Learning Generative Adversarial Networks

Qiyang Hu
UCLA Office of Advanced Research Computing
Mar 3rd, 2023

In this talk

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Generative Learning

- What is generative learning?
- Types of generative models

01

GAN Introduction

- What is GAN?
- Training of GANs

02

Coding GANs

- DCGANs
- In-house GANs in PyTorch
- GANs using Transfer Learning

03

GANs World

- Variant GANs
  - SAGAN, CGAN, CycleGAN
- Challenges in GANs

04

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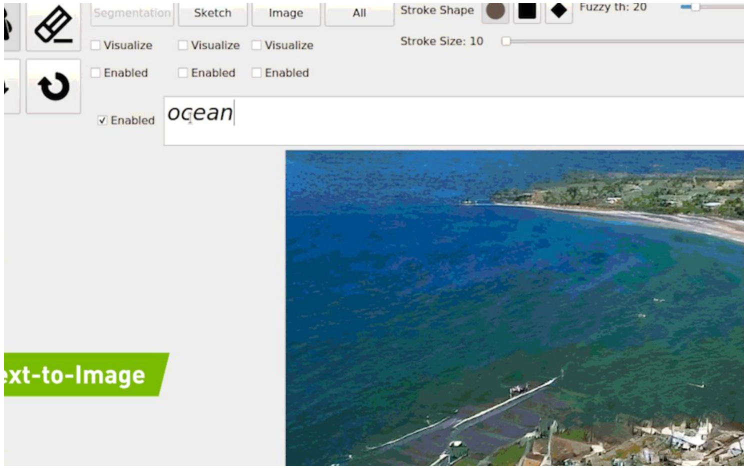
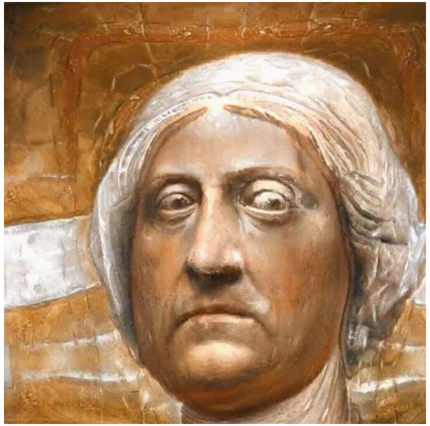
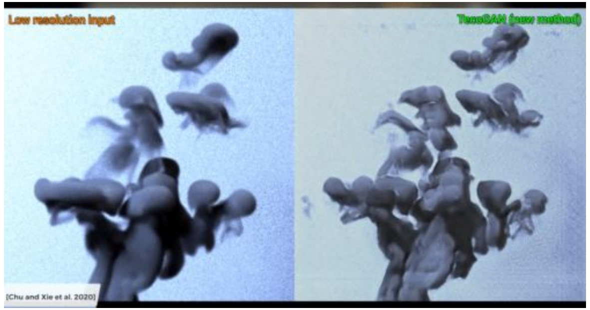
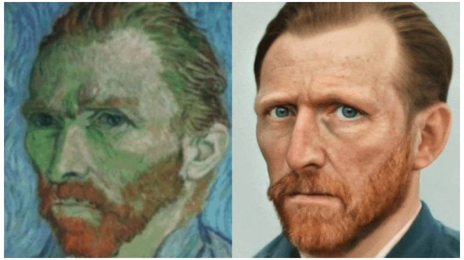
Generative = Creative = Imaginative/Unimaginable









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Generative Learning

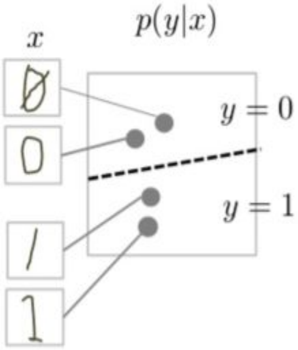
Training Data (source)

$p_{\text{data}}(\mathbf{x})$

Generated Samples (source)

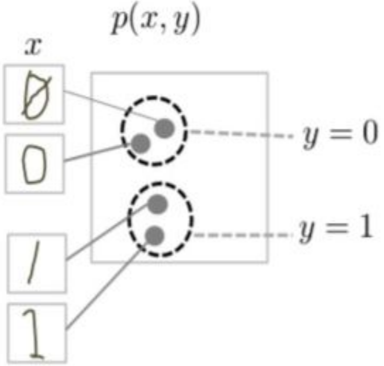
$p_{\text{model}}(\mathbf{x})$

- Discriminative model
  - discriminate labels of data instances
  - try to draw boundaries in the data space



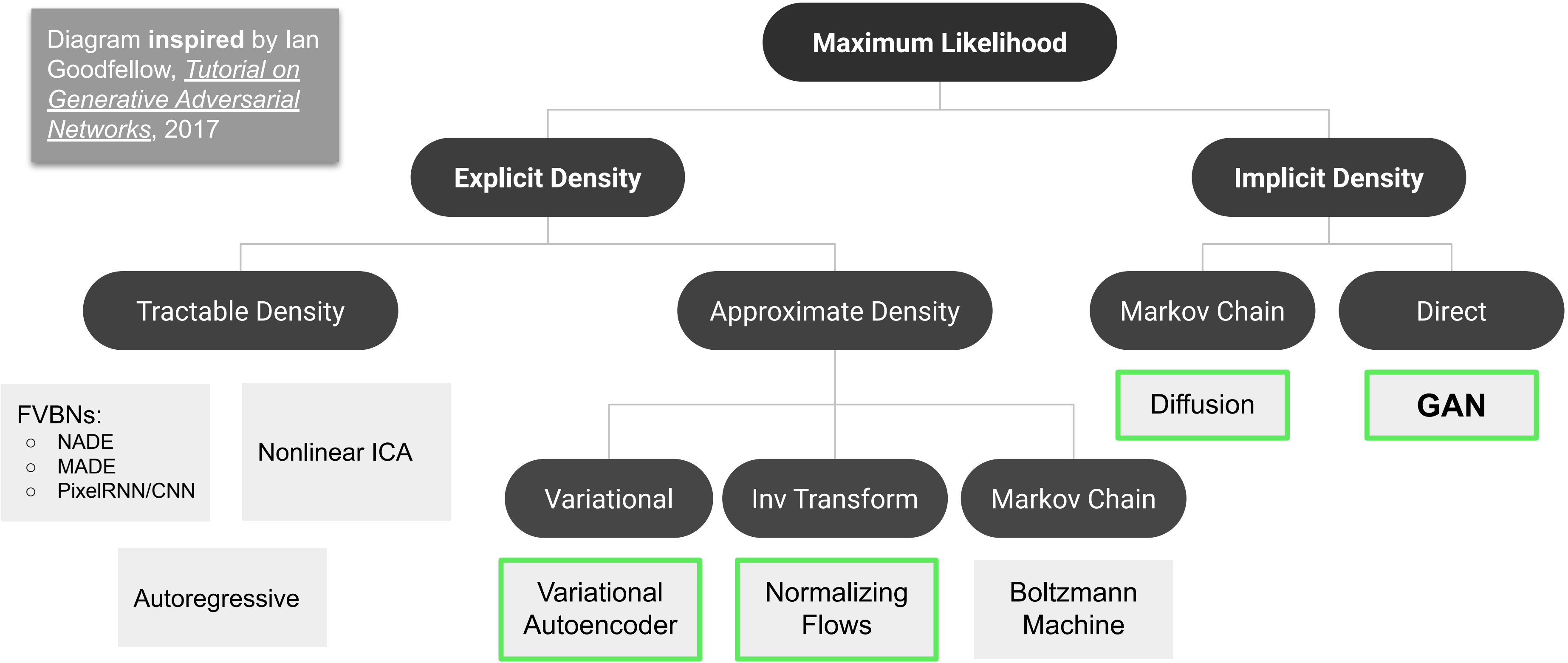
  - capture the conditional prob. *p(Y | X)*
  - measure the misfit of points
  - learn the difference, ignore correlations

- Generative model
  - generate new data instances
  - try to model how data is placed



  - capture the joint prob. *p(X, Y)*
  - measure the misfit of prob distributions
  - learn distributions to capture correlations

Taxonomy of Generative Models



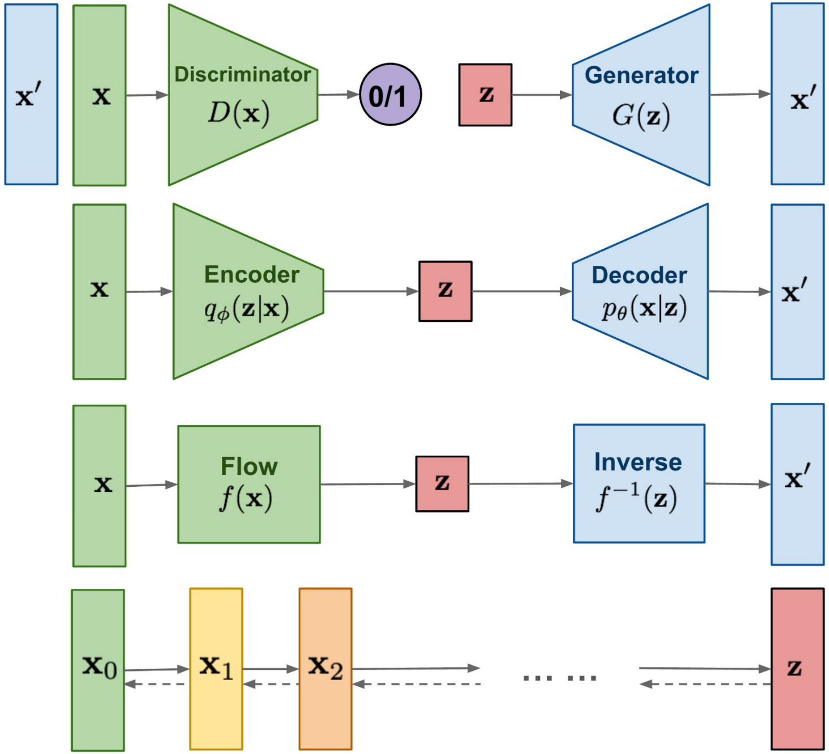
Network Architectures of 4 Generative Models

GAN: Adversarial training

VAE: maximize variational lower bound

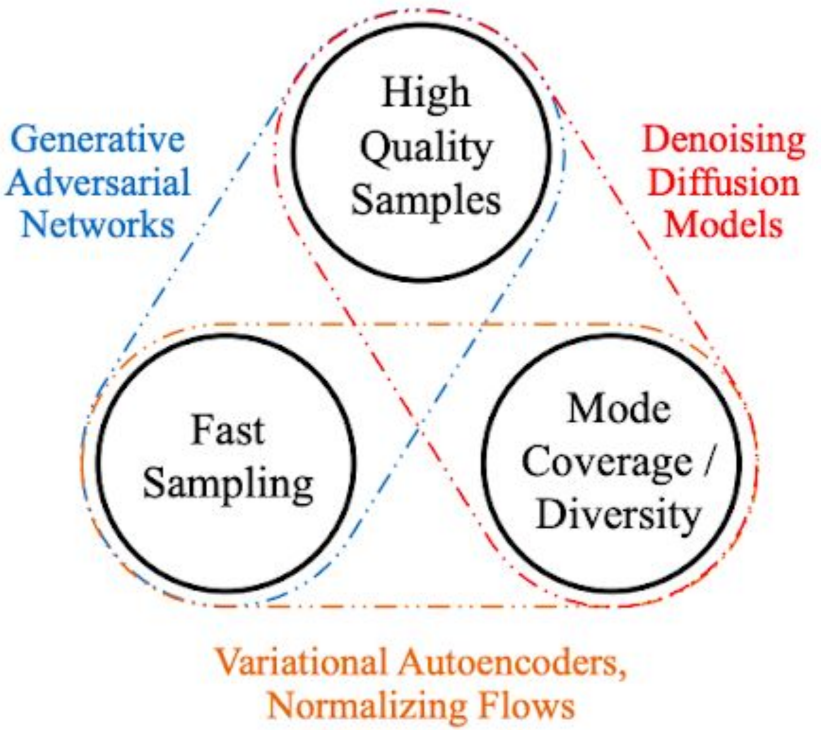
Flow-based models: Invertible transform of distributions

Diffusion models: Gradually add Gaussian noise and then reverse



[Source](#)

Generative Learning Trilemma



Source

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Generative Adversarial Networks

Ian Goodfellow @goodfellow_ian · Jan 14, 2019

4.5 years of GAN progress on face generation. arxiv.org/abs/1406.2661 arxiv.org/abs/1511.06434 arxiv.org/abs/1606.07536 arxiv.org/abs/1710.10196 arxiv.org/abs/1812.04948

42 1.5K 3.7K

2019 StyleGAN2

GAN: Adversarial

- Generator: generate plausible data
- Discriminator: distinguish the generator's fake data from real data

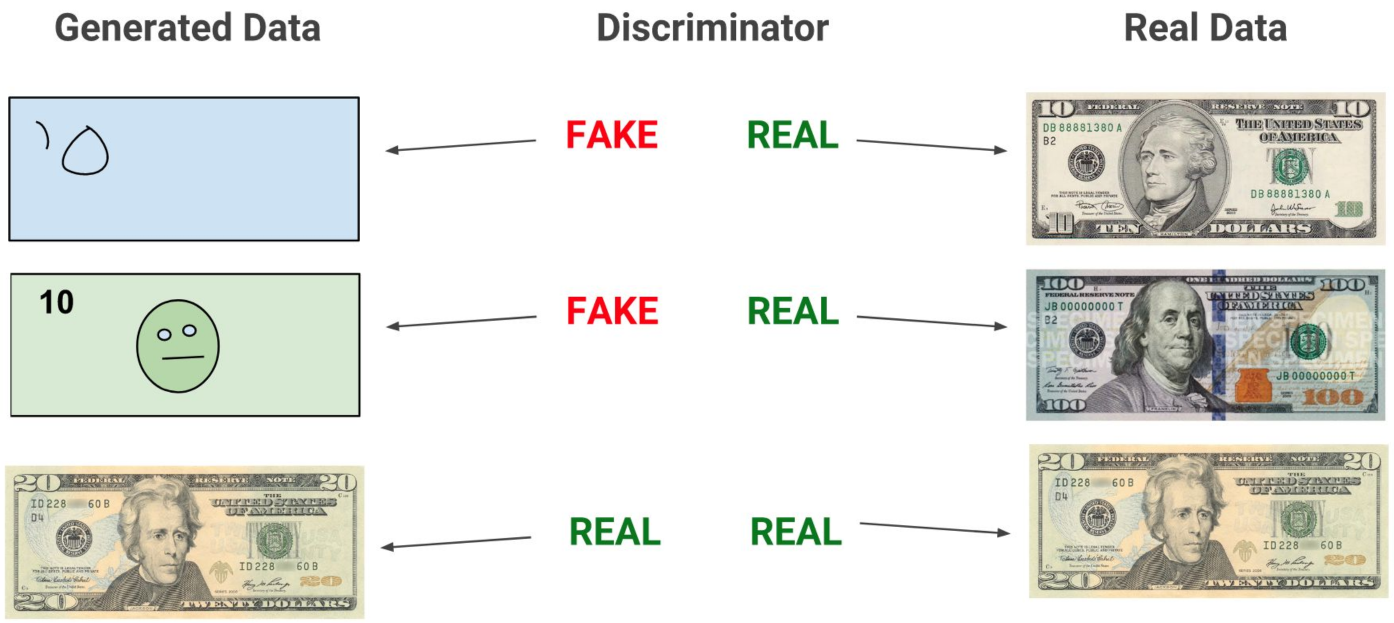

Image Source

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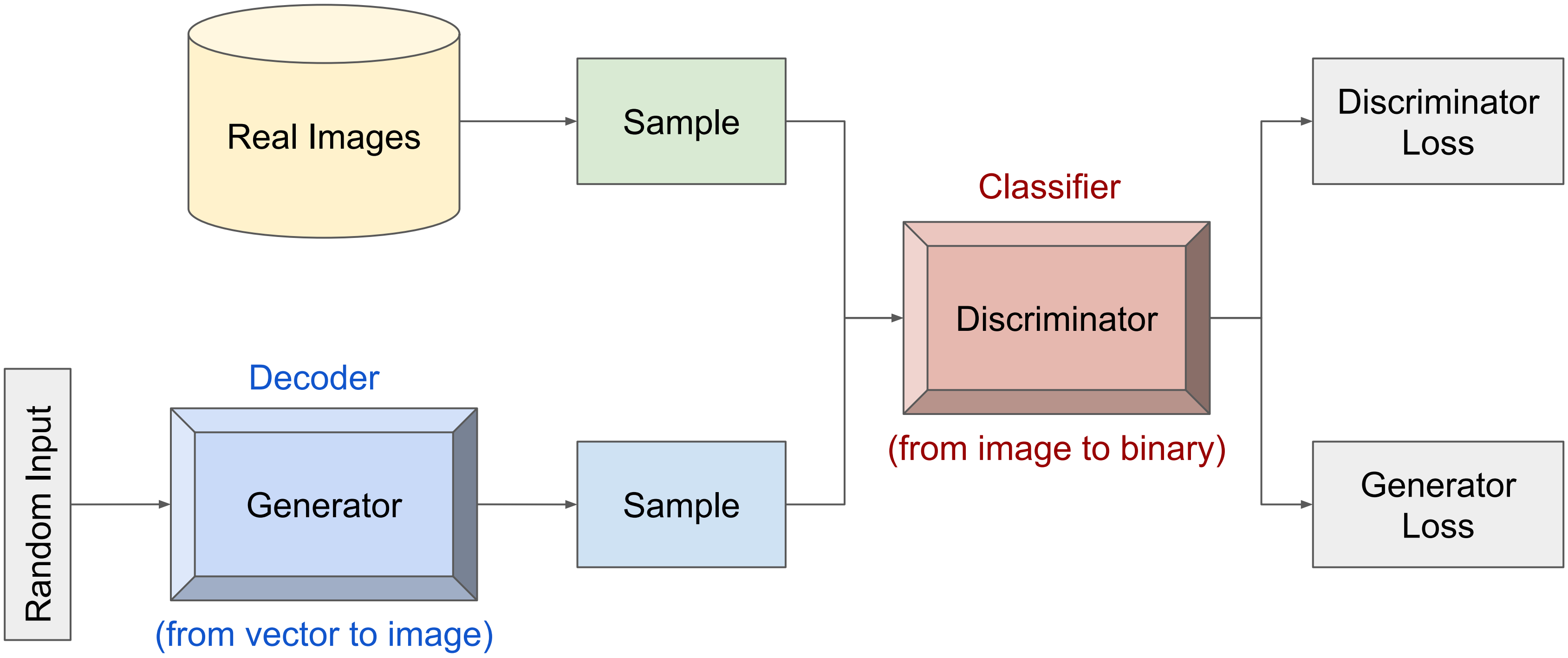
GAN: Network



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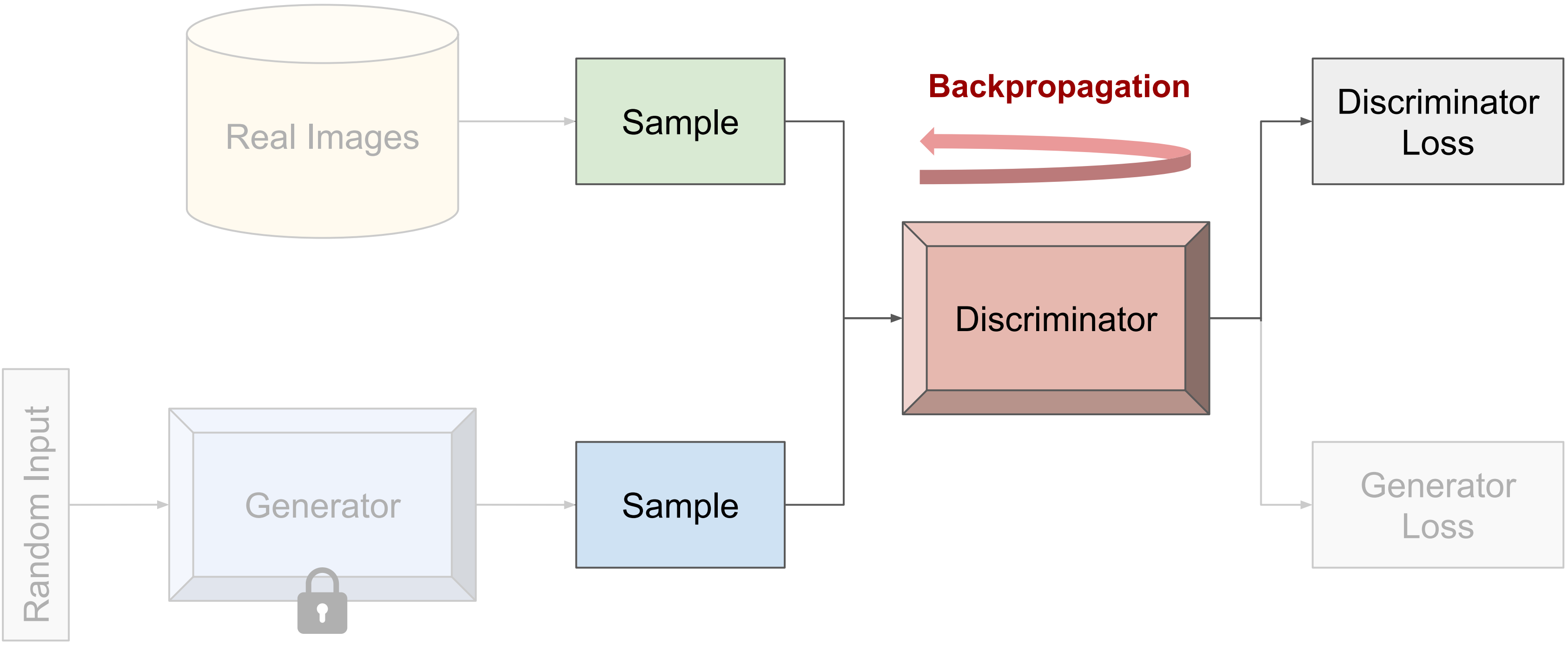
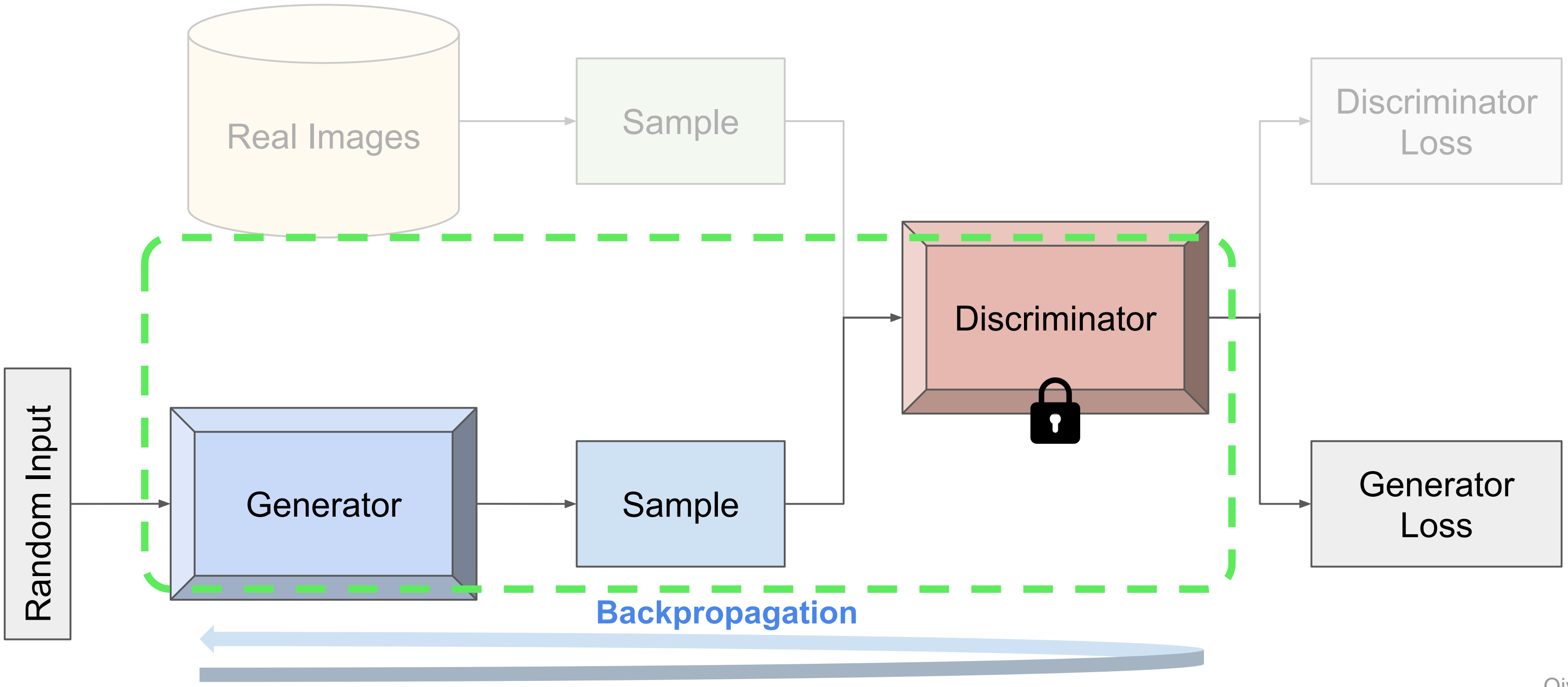
Training of GAN (1): update discriminator



Training of GAN (2): update generator



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Training of GAN (3): iterate the 2 steps to converge

- Alternate the training periods
  - The discriminator trains for one or more epochs with locking generator
  - The generator trains for one or more epochs with locking discriminator
  - Repeat the above steps
- When to stop
  - While generator improves, discriminator performance gets worse
    - Generator becomes perfect ⇒ discriminator gets 50% accuracy
  - Feedback from discriminator is less meaningful over time
    - At some point discriminator starts giving completely random feedback
    - Generator starts to train on junk feedback, and its own quality may collapse
  - Convergence of GANs is unstable, very hard to identify

The design logic behind the GAN structure

- Why do we need discriminator ?
  - There are generative models that can learn without discriminator
    - e.g. Variational Autoencoder (VAE)
  - Generator constructs the images in a bottom-up way
    - Very hard to capture the higher-level correlations
  - The discriminator can guide the generator with correlation info in a criticizing way
- Why do we need generator?
  - There are generative models that can learn without generator
    - e.g. Energy based model
  - Discriminator constructs the images in a top-down way
    - Very hard to learn from constructing negative sampling
  - The generated instances become negative training examples for the discriminator.

Standard Loss function for GAN

- Minimax Loss
  - Proposed in the original Goodfellow's paper

Real image sample

Noise sample

Fake image sample

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

Probability of the real image is real

Probability of the fake image is real

  - Derives from a single measure of distance (BCE) between the real and generated distributions
- In practice
  - Discriminator loss: maximize $\frac{1}{n}\sum_{i=0}^{n} \log(D(x_i)) + \frac{1}{n}\sum_{i=0}^{n} \log[1 - D(G(z_i))]$
  - Generator (not-saturating) loss: maximize $\frac{1}{n}\sum_{i=0}^{n} \log[D(G(z_i))]$

No Pain, No GANs

- Discriminator shouldn't be too good.
  - Good discriminator ⇒ always 100% accuracy
  - Generator has no positive case to follow for learning.
  - Mathematically, falling into the vanishing-gradient zone
  - Generator needs some success, esp. in early stages
- Discriminator shouldn't be too bad.
  - Bad discriminator ⇒ random guess
  - Generator cannot get helpful feedback, esp. in late stages

Training Tips For GANs

- https://github.com/soumith/ganhacks
- Need experiences as always

Input Normalizing

- normalize the images to (-1, 1)
- Tanh as the last layer of the generator output

Implemented in Demo: Yes

Tune the learning rates

- Make D not improve too fast
- Make D not improve too slow

Implemented in Demo: Yes

A modified loss function

- Generator loss function to be max log(D)
- Flip labels when training generator:
  real = fake, fake=real

Implemented in Demo: Yes

BatchNorm

Construct different mini-batches for real and generated samples

Implemented in Demo: Yes

Add noise to inputs

- Perturb the both real and fake images when training D
- Decay the noise over time.

Implemented in Demo: No

• • •

Avoid Sparse Gradients: ReLU, MaxPool

- LeakyRL is good for G and D
- Use stride, not pooling

Implemented in Demo: Yes

Use Soft and Noisy Labels

- Real ~ Uniform(0.7, 1.2)
- Fake ~ Uniform(0.0, 0.3)

As homework

Use DCGAN or Hybrid

- Use DCGAN if possible
- If not, use hybrid of KL + GAN or VAE + GAN

Implemented in Demo: Yes

ADAM

Use the ADAM Optimizer

optim.Adam rules.

Implemented in Demo: Yes

Use Dropouts in G

- Provide noise in the form of dropout (50%)
- Apply at both training and test time

Implemented in Demo: No

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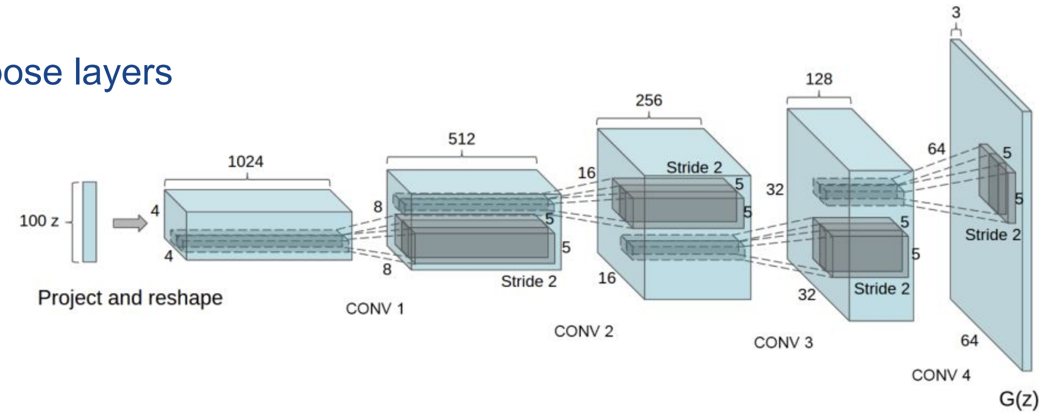
Neural Networks for Generator and Discriminator

- Deep Convolutional Generative Adversarial Networks ([DCGANs]())
- Generator
  - Input: a std-norm latent vector
  - Strided 2D Convolutional-transpose layers
  - Batch norm layers
  - ReLU activations
  - Convtrans+*Tanh* before output
  - Output: a 3x64x64 RGB image



- Discriminator
  - Input: 3x64x64 input image
  - Strided convolution layers, batch norm layers, LeakyReLU activations
  - Conv+*Sigmoid* before output
  - Output: a scalar probability

Generator Implementation in PyTorch

```
class Generator(nn.Module):
    def __init__(self, nz=128, channels=3):
        super(Generator, self).__init__()

        self.nz = nz
        self.channels = channels

        def convlayer(n_input, n_output, k_size=4, stride=2, padding=0):
            block = [
                nn.ConvTranspose2d(n_input, n_output, kernel_size=k_size, stride=stride, padding=padding, bias=False),
                nn.BatchNorm2d(n_output),
                nn.ReLU(inplace=True),
            ]
            return block

        self.model = nn.Sequential(
            *convlayer(self.nz, 1024, 4, 1, 0), # Fully connected layer via convolution.
            *convlayer(1024, 512, 4, 2, 1),
            *convlayer(512, 256, 4, 2, 1),
            *convlayer(256, 128, 4, 2, 1),
            *convlayer(128, 64, 4, 2, 1),
            nn.ConvTranspose2d(64, self.channels, 3, 1, 1),
            nn.Tanh()
        )

    def forward(self, z):
        z = z.view(-1, self.nz, 1, 1)
        img = self.model(z)
        return img
```

Discriminator Implementation in PyTorch

```
class Discriminator(nn.Module):
    def __init__(self, channels=3):
        super(Discriminator, self).__init__()

        self.channels = channels

        def convlayer(n_input, n_output, k_size=4, stride=2, padding=0, bn=False):
            block = [nn.Conv2d(n_input, n_output, kernel_size=k_size, stride=stride, padding=padding, bias=False)]
            if bn:
                block.append(nn.BatchNorm2d(n_output))
            block.append(nn.LeakyReLU(0.2, inplace=True))
            return block

        self.model = nn.Sequential(
            *convlayer(self.channels, 32, 4, 2, 1),
            *convlayer(32, 64, 4, 2, 1),
            *convlayer(64, 128, 4, 2, 1, bn=True),
            *convlayer(128, 256, 4, 2, 1, bn=True),
            nn.Conv2d(256, 1, 4, 1, 0, bias=False),  # FC with Conv.
        )

    def forward(self, imgs):
        logits = self.model(imgs)
        out = torch.sigmoid(logits)

        return out.view(-1, 1)
```

Training loop

```
############################
# (1) Update D network: maximize log(D(x)) + log(1 - D(G(z)))
###########################
# train with real
netD.zero_grad()
real_images = real_images.to(device)
batch_size = real_images.size(0)
labels = torch.full((batch_size, 1), real_label, device=device)

output = netD(real_images)
errD_real = criterion(output, labels)
errD_real.backward()
D_x = output.mean().item()

# train with fake
noise = torch.randn(batch_size, nz, 1, 1, device=device)
fake = netG(noise)
labels.fill_(fake_label)
output = netD(fake.detach())
errD_fake = criterion(output, labels)
errD_fake.backward()
D_G_z1 = output.mean().item()
errD = errD_real + errD_fake
optimizerD.step()
```

```
real_label = 0.9
fake_label = 0
```

real_label **≠ 1** to make the discriminator not learn too quickly

```
############################
# (2) Update G network: maximize log(D(G(z)))
###########################
netG.zero_grad()
labels.fill_(real_label)  # fake labels are real for generator cost
output = netD(fake)
errG = criterion(output, labels)
errG.backward()
D_G_z2 = output.mean().item()
optimizerG.step()
```

Today’s Demo — Generative Dog Images from Kaggle

- Experiment with creating puppy pics
  - A Kernels-only competition (total 10K prize, expired years ago)
  - Evaluation
    - Using a pre-trained model (Inception)
    - Calculating MiFID scores
- Using Stanford Dogs Dataset
  - 20,580 images with annotation info (120 breeds, bounding box)
  - Some dog pictures are very *tricky*
    - Only part of the dogs body
    - Having multiple dogs
    - Having multiple persons
    - Dogs may occupy <⅕ of the picture
    - With various texts (from memes, magazine, etc)
    - Even wild predators included

Colab Hands-on

bit.ly/**LDL_gan**

Using Transfer Learning for GANs

- StyleGAN from Nvidia
    - StyleGAN (2018), StyleGAN2 (2019)
    - StyleGAN3 (2021): w/ diffusion models
    - StyleGAN-T(2023)
- Animal Faces HQ v2
    - 15,000 images at 512×512 res.
    - Cat, dog and wildlife
- Test for the dog project:
    - StyleGAN3 pretrained model:
      stylegan3-r-afhqv2-512x512.pkl
    - AFHQv2 dogs (5000 images)
    - Request one A100 GPU from H2
    - Trained through “python train.py”
    - Ran 2 days with 500 epochs

Real

Fake
Initial

Fake
Trained

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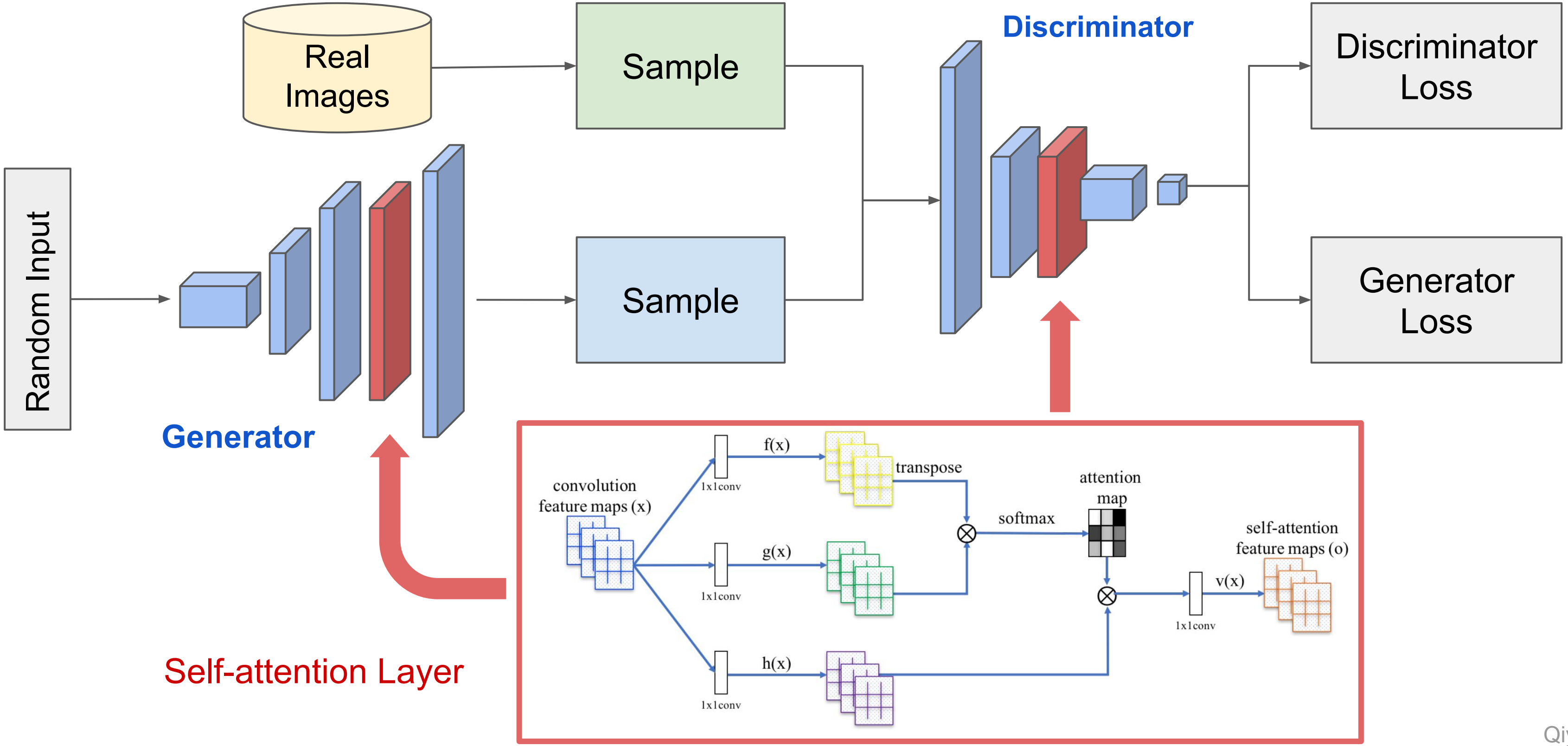
A *lot* of different GANs!

- Various design of network structures
    - SAGANs
    - Conditional GANS
    - CycleGANs
    - InfoGANs
    - EB-GANs
    - VAE-GANs
    - BiGANs
    - Triple-GANs
    - …
- Various metrics for objective functions
    - WGANs
    - LSGANs
    - RGANs
    - Cramer GANs
    - Fisher GANs
    - MMD GANs
    - McGANs
    - HingeGANs
    - ...
- Combining the two
    - BEGAN
    - MAGANs
    - ...

SAGAN: DCGANs + Self-Attention Layer (Zhang, et al. 2018)



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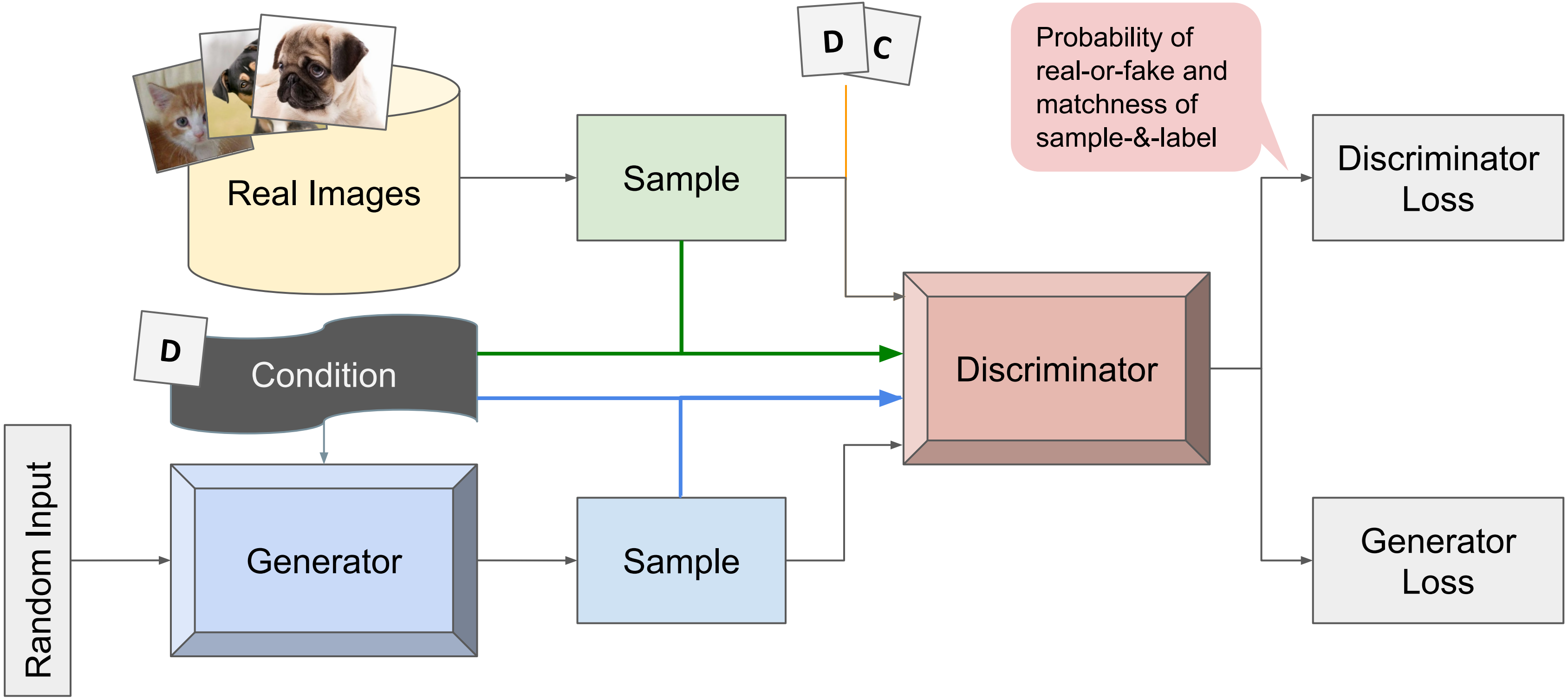
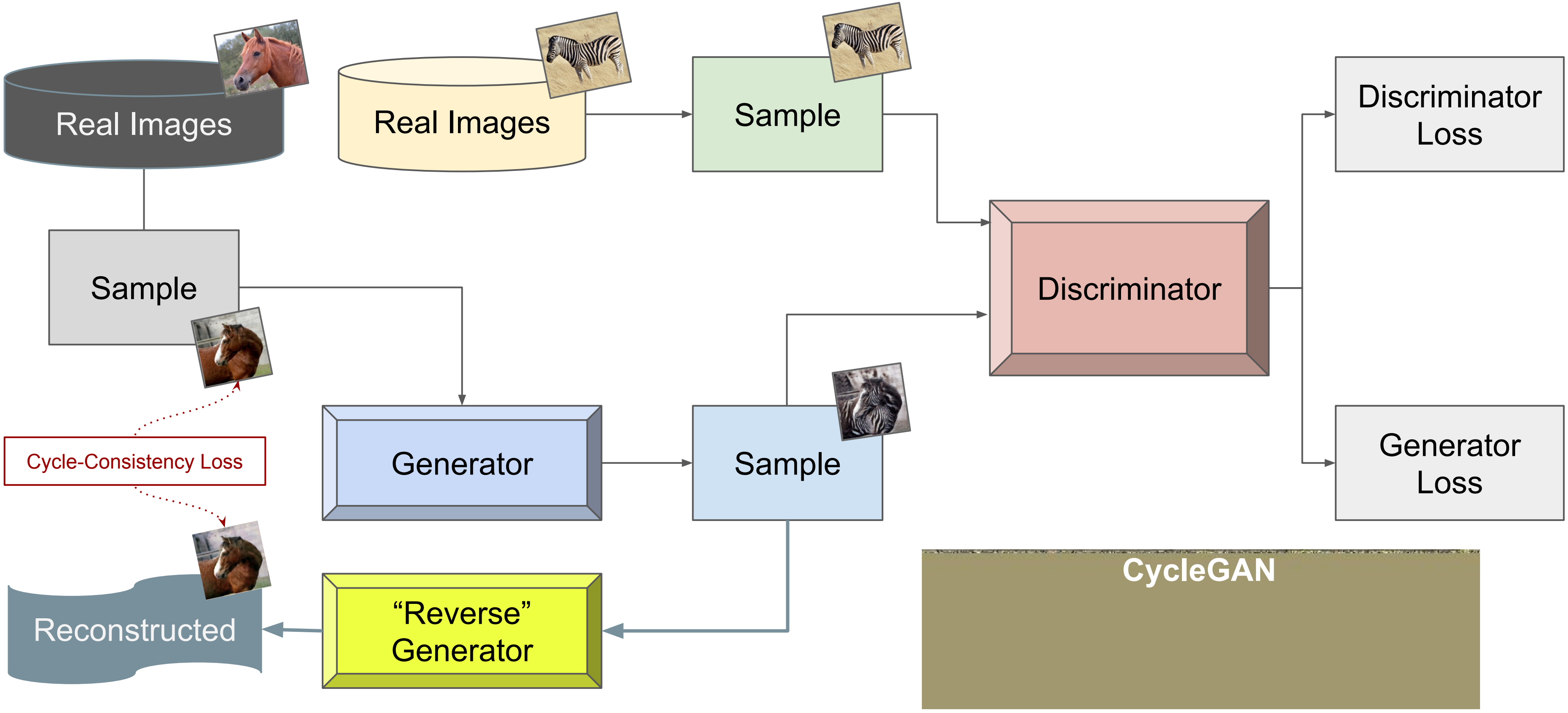
Conditional GAN: generate images with specific class



CycleGAN: *unsupervised* conditional GAN



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Some GAN loss function variations

SGAN (non-saturating)

$$L_D^{SGAN} = -\mathbb{E}_{x_r \sim \mathbb{P}}\left[\log\left(\text{sigmoid}(C(x_r))\right)\right] - \mathbb{E}_{x_f \sim \mathbb{Q}}\left[\log\left(1 - \text{sigmoid}(C(x_f))\right)\right]$$

$$L_G^{SGAN} = -\mathbb{E}_{x_f \sim \mathbb{Q}}\left[\log\left(\text{sigmoid}(C(x_f))\right)\right]$$

RSGAN

$$L_D^{RSGAN} = -\mathbb{E}_{(x_r, x_f) \sim (\mathbb{P}, \mathbb{Q})}\left[\log(\text{sigmoid}(C(x_r) - C(x_f)))\right]$$

$$L_G^{RSGAN} = -\mathbb{E}_{(x_r, x_f) \sim (\mathbb{P}, \mathbb{Q})}\left[\log(\text{sigmoid}(C(x_f) - C(x_r)))\right]$$

RaSGAN

$$L_D^{RaSGAN} = -\mathbb{E}_{x_r \sim \mathbb{P}}\left[\log\left(\tilde{D}(x_r)\right)\right] - \mathbb{E}_{x_f \sim \mathbb{Q}}\left[\log\left(1 - \tilde{D}(x_f)\right)\right]$$

$$L_G^{RaSGAN} = -\mathbb{E}_{x_f \sim \mathbb{Q}}\left[\log\left(\tilde{D}(x_f)\right)\right] - \mathbb{E}_{x_r \sim \mathbb{P}}\left[\log\left(1 - \tilde{D}(x_r)\right)\right]$$

$$\tilde{D}(x_r) = \text{sigmoid}\left(C(x_r) - \mathbb{E}_{x_f \sim \mathbb{Q}} C(x_f)\right)$$
$$\tilde{D}(x_f) = \text{sigmoid}\left(C(x_f) - \mathbb{E}_{x_r \sim \mathbb{P}} C(x_r)\right)$$

LSGAN

$$L_D^{LSGAN} = \mathbb{E}_{x_r \sim \mathbb{P}}\left[(C(x_r) - 0)^2\right] + \mathbb{E}_{x_f \sim \mathbb{Q}}\left[(C(x_f) - 1)^2\right]$$

$$L_G^{LSGAN} = \mathbb{E}_{x_f \sim \mathbb{Q}}\left[(C(x_f) - 0)^2\right]$$

RaLSGAN

$$L_D^{RaLSGAN} = \mathbb{E}_{x_r \sim \mathbb{P}}\left[(C(x_r) - \mathbb{E}_{x_f \sim \mathbb{Q}} C(x_f) - 1)^2\right] + \mathbb{E}_{x_f \sim \mathbb{Q}}\left[(C(x_f) - \mathbb{E}_{x_r \sim \mathbb{P}} C(x_r) + 1)^2\right]$$

$$L_G^{RaLSGAN} = \mathbb{E}_{x_f \sim \mathbb{P}}\left[(C(x_f) - \mathbb{E}_{x_r \sim \mathbb{P}} C(x_r) - 1)^2\right] + \mathbb{E}_{x_r \sim \mathbb{P}}\left[(C(x_r) - \mathbb{E}_{x_f \sim \mathbb{Q}} C(x_f) + 1)^2\right]$$

HingeGAN

$$L_D^{HingeGAN} = \mathbb{E}_{x_r \sim \mathbb{P}}\left[\max(0, 1 - C(x_r))\right] + \mathbb{E}_{x_f \sim \mathbb{Q}}\left[\max(0, 1 + C(x_f))\right]$$

$$L_G^{HingeGAN} = -\mathbb{E}_{x_f \sim \mathbb{Q}}\left[C(x_f)\right]$$

RaHingeGAN

$$L_D^{HingeGAN} = \mathbb{E}_{x_r \sim \mathbb{P}}\left[\max(0, 1 - \tilde{D}(x_r))\right] + \mathbb{E}_{x_f \sim \mathbb{Q}}\left[\max(0, 1 + \tilde{D}(x_f))\right]$$

$$L_G^{HingeGAN} = \mathbb{E}_{x_f \sim \mathbb{P}}\left[\max(0, 1 - \tilde{D}(x_f))\right] + \mathbb{E}_{x_r \sim \mathbb{Q}}\left[\max(0, 1 + \tilde{D}(x_r))\right]$$

$$\tilde{D}(x_r) = C(x_r) - \mathbb{E}_{x_f \sim \mathbb{Q}} C(x_f)$$
$$\tilde{D}(x_f) = C(x_f) - \mathbb{E}_{x_r \sim \mathbb{P}} C(x_r)$$

WGAN-GP

$$L_D^{WGAN-GP} = -\mathbb{E}_{x_r \sim \mathbb{P}}\left[C(x_r)\right] + \mathbb{E}_{x_f \sim \mathbb{Q}}\left[C(x_f)\right] + \lambda \mathbb{E}_{\hat{x} \sim \mathbb{P}_{\hat{x}}}\left[(\|\nabla_{\hat{x}} C(\hat{x})\|_2 - 1)^2\right]$$

$$L_G^{WGAN-GP} = -\mathbb{E}_{x_f \sim \mathbb{Q}}\left[C(x_f)\right]$$

$\mathbb{P}_{\hat{x}}$ is the distribution of $\hat{x} = \epsilon x_r + (1 - \epsilon) x_f$, where $x_r \sim \mathbb{P}$, $x_f \sim \mathbb{Q}$, $\epsilon \sim U[0, 1]$.

RSGAN-GP

$$L_D^{RSGAN} = -\mathbb{E}_{(x_r, x_f) \sim (\mathbb{P}, \mathbb{Q})}\left[\log(\text{sigmoid}(C(x_r) - C(x_f)))\right] + \lambda \mathbb{E}_{\hat{x} \sim \mathbb{P}_{\hat{x}}}\left[(\|\nabla_{\hat{x}} C(\hat{x})\|_2 - 1)^2\right]$$

$$L_G^{RSGAN} = -\mathbb{E}_{(x_r, x_f) \sim (\mathbb{P}, \mathbb{Q})}\left[\log(\text{sigmoid}(C(x_f) - C(x_r)))\right]$$

$\mathbb{P}_{\hat{x}}$ is the distribution of $\hat{x} = \epsilon x_r + (1 - \epsilon) x_f$, where $x_r \sim \mathbb{P}$, $x_f \sim \mathbb{Q}$, $\epsilon \sim U[0, 1]$.

RaSGAN-GP

$$L_D^{RaSGAN} = -\mathbb{E}_{x_r \sim \mathbb{P}}\left[\log\left(\tilde{D}(x_r)\right)\right] - \mathbb{E}_{x_f \sim \mathbb{Q}}\left[\log\left(1 - \tilde{D}(x_f)\right)\right] + \lambda \mathbb{E}_{\hat{x} \sim \mathbb{P}_{\hat{x}}}\left[(\|\nabla_{\hat{x}} C(\hat{x})\|_2 - 1)^2\right]$$

$$L_G^{RaSGAN} = -\mathbb{E}_{x_f \sim \mathbb{Q}}\left[\log\left(\tilde{D}(x_f)\right)\right] - \mathbb{E}_{x_r \sim \mathbb{P}}\left[\log\left(1 - \tilde{D}(x_r)\right)\right]$$

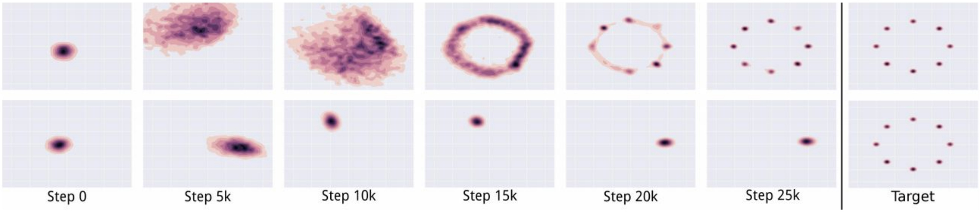
$$\tilde{D}(x_r) = \text{sigmoid}\left(C(x_r) - \mathbb{E}_{x_f \sim \mathbb{Q}} C(x_f)\right)$$
$$\tilde{D}(x_f) = \text{sigmoid}\left(C(x_f) - \mathbb{E}_{x_r \sim \mathbb{P}} C(x_r)\right)$$

$\mathbb{P}_{\hat{x}}$ is the distribution of $\hat{x} = \epsilon x_r + (1 - \epsilon) x_f$, where $x_r \sim \mathbb{P}$, $x_f \sim \mathbb{Q}$, $\epsilon \sim U[0, 1]$.

Challenges in GANs

- Mode collapse

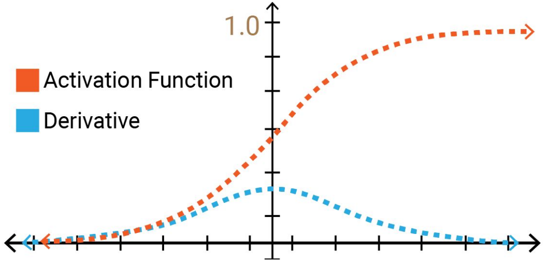
  Generator produces samples with a limited set of modes



Source

  ✔ Wasserstein loss
  ✔ Unrolled and packing

- Vanishing gradient



  ✔ Gradient Penalty
  ✔ Spectral Normalization

- Convergence failure
  ✔ Adding noise to discriminator inputs
  ✔ Penalizing discriminator weights
  ✔ Relativistic metrics

- Result evaluation
  ✔ Inception Score
  ✔ Fréchet Inception Distance (FID, MiFID)

Survey

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