Generative Adversarial Networks

EECS 6894

Deep Learning for Computer Vision, Speech, and Language

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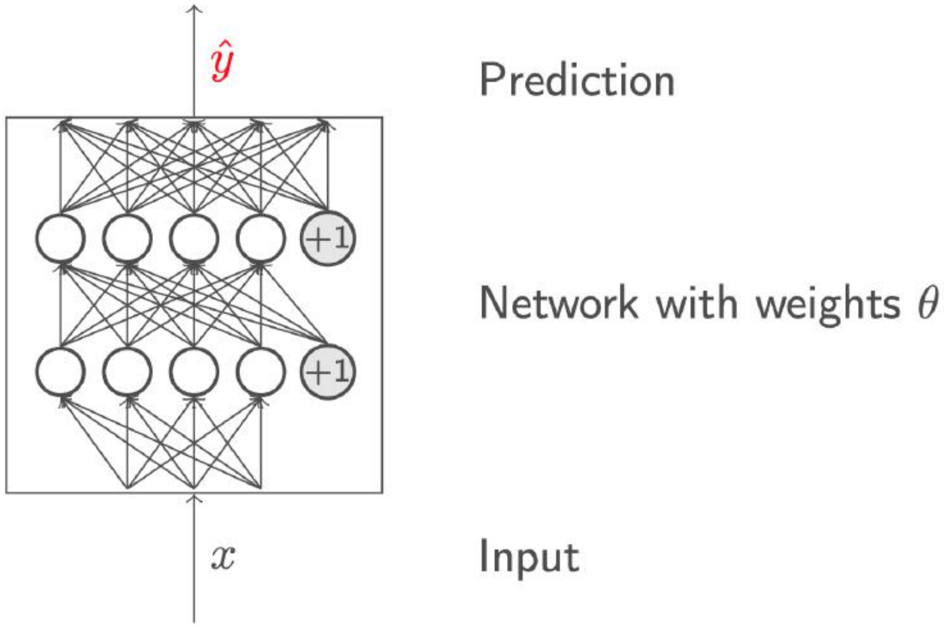
Outline

- Generative vs Discriminative
- Generative Adversarial Networks
- Applications
  - Realistic Image Generation
  - Domain Adaptation
  - Super resolution
  - Style Transfer
  - Disentangling Factors in Data
  - …Surprise

Generative vs Discriminative

- Deep learning has mainly focused on discriminative models (e.g. neural nets)



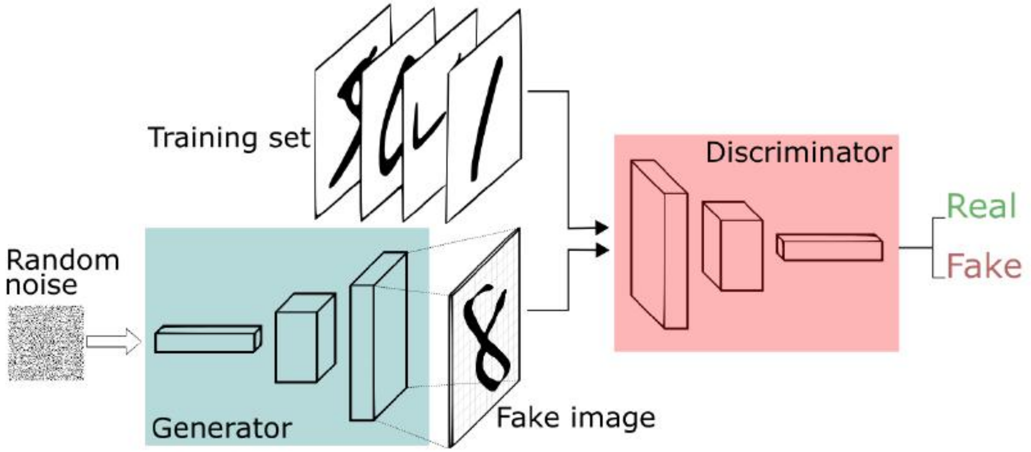
Slide from Kapil Thadani's lecture

Generative vs Discriminative

- Discriminative: Learns posterior distribution $p(y|x)$ directly
  - Only interested in learning the decision boundary
  - Examples: Neural nets, SVMs, Logistic Regression

- Generative: Learns joint distribution $p(x, y)$
  - Learn how the data is generated
  - Can convert to $p(y|x)$ using Bayes Rule
  - Examples: Naive Bayes, HMM, GMM

Generative Adversarial Nets [Goodfellow et al 2014]



Goal: Learn to generate realistic samples from given distribution

Optimization: Minimax game between Generator (G) and Discriminator (D)

Generative Adversarial Nets [Goodfellow et al 2014]

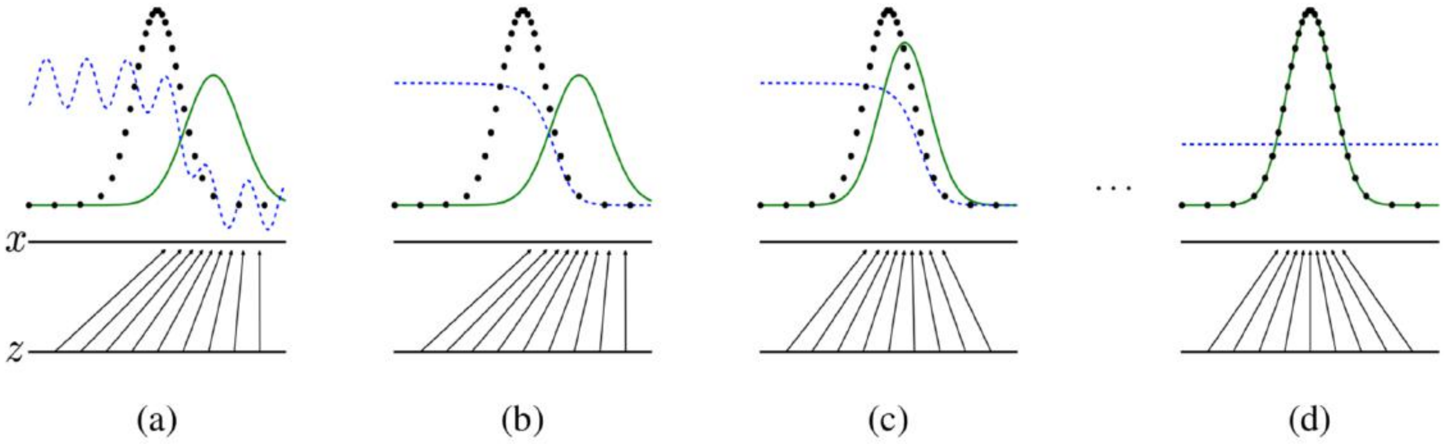
- Define
  - Noise $z \sim p(z)$
  - Generator $G(z)$
  - Samples $x_1, \ldots, x_n$
  - Discriminator $D(x)$
- Optimize: $\underset{G}{min}\,\underset{D}{max}\,\mathbb{E}_x[\log D(x)] + \mathbb{E}_z[\log(1 - D(G(z))]$
  - D: D(real) = 1 and D(fake) = 0
  - G: D(fake) = 1

GAN Optimization

$$\min_G \max_D \mathbb{E}_x[\log D(x)] + \mathbb{E}_z[\log(1 - D(G(z))]$$

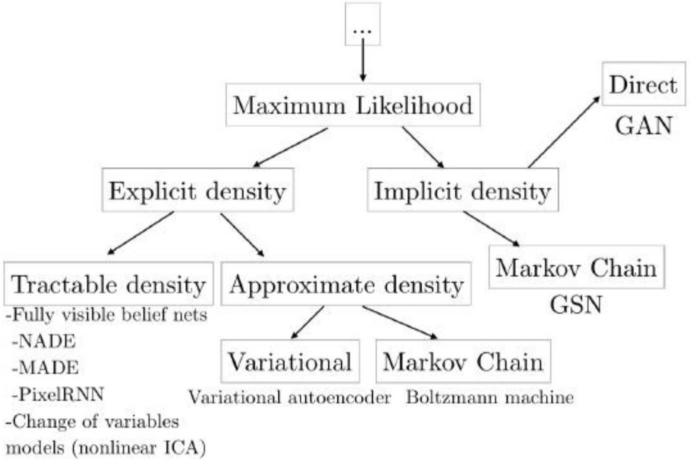
- Ideally after training
  - Data distribution and G converge (Nash equilibrium)
  - D is unable to distinguish between real and fake, i.e. $D(x) = 1/2$
- In practice may be easier to maximize $\log(D(G(z))$ wrt to G
- Iterative updates between D,G
- In the end
  - Easy to sample from $G(z)$
  - No explicit formulation for $P(x)$

GAN Optimization



- G,D at equilibrium
  - No further updates

How do GANs relate to other generative models? [link]

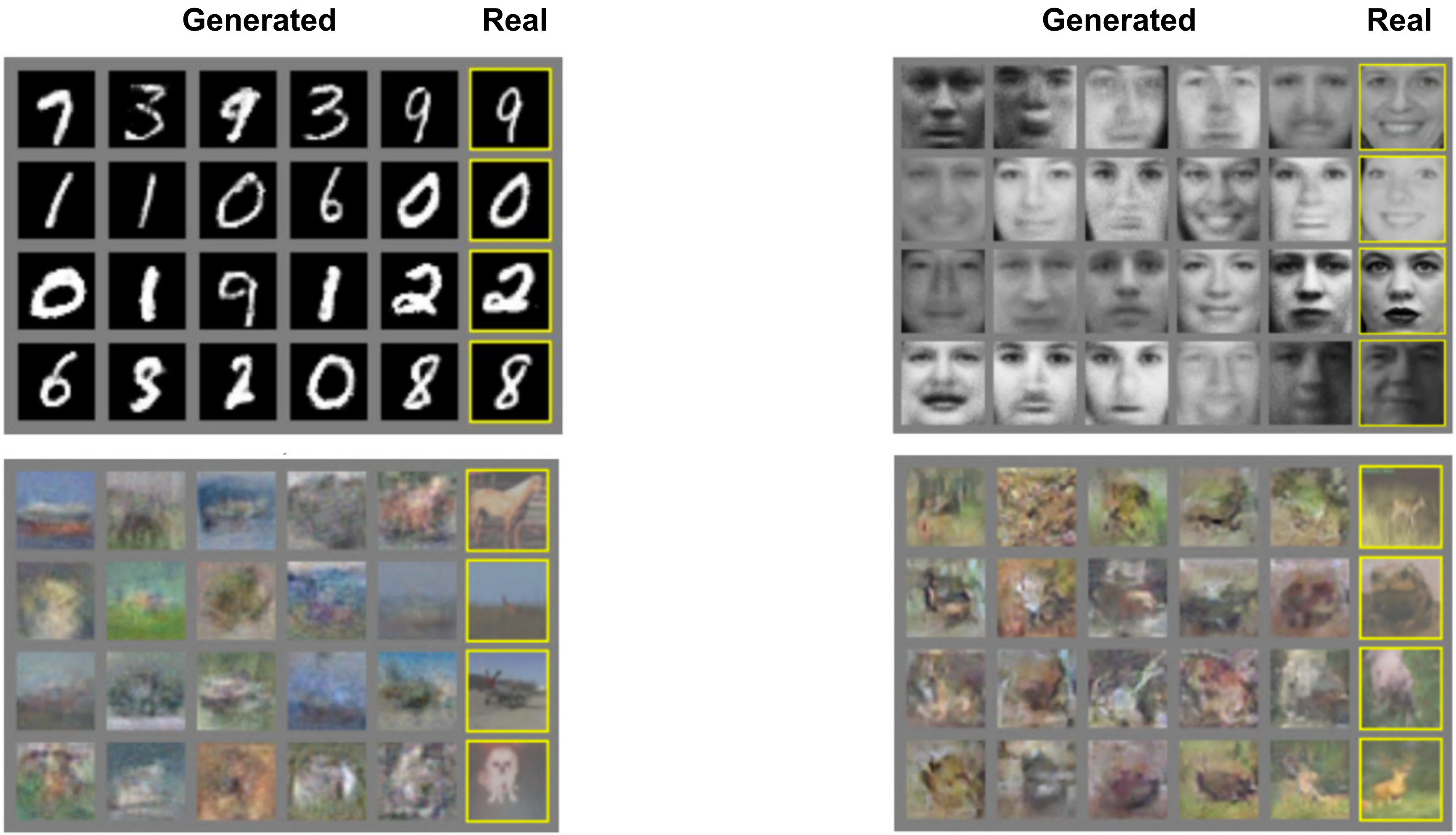


- Some key differences:
  - No explicit representation for $p(x;\theta)$
  - No markov chain needed
  - GANs produce (subjectively) better samples than other models

GAN Code

```python
G_solver = optim.Adam(G_params, lr=1e-3)
D_solver = optim.Adam(D_params, lr=1e-3)

ones_label = Variable(torch.ones(mb_size))
zeros_label = Variable(torch.zeros(mb_size))

for it in range(100000):
    # Sample data
    z = Variable(torch.randn(mb_size, Z_dim))
    X, _ = mnist.train.next_batch(mb_size)
    X = Variable(torch.from_numpy(X))

    # Discriminator forward-loss-backward-update
    G_sample = G(z)
    D_real = D(X)
    D_fake = D(G_sample)

    D_loss_real = nn.binary_cross_entropy(D_real, ones_label)
    D_loss_fake = nn.binary_cross_entropy(D_fake, zeros_label)
    D_loss = D_loss_real + D_loss_fake

    D_loss.backward()
    D_solver.step()

    # Generator forward-loss-backward-update
    G_loss = nn.binary_cross_entropy(D_fake, ones_label)

    G_loss.backward()
    G_solver.step()
```

Modified from https://github.com/wiseodd/generative-models

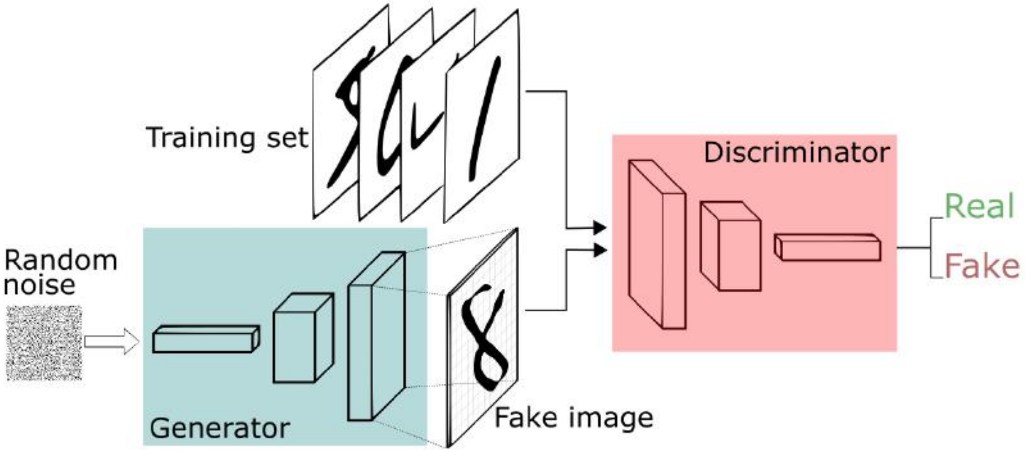

Generated
Real
Generated
Real

Difficulties in Training GANs

- Model doesn't converge
  - Never reaches Nash equilibrium (i.e. no further changes to G or D)
    - G,D parameters may oscillate
  - Uneven progress between G,D
    - May need to let G train a few iterations and not update D
- Mode collapse (aka Helvetica scenario)
  - G will only generate samples (even one sample) from a single mode
  - Restart training
- Samples may lack global structure
  - i.e. some generated faces will have 3 eyes
- Some of these problems are addressed in Wasserstein GAN [(WGAN)]

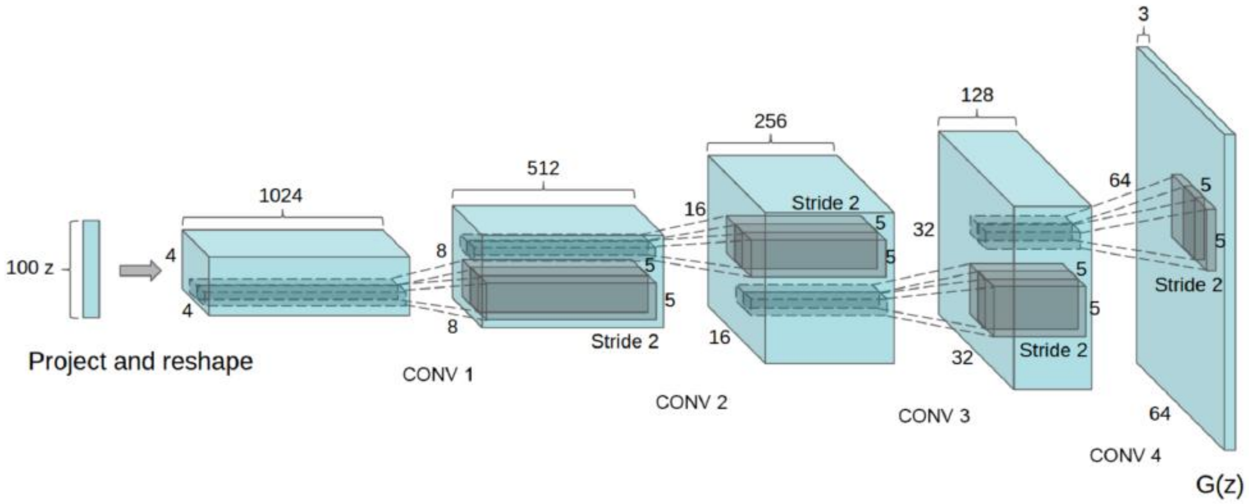
Applications

More realistic generator



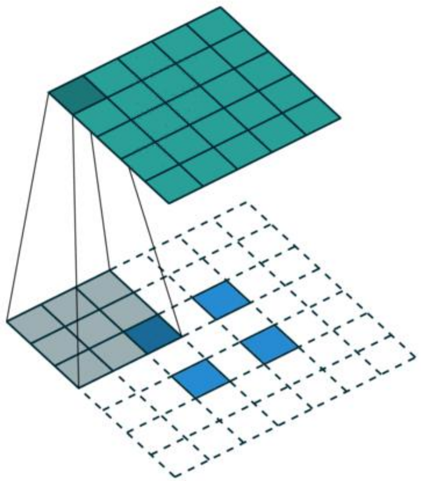
- Original GAN used MLP
    - Generated samples were OK for digits but not so great for real-world images

Deep Convolution GAN (DCGan) [link]



- No FC layers
- Pooling layers replaced w/ fractional stride convolutions
- Batchnorm used throughout G, D
    - Normalize input in each layer to have zero mean and unit variance

Fractional (Transposed) Convolution [link]



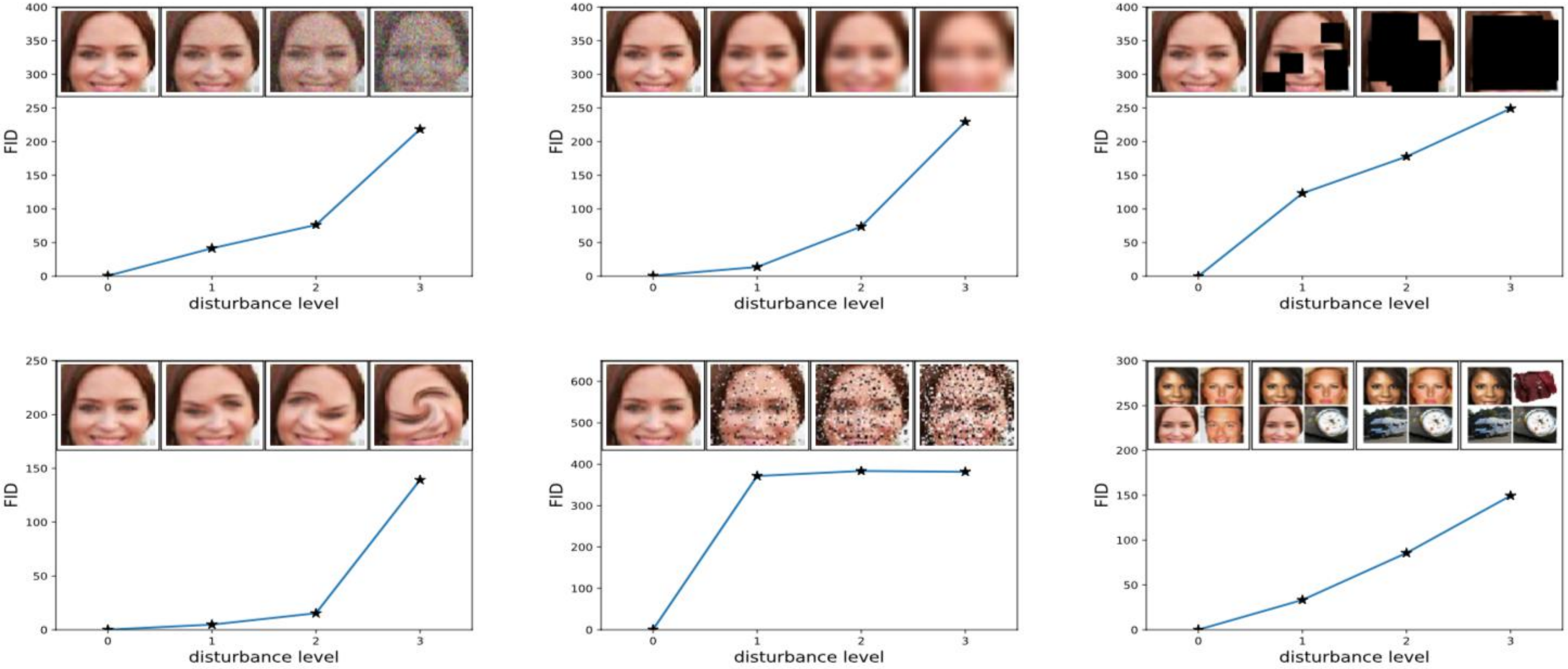
- Zero values inserted between input pixels
- Useful for upsampling

DCGan Output

How to evaluate these models?

- Inception score [link]
  - Good quality: $p(y|x)$ should have low entropy (i.e. the image should correspond to a small number of classes)
  - Variation: $p(y) = \int_z p(y|x = G(z))\,dz$ should have high entropy
  - $IS(G) = \exp[\mathbb{E}_x KL(p(y|x)||p(y))]$ combines the two factors
  - Higher is better
- “Fréchet Inception Distance [link]
  - Extract Inception features for real and generated images
  - Compute means and covariances $\mu_x, \mu_g, \Sigma_x, \Sigma_g$
  - $FID(x, g) = ||\mu_x - \mu_g|| + tr(\Sigma_x + \Sigma_g + 2(\Sigma_x\Sigma_g)^{1/2})$ computes difference b/w dist
  - Lower is better

FID Score [link]



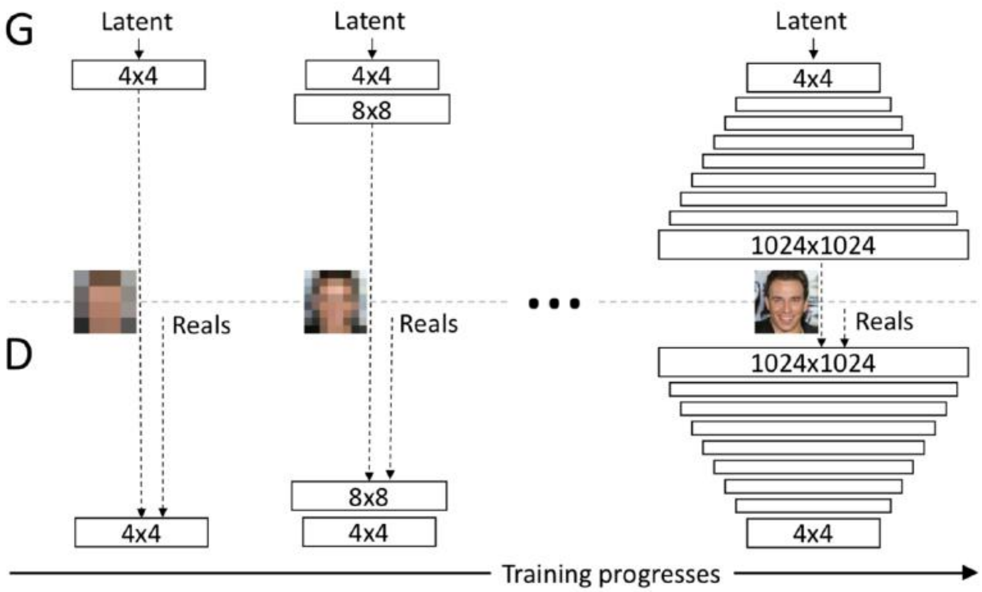
BigGAN [link]

- Can you tell which images are real vs generated?

BigGAN [link]

- They are ALL generated!
- Scale up
  - Batch Size
  - Number of channels (2x overall number parameters)
- But still susceptible to mode collapse

Realistic Face Image Generation [link]

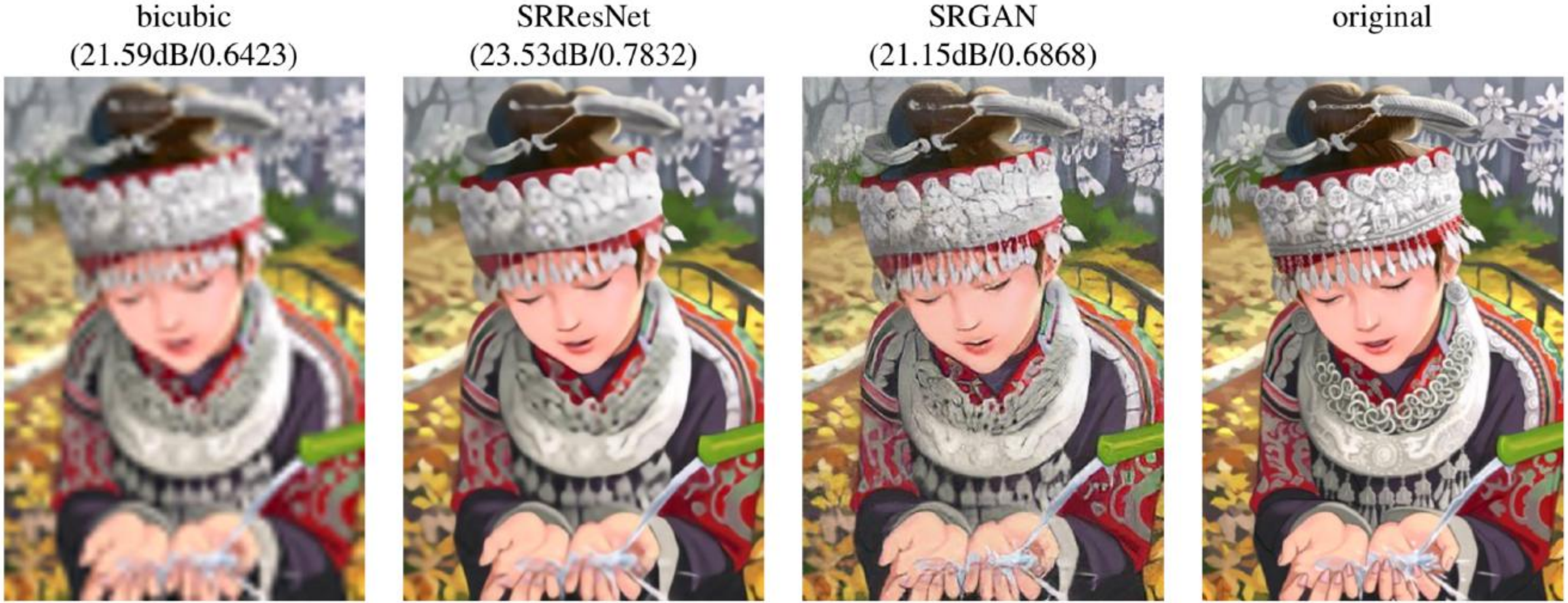


- Start at low spatial resolution and progressively add more, wider layers

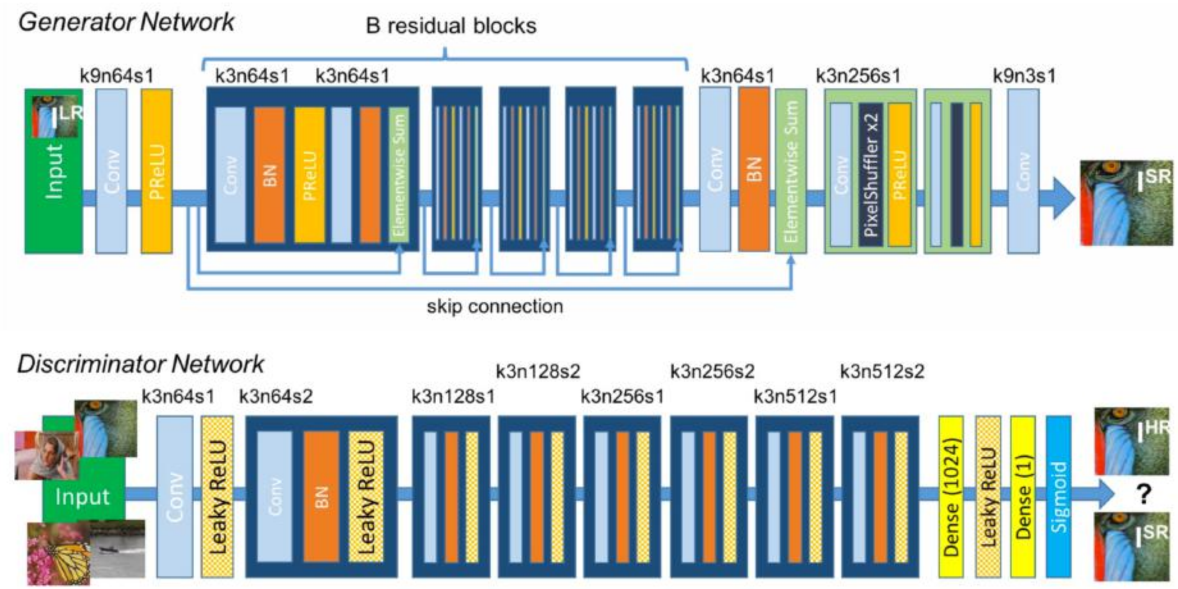
Realistic Face Image Generation [link]

- Scales up to 1024 x 1024
- Some artifacts at perimeter

Super-resolution GAN [link]



Super-resolution GAN [link]

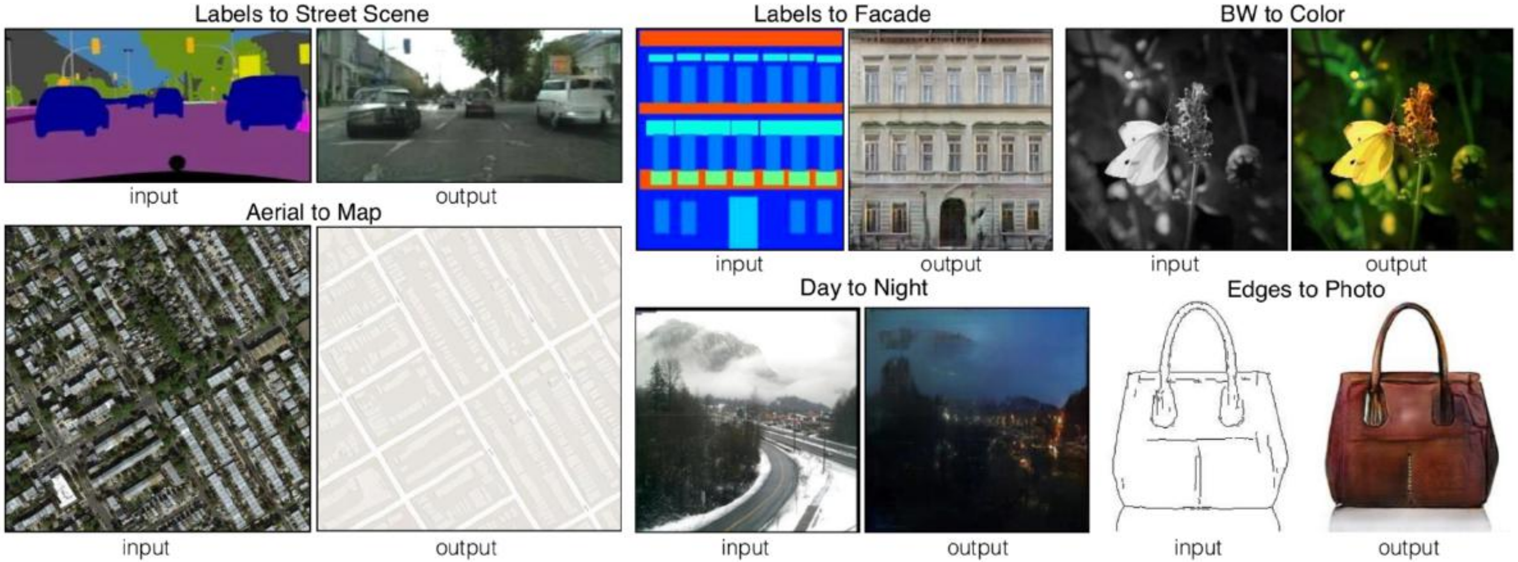


- Notation: k (kernel size), n (# feature maps), s (stride)
- Discriminator distinguishes between original high-res and generated images

SRGan Perceptual Loss

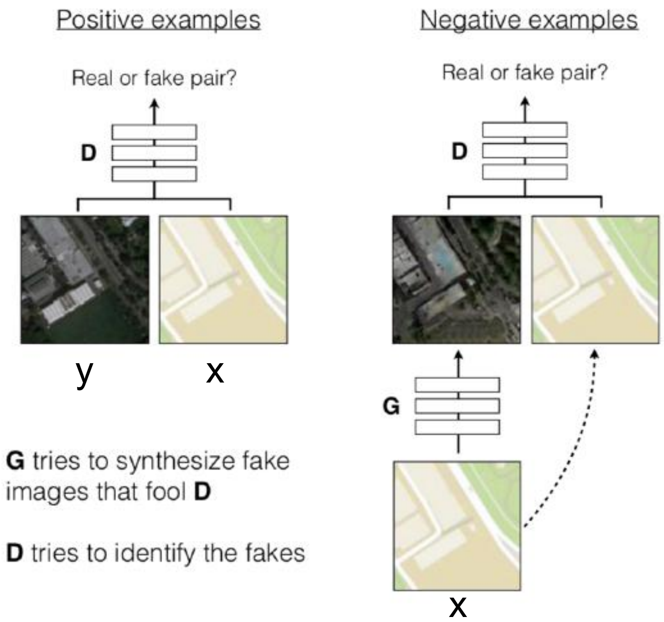
- Optimize $\min_G \max_D \mathbb{E}_{I^{HR}}[\log D(I^{HR})] + \mathbb{E}_{I^{LR}}[\log(1 - D(G(I^{LR}))]$
- G is optimized for $\hat{\theta}_G = \underset{\theta_G}{argmin} \frac{1}{N} \sum_{n=1}^{N} l^{SR}(G(I_n^{LR}), I_n^{HR})$
- Perceptual loss $l_{SR} = l_X^{SR} + \lambda l_{Gen}^{SR}$
  - Content Loss $l_X^{SR} = \frac{1}{W_{i,j}H_{i,j}} \sum_{x=1}^{W_{i,j}} \sum_{y=1}^{H_{i,j}} (\phi_{i,j}(I^{HR})_{x,y} - \phi_{i,j}(G(I^{LR})_{x,y})^2$
  - Adversarial Loss $l_{Gen}^{SR} = \sum_{n=1}^{N} - \log D(G(I^{LR}))$

Pix2Pix [link]



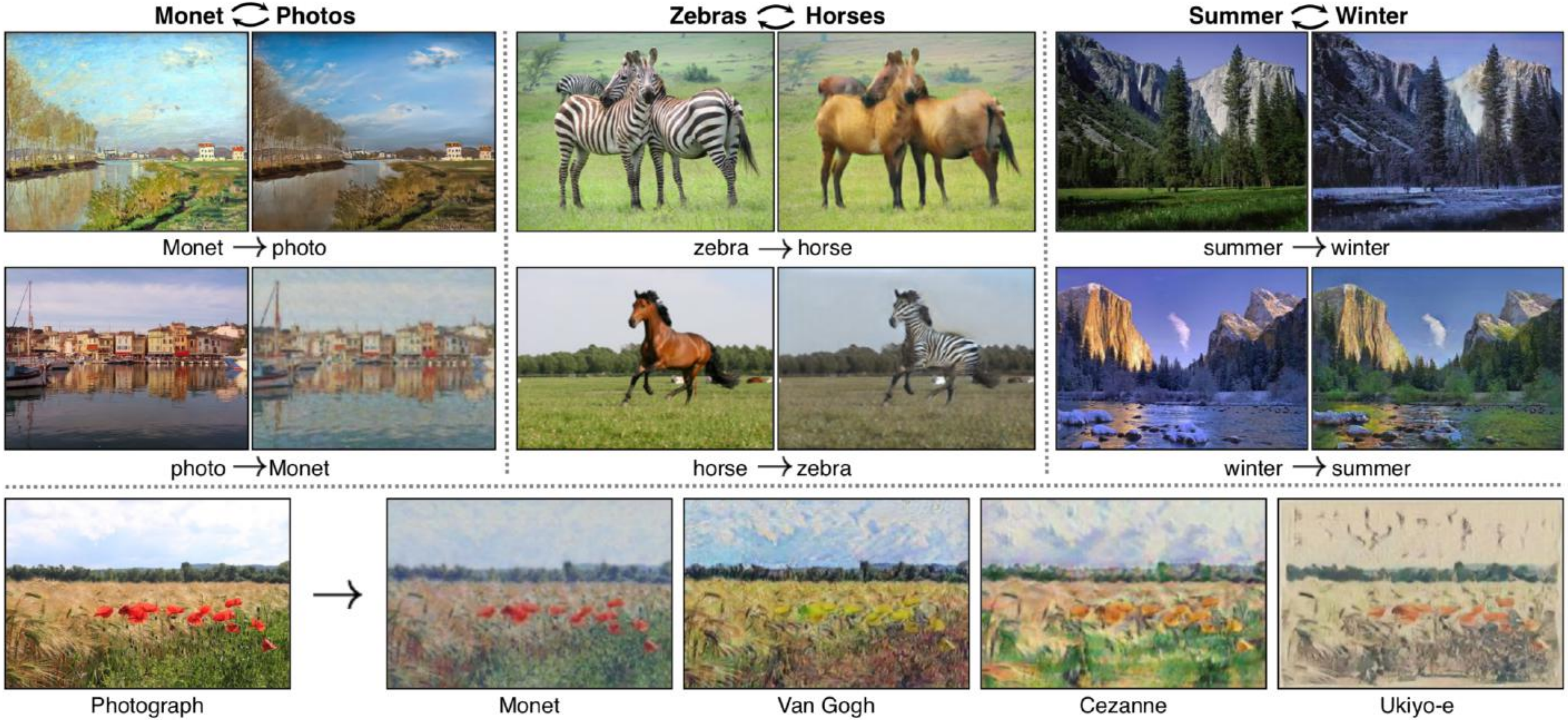
- Uses conditional adversarial network for image translation

Pix2Pix [link]

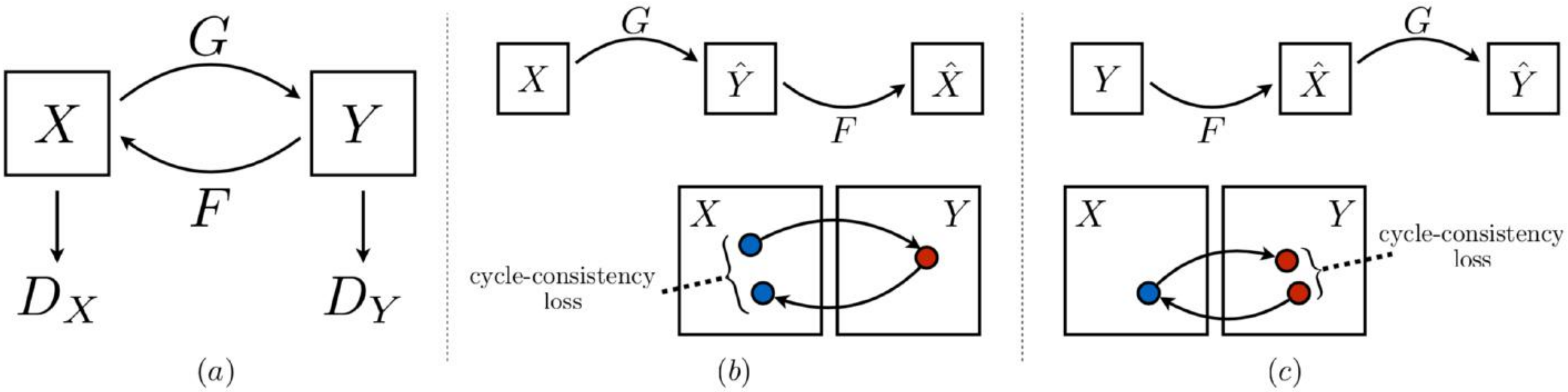


- Conditional GAN: $L_{cGAN}(G, D) = \mathbb{E}_{x,y\sim data}[\log D(x, y)] + \mathbb{E}_{x\sim data, z\sim p(z)}[log(1 - D(G(x, z))]$
- L1: $L_{L_1}(G) = \mathbb{E}_{x,y\sim data, z\sim p(z)} \|y - G(x, z)\|_1$
- Total: $\min_G \max_D L_{cGAN}(G, D) + \lambda L_{L_1}(G)$

CycleGAN [link]

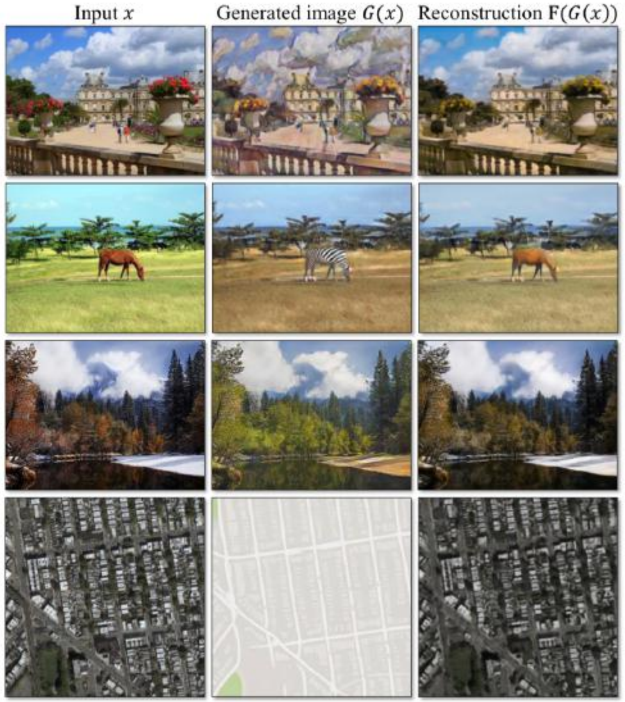


CycleGAN [link]



- Pairs of generators G,F. G: X->Y and F: Y->X
- Pair of discriminators
- Extension from Pix2Pix

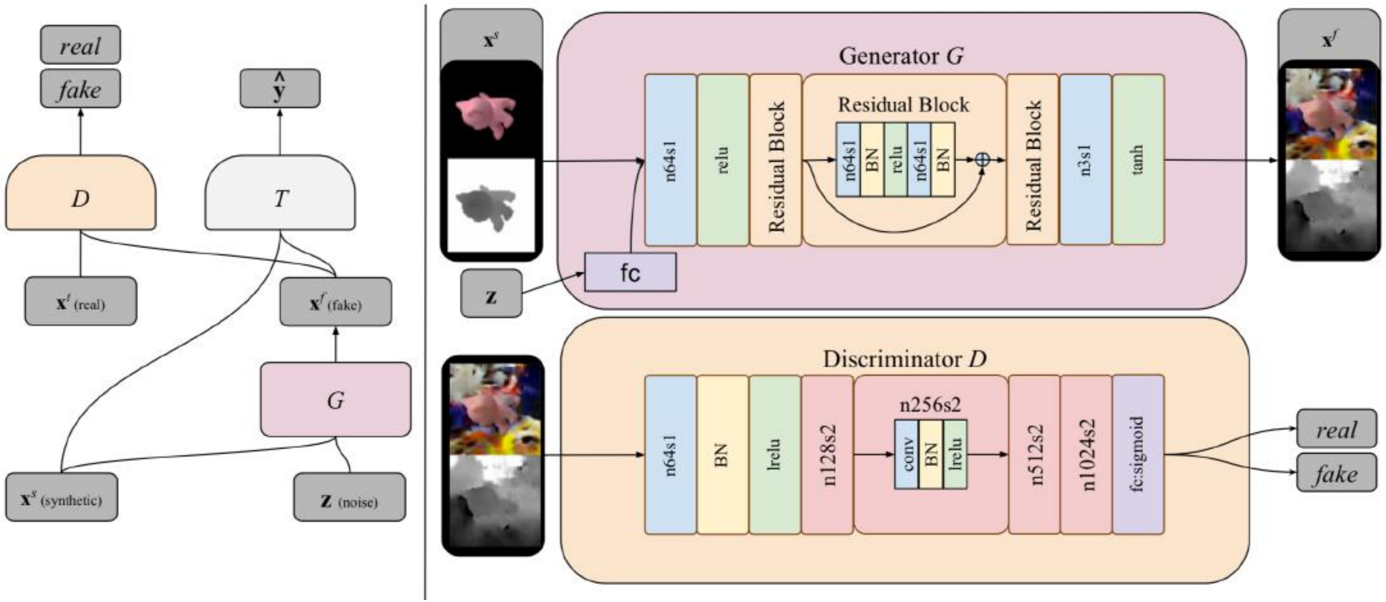
CycleGAN [link]



- Adversarial Loss: $L_{GAN}(G, D_Y, X, Y) = \mathbb{E}_{y \sim data}[\log D_Y(y)] + \mathbb{E}_{x \sim data}[\log(1 - D_Y(G(x))]$
- Cycle Consistency Loss: $L_{cyc}(G, F) = \mathbb{E}_{x \sim data}[\|F(G(x)) - x\|_1] + \mathbb{E}_{y \sim data}[\|G(F(y)) - y\|_1]$
- Total: $L(G, F, D_X, D_Y) = L_{GAN}(G, D_Y, X, Y) + L_{GAN}(F, D_X, Y, X) + \lambda L_{cyc}(G, F)$

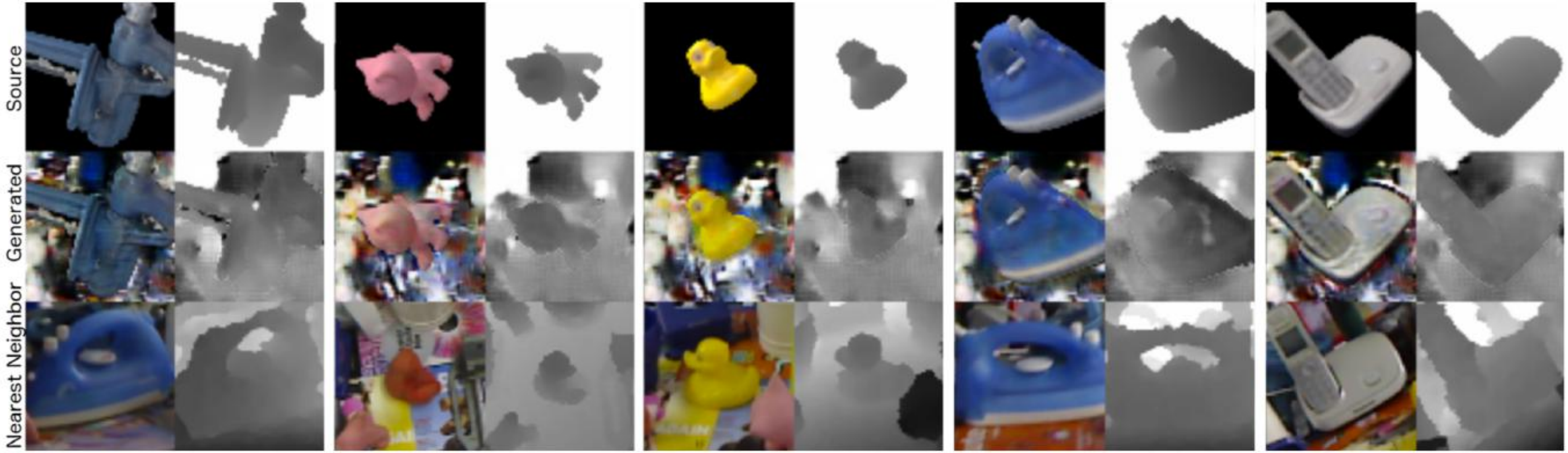
Domain Adaptation (PixelDA)

- Unsupervised DA
- Use G to adapt synthetic images into target domain



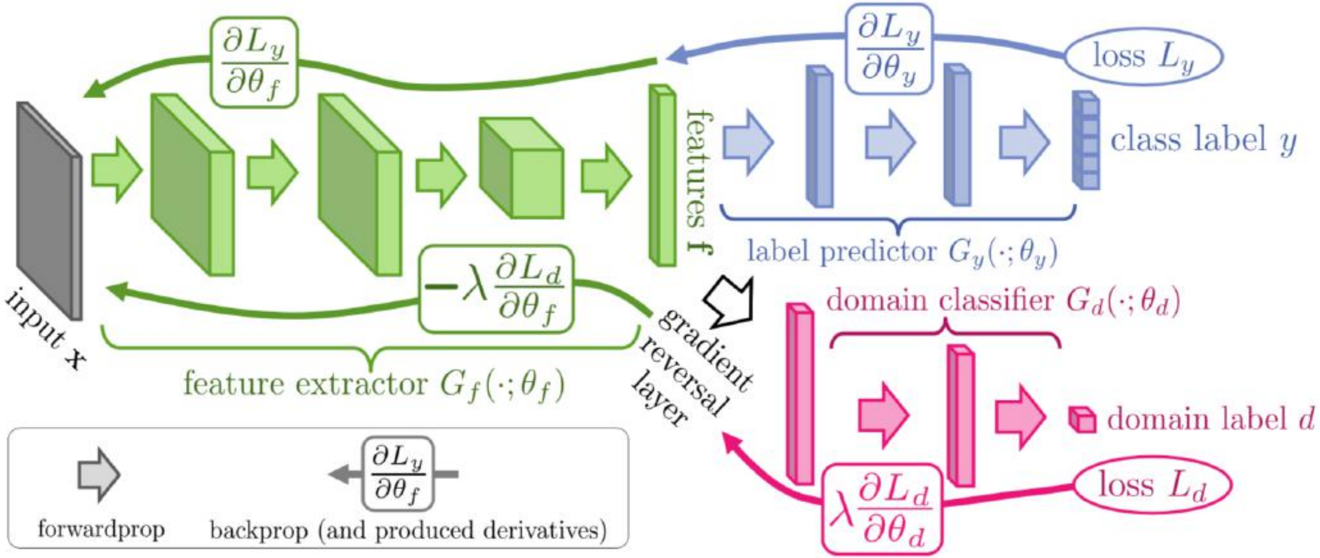
Domain Adaptation (PixelDA)

- Sample output
- Can update G,D in one step



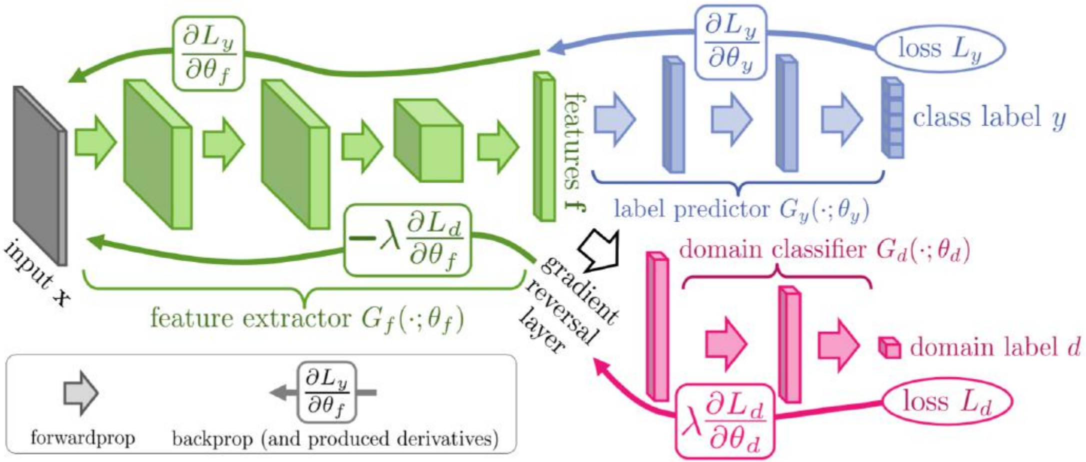
Domain Adaptation

- [Domain Adversarial Neural Network (DANN)]
    - Uses a gradient reversal layer that multiplies gradient from domain classifier by a negative constant during training



Domain Adaptation

- Domain Adversarial Neural Network (DANN)



$$\theta_f \longleftarrow \theta_f - \mu \left(\frac{\partial \mathcal{L}_y^i}{\partial \theta_f} - \lambda \frac{\partial \mathcal{L}_d^i}{\partial \theta_f} \right),$$

$$\theta_y \longleftarrow \theta_y - \mu \frac{\partial \mathcal{L}_y^i}{\partial \theta_y},$$

$$\theta_d \longleftarrow \theta_d - \mu \lambda \frac{\partial \mathcal{L}_d^i}{\partial \theta_d},$$

- Green and blue regions correspond to standard CNN
- Red region corresponds to discriminator

InfoGAN [link]

- Learn disentangled representations of data
- Instead of a single noise variable z, also include latent code c
  - e.g. c can correspond to 0-9 when generating digits
- Enforce high mutual information $I(c; G(z, c))$
- Optimize: $\min_G \max_D \mathbb{E}_x[\log D(x)] + \mathbb{E}_z[\log(1 - D(G(z))] - \lambda I(c; G(z, c))$
  - Add the MI term

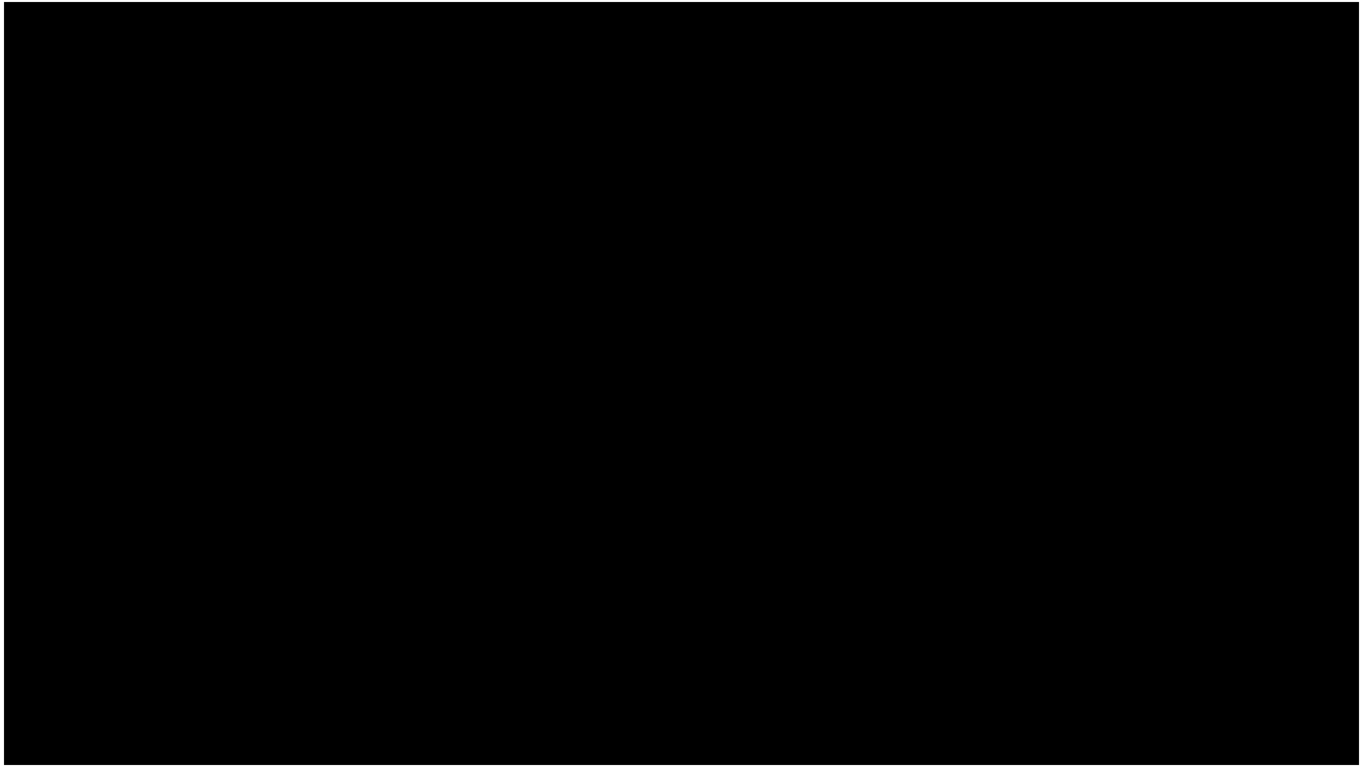
InfoGAN [link]

(a) Azimuth (pose) (b) Elevation

(a) Rotation (b) Width

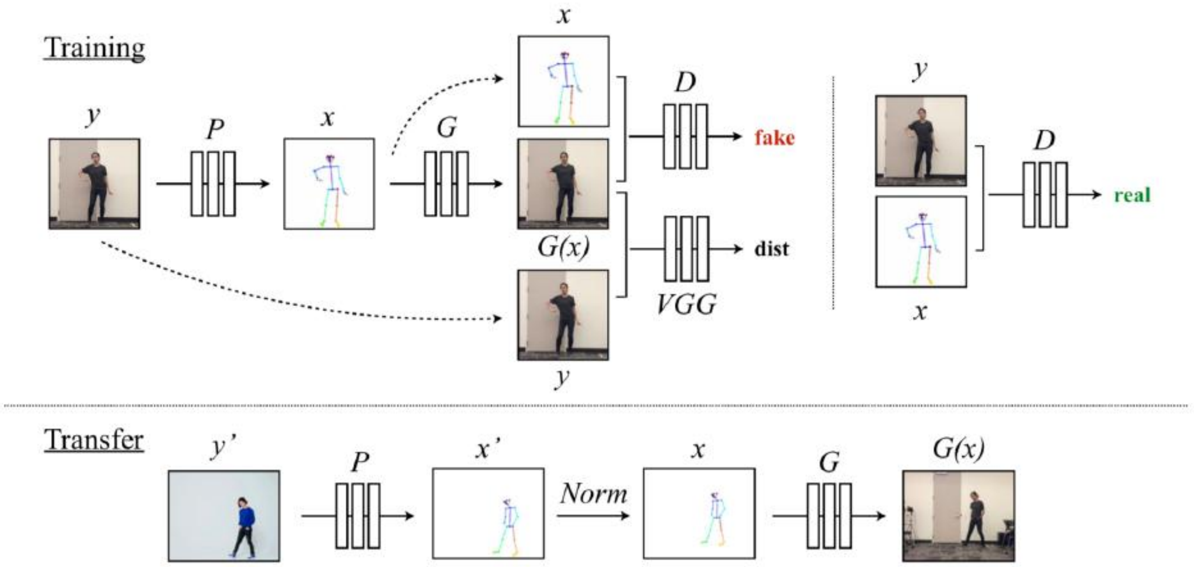
- Latent coded correspond to attributes

Everybody Dance Now [link]



- https://www.youtube.com/watch?v=PCBTZh41Ris

Everybody Dance Now [link]



- G maps from pose "stick figure" to synthesized target
- D distinguishes (x, y) from (x, G(x))

Links to papers

- GAN
    - WGAN
- Applications
    - DCGan
    - Face Generation
    - BigGAN
    - Pix2Pix
    - CycleGAN
    - SRGan
    - DANN
    - InfoGAN
    - Dancing GAN

Thank you!

Any questions?