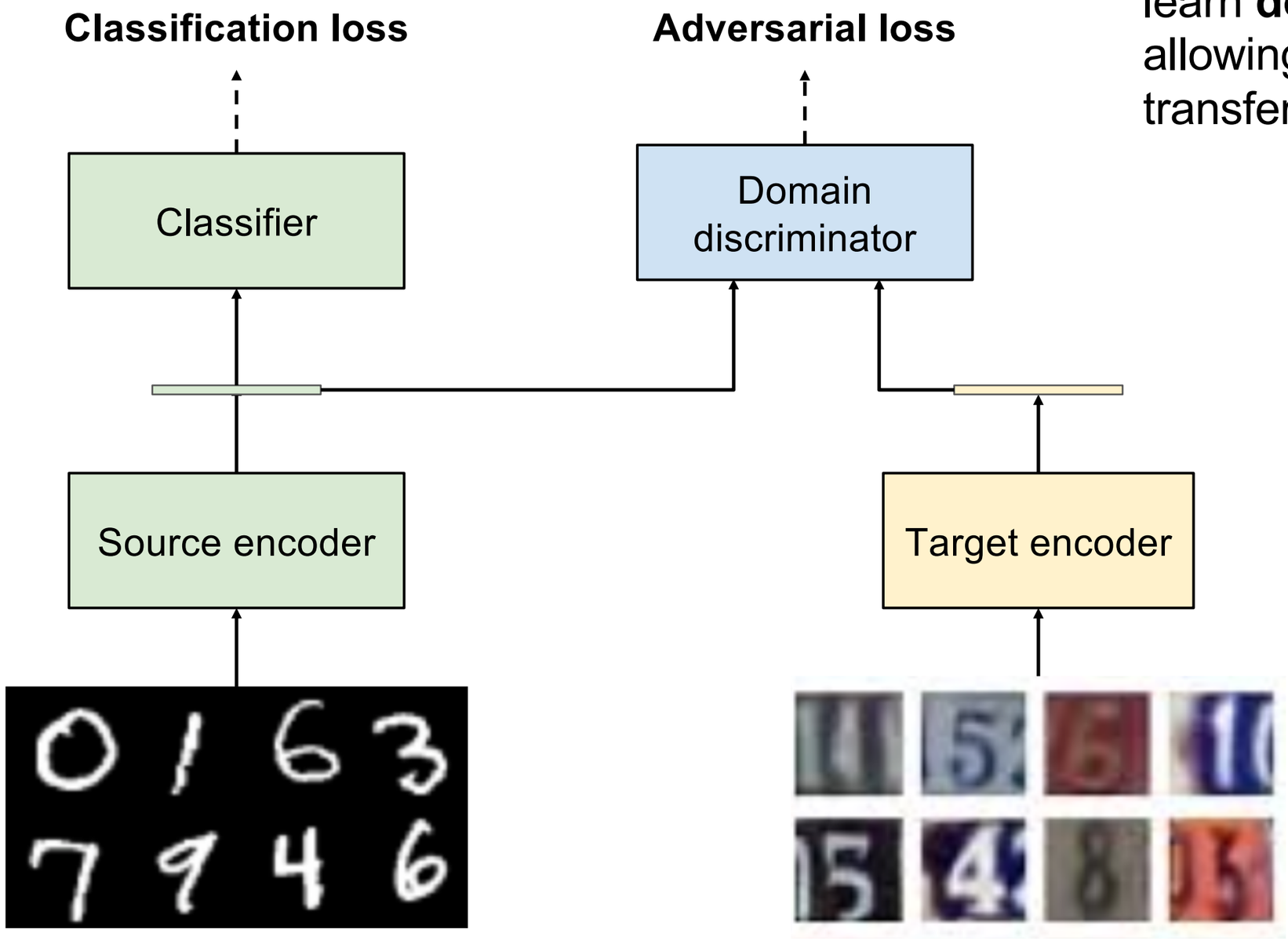


Labelled examples from **source domain**,
few or no labels from **target domain**

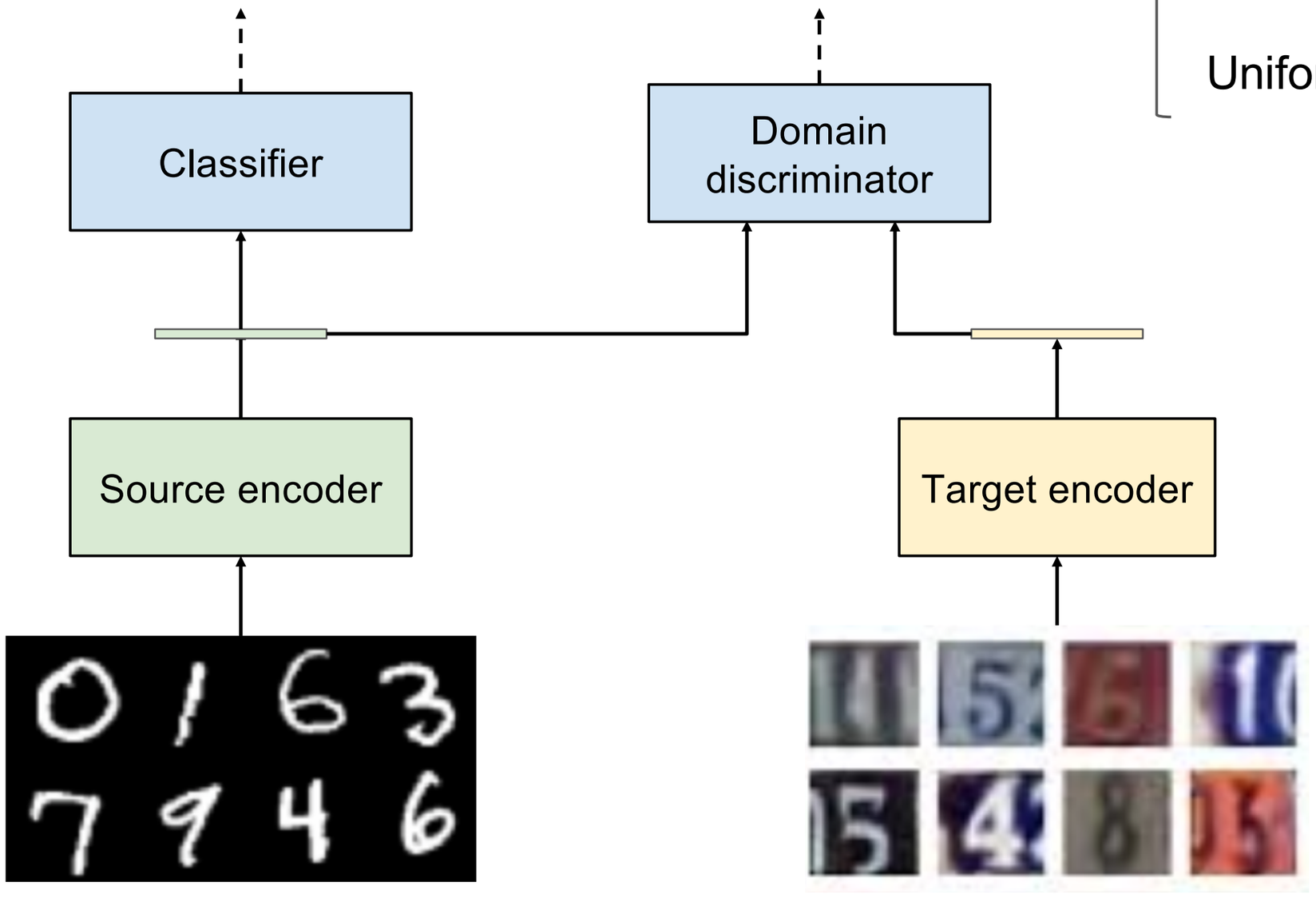
Target domain

Domain adaptation

Adversarial loss can be used to learn **domain invariant features,** allowing source classifier to transfer to target domain



Domain adaptation

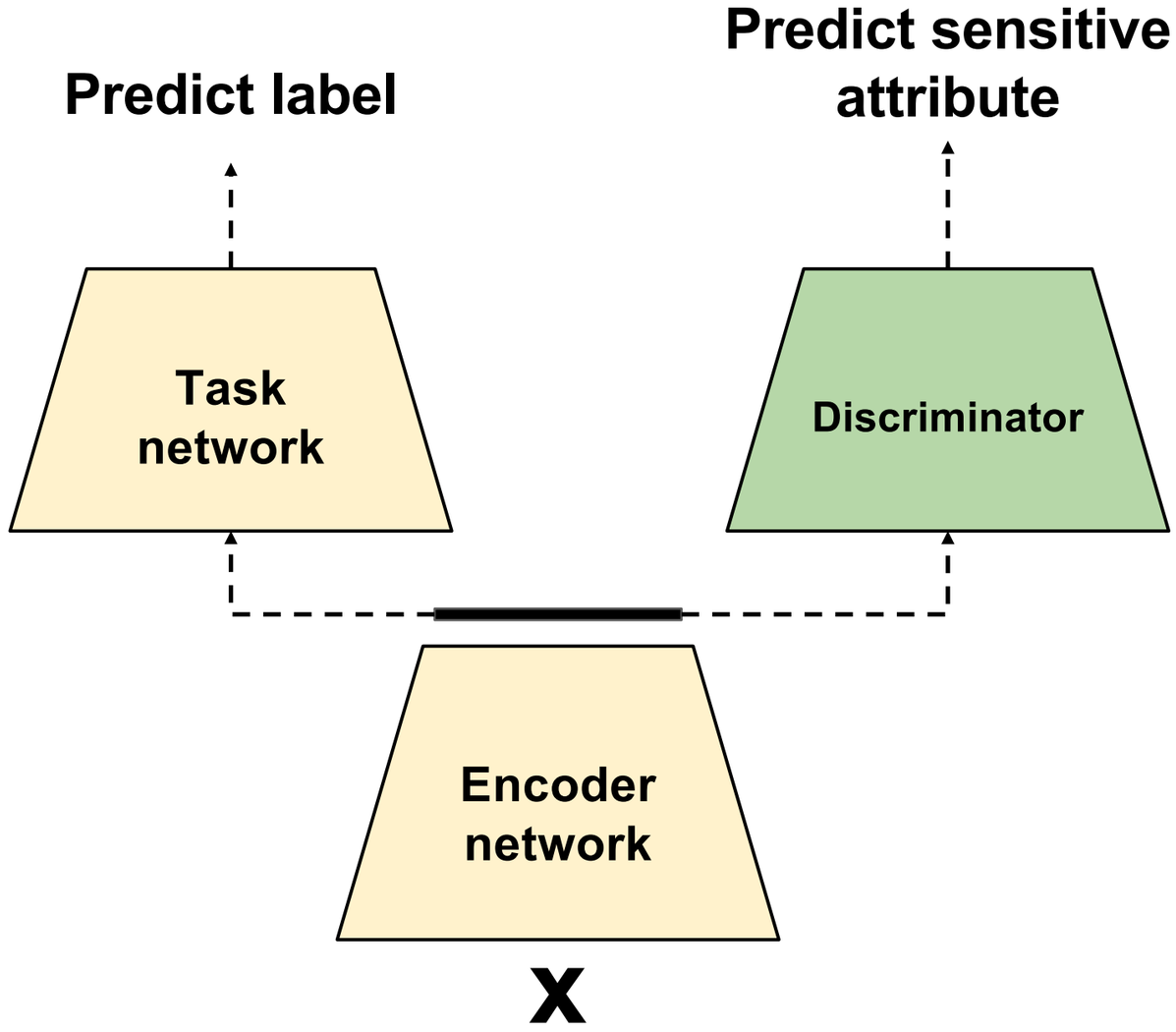


- Gradient reversal [*Ganin and Lempitsky, 2015*]
- Label flip [*Tzeng et al. 2017*]
- Uniform target [*Tzeng et al. 2015*]

Learning fair representations

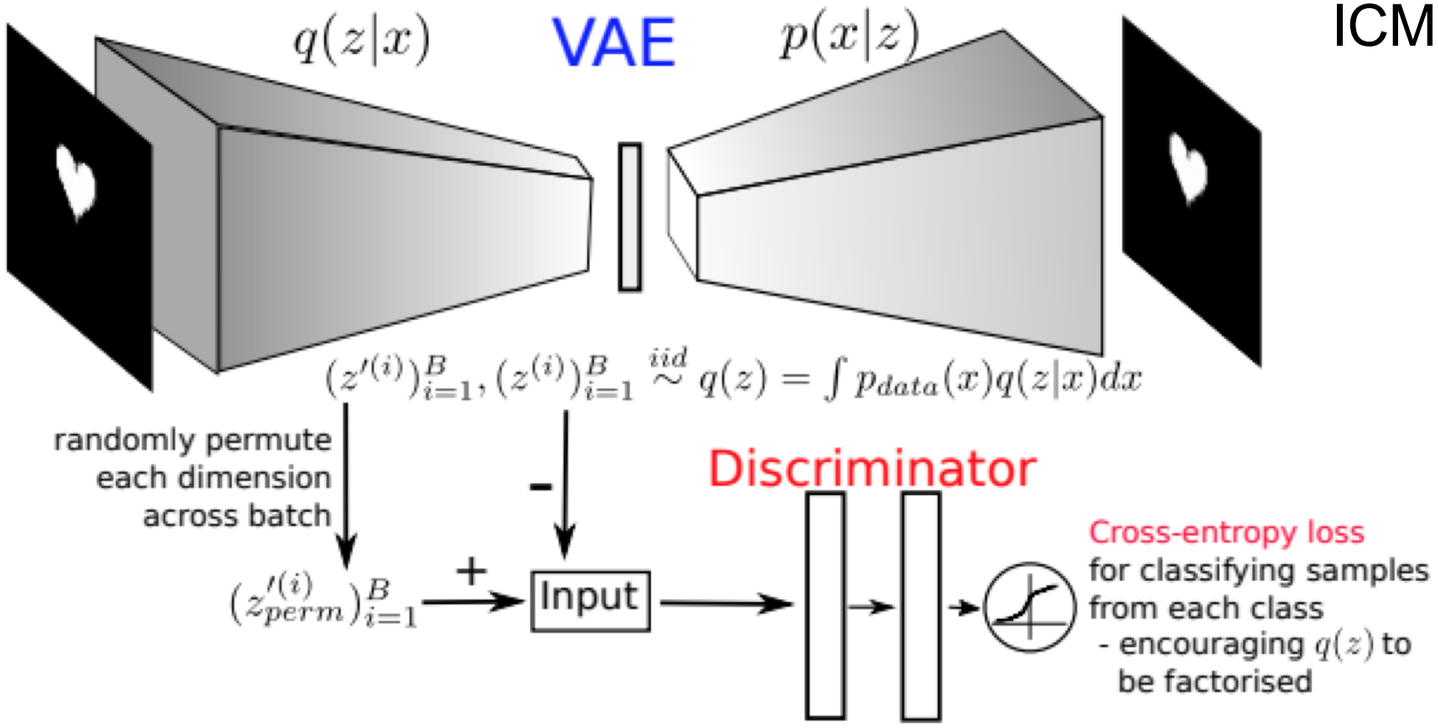
- Closely related to problem of domain adaptation
  - source/transfer domain vs. demographic groups

- Different formulations of adversarial objectives achieve different notions of fairness
  - Edwards & Storkey, 2016
  - Beutel et al. 2017
  - Zhang et al. 2018
  - Madras et al. 2018



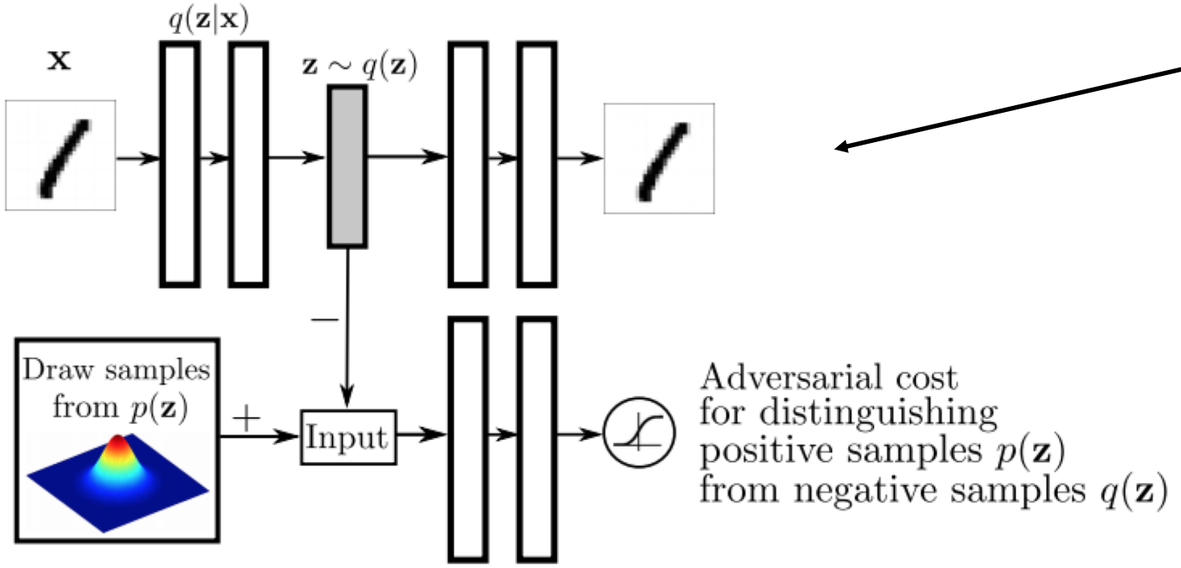
Independent components

Kim and Mnih. Disentangling by Factorising. ICML, 2018



- Discriminate marginal distribution vs. product of marginals: $q(z_1, ..., z_n)$ vs. $\prod q(z_i)$
- Earlier work on discrete code setting by Schmidhuber (1992)

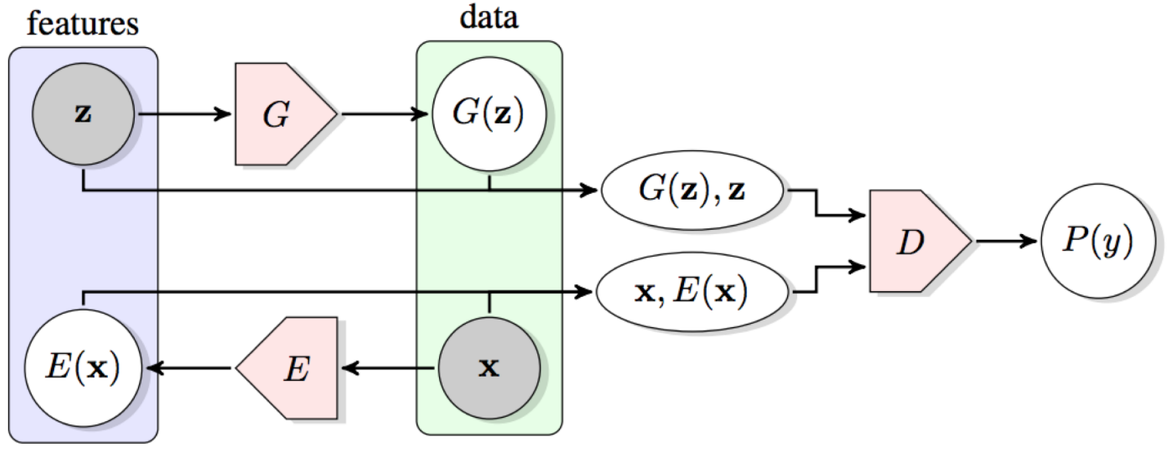
Prior distributions of generative models



Adversarial autoencoders:
Match aggregate approx posterior q(z)
[Makhzani et al. 2016]

Adversarial variational bayes:
Match approx posterior q(z|x)
[Mescheder et al. 2017]

Adversarial feature learning:
GAN loss in image space and latent space
[Dumoulin et al. 2017; Donahue et al. 2017]



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Edwards & Storkey. *Censoring Representations with an Adversary*. ICLR, 2016.

Ganin and Lempitsky. *Unsupervised domain adaptation by backpropagation.* ICML, 2015.

Kim and Mnih. *Disentangling by Factorising*. ICML, 2018.

Madras et al. *Learning Adversarially Fair and Transferable Representations*. ICML, 2018.

Makhzani et al. *Adversarial Autoencoders*. ICLR Workshop, 2016.

Mescheder et al. *Adversarial Variational Bayes: Unifying Variational Autoencoders and Generative Adversarial Networks*. ICML, 2017.

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Villegas, et al. D*ecomposing motion and content for natural video sequence prediction.* In ICLR, 2017.

Zhang et al. M*itigating Unwanted Biases with Adversarial Learning*. AIES, 2018.