Generative Adversarial Network (GAN)

Practice

- Open “8.1. GAN.ipynb"

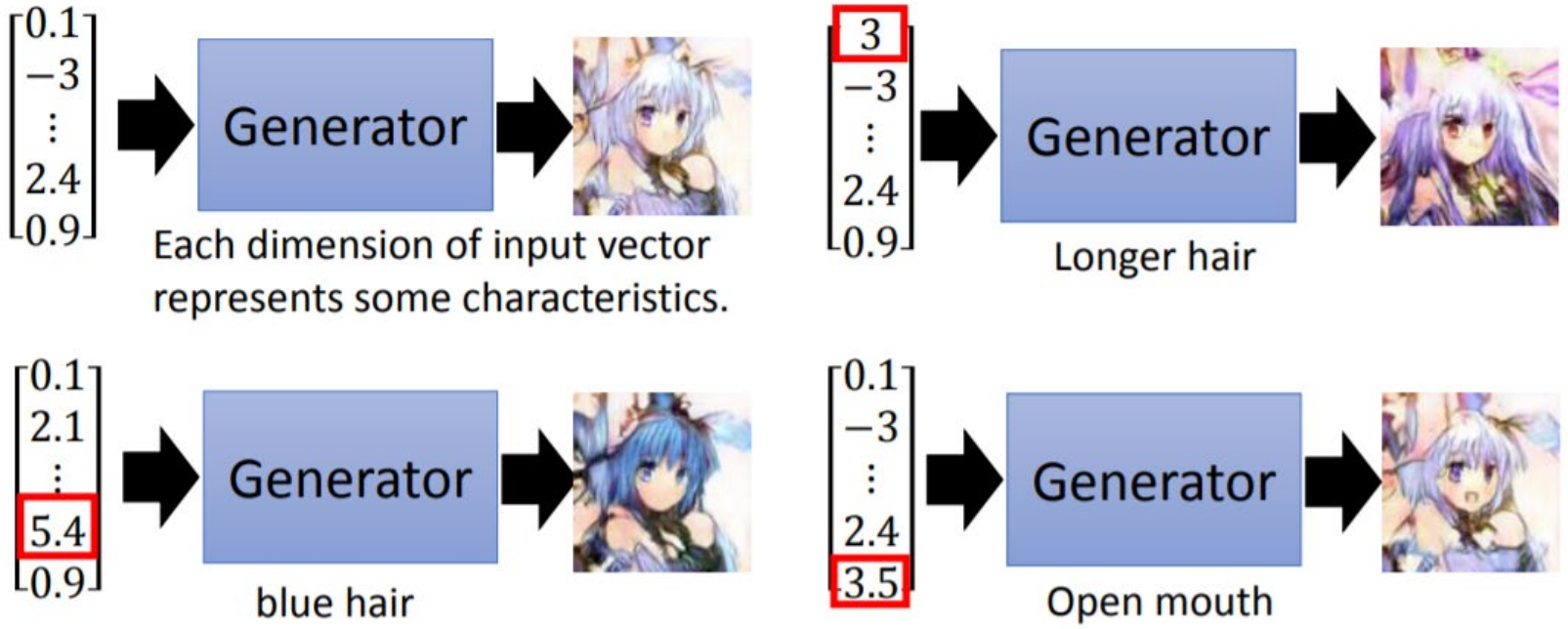
Generator takes a feature vector and generates an output image (using deconvolution to do up-sampling)

[10]:
```
latent_size= 128
```

[11]:
```
generator = nn.Sequential(
    # in: latent_size x 1 x 1

    nn.ConvTranspose2d(latent_size, 512, kernel_size=4, stride=1, padding=0, bias=False),
    nn.BatchNorm2d(512),
    nn.ReLU(True),
    # out: 512 x 4 x 4

    nn.ConvTranspose2d(512, 256, kernel_size=4, stride=2, padding=1, bias=False),
    nn.BatchNorm2d(256),
    nn.ReLU(True),
    # out: 256 x 8 x 8

    nn.ConvTranspose2d(256, 128, kernel_size=4, stride=2, padding=1, bias=False),
    nn.BatchNorm2d(128),
    nn.ReLU(True),
    # out: 128 x 16 x 16

    nn.ConvTranspose2d(128, 64, kernel_size=4, stride=2, padding=1, bias=False),
    nn.BatchNorm2d(64),
    nn.ReLU(True),
    # out: 64 x 32 x 32
```

Each dimension in the feature vector represent a property of the output image

```
[10]: latent_size= 128

[11]: generator = nn.Sequential(
          # in: latent_size x 1 x 1

          nn.ConvTranspose2d(latent_size, 512, kernel_size=4, stride=1, padding=0, bias=False)
          nn.BatchNorm2d(512),
```

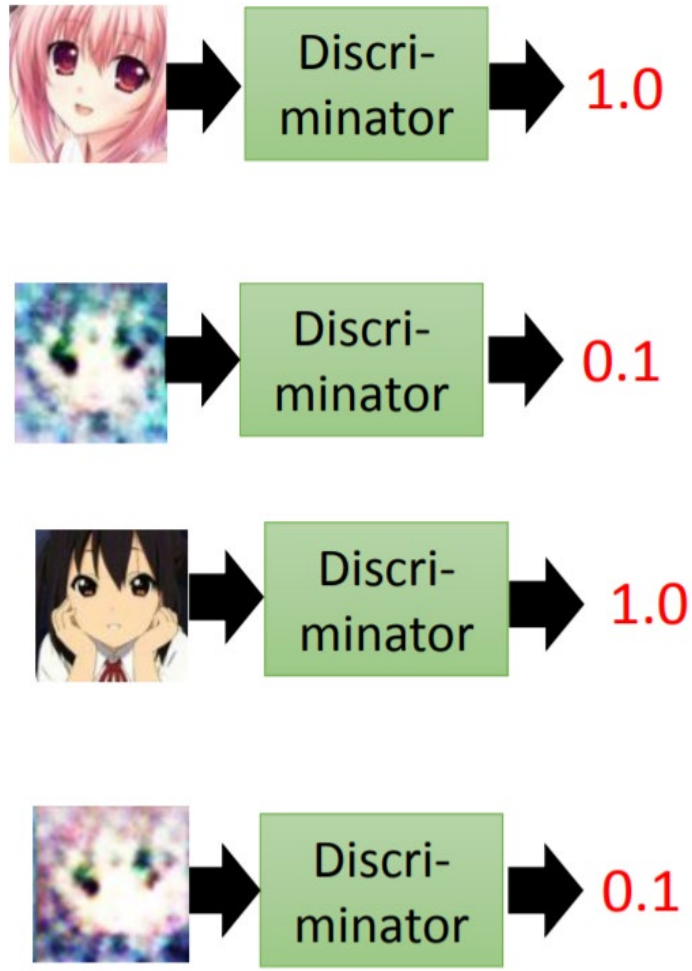


Reference: 李弘毅 GAN Lecture 1 (2018): https://youtu.be/DQNNMiAP5lw

Discriminator takes an input image and tells whether it is a true image or not

[15]:
```
discriminator = nn.Sequential(
    # in: 3 x 128 x 128

    nn.Conv2d(3, 64, kernel_size=4, stride=2, padding=1, bias=Fals
    nn.BatchNorm2d(64),
    nn.LeakyReLU(0.2, inplace=True),
    # out: 64 x 64 x 64

    nn.Conv2d(64, 128, kernel_size=4, stride=2, padding=1, bias=Fa
    nn.BatchNorm2d(128),
    nn.LeakyReLU(0.2, inplace=True),
    # out: 128 x 32 x 32

    nn.Conv2d(128, 256, kernel_size=4, stride=2, padding=1, bias=F
    nn.BatchNorm2d(256),
    nn.LeakyReLU(0.2, inplace=True),
    # out: 256 x 16 x 16

    nn.Conv2d(256, 512, kernel_size=4, stride=2, padding=1, bias=F
    nn.BatchNorm2d(512),
    nn.LeakyReLU(0.2, inplace=True),
    # out: 512 x 8 x 8

    nn.Conv2d(512, 1024, kernel_size=4, stride=2, padding=1, bias=
    nn.BatchNorm2d(1024),
    nn.LeakyReLU(0.2, inplace=True),
    # out: 1024 x 4 x 4

    nn.Conv2d(1024, 1, kernel_size=4, stride=1, padding=0, bias=Fa
    # out: 1 x 1 x 1
```

Larger value means real, smaller value means fake

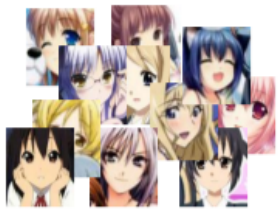


Reference: 李弘毅 GAN Lecture 1 (2018)

Step1 – Fix G and train D

- Initialize generator and discriminator G D
- In each training iteration:

Step 1: Fix generator G, and update discriminator D



Database

samp

gene
ob

randomly
sampled

[12]:
```
generator.to(device)
```

[16]:
```
discriminator.to(device)
```

[35]:
```
for epoch in range(epochs):
  if(epoch % 10 ==0):
    print(epoch, end=",")
  for real_images, _ in train_dl:
    # Train discriminator
    loss_d, real_score, fake_score = train_discriminator(real_images.
    # Train generator
    loss_g = train_generator(opt_g)
```

Reference: 李弘毅 GAN Lecture 1 (2018): https://youtu.be/DQNNMiAP5lw

Train discriminator

- Sample m examples $\{x^1, x^2, \dots, x^m\}$ from database
- Sample m noise samples $\{z^1, z^2, \dots, z^m\}$ from a distribution
- Obtaining generated data $\{\tilde{x}^1, \tilde{x}^2, \dots, \tilde{x}^m\}$, $\tilde{x}^i = G(z^i)$

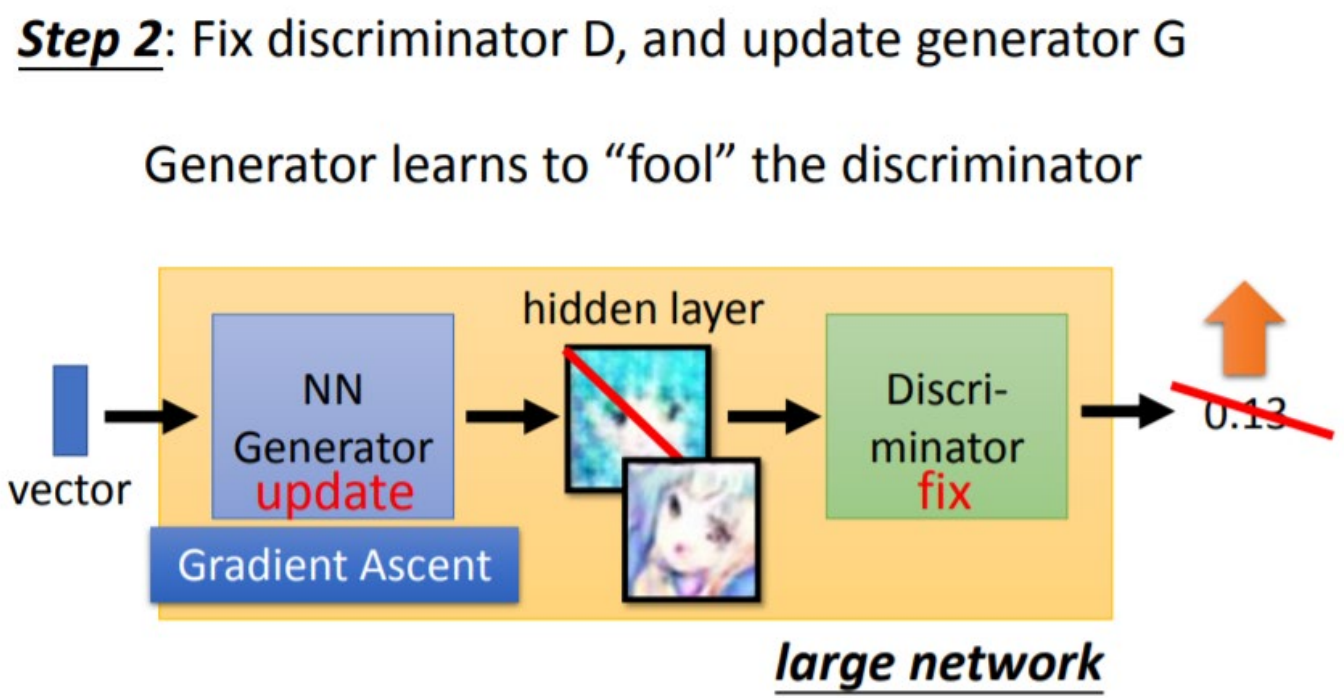
Update discriminator parameters θ_d to maximize

- $\tilde{V} = \frac{1}{m}\sum_{i=1}^{m} logD(x^i) + \frac{1}{m}\sum_{i=1}^{m} log\left(1 - D(\tilde{x}^i)\right)$
- $\theta_d \leftarrow \theta_d + \eta\nabla\tilde{V}(\theta_d)$

[19]:

```
def train_discriminator(real_images, opt_d):
    # Clear discriminator gradients
    opt_d.zero_grad()

    # Pass real images through discriminator
    real_preds = discriminator(real_images)
    real_targets = torch.ones(real_images.size(0)
    real_loss = F.binary_cross_entropy(real_preds
    real_score = torch.mean(real_preds).item()

    # Generate fake images
    latent = torch.randn(batch_size, latent_size,
    fake_images = generator(latent.to(device))

    # Pass fake images through discriminator
    fake_targets = torch.zeros(fake_images.size(0
    fake_preds = discriminator(fake_images)
    fake_loss = F.binary_cross_entropy(fake_preds
    fake_score = torch.mean(fake_preds).item()

    # Update discriminator weights
    loss = real_loss + fake_loss
    loss.backward()
    opt_d.step()
    return loss.item(), real_score, fake_score
```

Step2 – Fix D and train G



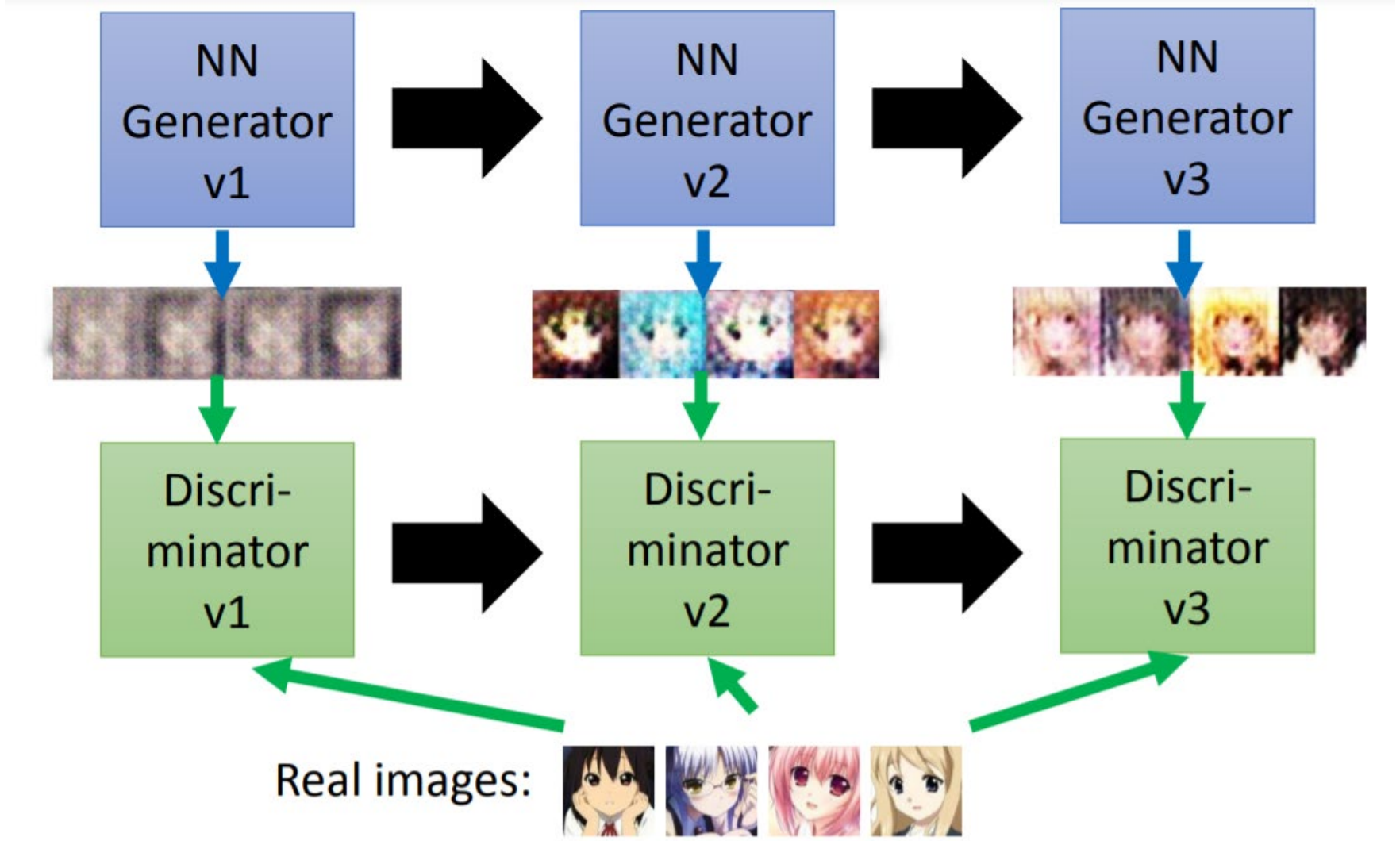
[35]:
```
for epoch in range(epochs):
  if(epoch % 10 ==0):
    print(epoch, end=",")
  for real_images, _ in train_dl:
    # Train discriminator
    loss_d, real_score, fake_score = train_discriminator(real_images.
    # Train generator
    loss_g = train_generator(opt_g)
```

Train generator

- Sample m noise samples$\{z^1, z^2, \ldots, z^m\}$ from a distribution
- Update generator parameters θ_g to maximize
  - $\tilde{V} = \frac{1}{m}\sum_{i=1}^{m} log\left(D\left(G\left(z^i\right)\right)\right)$
  - $\theta_g \leftarrow \theta_g - \eta\nabla\tilde{V}(\theta_g)$

[28]:
```
def train_generator(opt_g):
  # Clear generator gradients
  opt_g.zero_grad()

  # Generate fake images
  latent = torch.randn(batch_size, latent_size,
  fake_images = generator(latent)

  # Try to fool the discriminator
  preds = discriminator(fake_images)
  targets = torch.ones(batch_size, 1, device=dev
  loss = F.binary_cross_entropy(preds, targets)

  # Update generator weights
  loss.backward()
  opt_g.step()

  return loss.item()
```

An evolution process



Reference: 李弘毅 GAN Lecture 1 (2018): https://youtu.be/DQNNMiAP5lw

Visualize the fake images from *G* during the evolution process

[17]:
```
sample_dir = 'generated'
os.makedirs(sample_dir, exist_ok=True)
```

[34]:
```
fixed_latent = torch.randn(64, latent_size,
# used to generate saved images
```

```
if(epoch % 50 ==0):
  # Log losses & scores (last batch)
  print("Epoch [{}/{}], loss_g: {:.4f}, loss_d:
      epoch+1, epochs, loss_g, loss_d, real_sc
  # Save generated images
  save_samples(epoch+start_idx, fixed_latent, s
```

[18]:
```
def save_samples(index, latent_tensors, show=True):
  fake_images = generator(latent_tensors)
  fake_fname = 'generated-images-{0:0=4d}.png'.format(index)
  save_image(denorm(fake_images), os.path.join(sample_dir, f
  print('Saving', fake_fname)
  if show:
    fig, ax = plt.subplots(figsize=(8, 8))
    ax.set_xticks([]); ax.set_yticks([])
    ax.imshow(make_grid(fake_images.cpu().detach(), nrow=8).
```

8.1. GAN.ipynb

檔案 編輯 檢視畫面 插入 執行階段 工具 說明 無法儲存變更

共用

+ 程式碼 + 文字 複製到雲端硬碟

RAM 磁碟 編輯

檔案

..

gdrive

generated

generated-images-0001.png

generated-images-0051.png

generated-images-0101.png

generated-images-0151.png

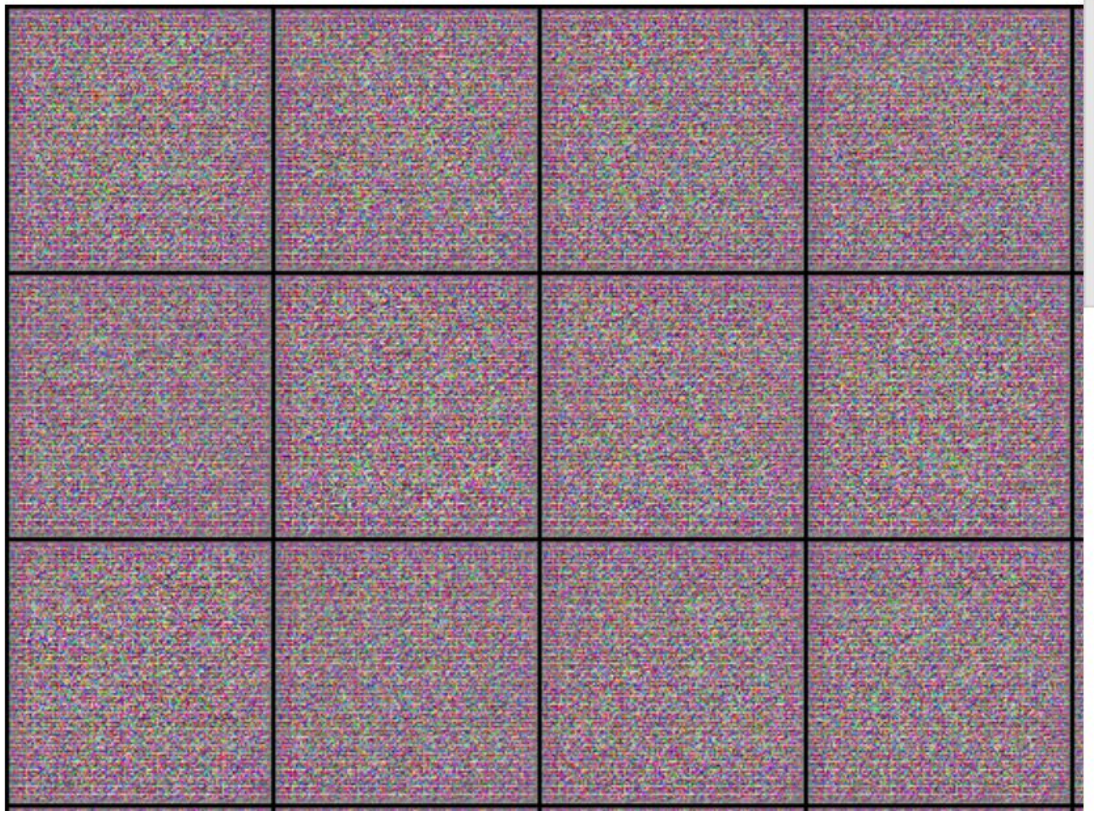
generated-images-0201.png

sample_data

```
        # Log losses & scores (l
        print("Epoch [{}/{}], loss_
              epoch+1, epochs, lo
        # Save generated images
        latent = torch.randn(batch_
        save_samples(epoch+start_idx,
        #save_samples(epoch+start_idx
```

```
0, Epoch [1/1200], loss_g: 5.6803, los
Saving generated-images-0001.png
10, 20, 30, 40, 50, Epoch [51/1200], loss_
Saving generated-images-0051.png
60, 70, 80, 90, 100, Epoch [101/1200], los
Saving generated-images-0101.png
110, 120, 130, 140, 150, Epoch [151/1200],
Saving generated-images-0151.png
160, 170, 180, 190, 200, Epoch [201/1200],
Saving generated-images-0201.png
210, 220,
```

generated-images-0201.png generated-images-0001.png



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RAM 磁碟 編輯

檔案

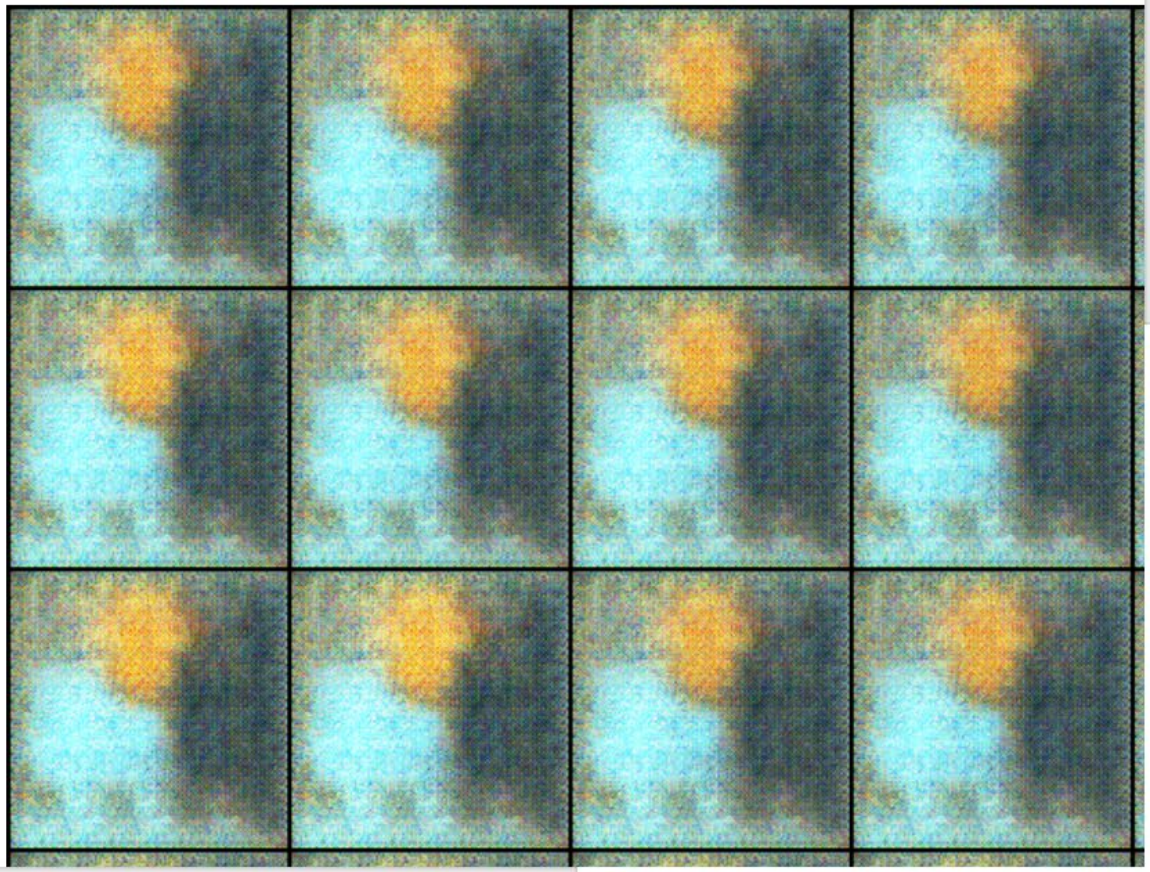
..
gdrive
generated
generated-images-0001.png
generated-images-0051.png
generated-images-0101.png
generated-images-0151.png
generated-images-0201.png
generated-images-0251.png
sample_data

磁碟 29.48 GB 可用

```
Saving generated-images-0001.png
10, 20, 30, 40, 50, Epoch [51/1200], loss_
Saving generated-images-0051.png
60, 70, 80, 90, 100, Epoch [101/1200], los
Saving generated-images-0101.png
110, 120, 130, 140, 150, Epoch [151/1200],
Saving generated-images-0151.png
160, 170, 180, 190, 200, Epoch [201/1200],
Saving generated-images-0201.png
210, 220, 230, 240, 250, Epoch [251/1200],
Saving generated-images-0251.png
260, 270, 280,
```

[ ]

generated-images-0251.png



8.1. GAN.ipynb

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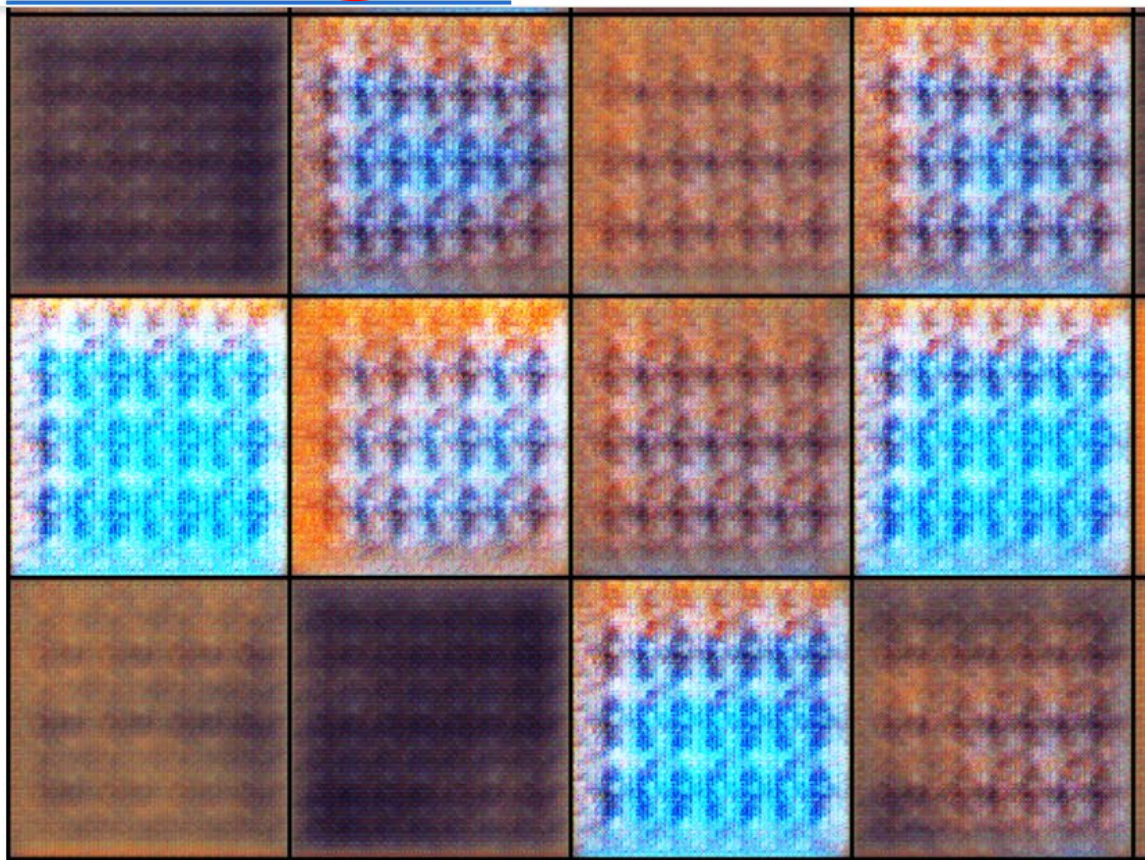
generated-images-0101.png
generated-images-0151.png
generated-images-0201.png
generated-images-0251.png
generated-images-0301.png
sample_data

+ 程式碼 + 文字 複製到雲端硬碟

RAM 磁碟 編輯

```
Saving generated-images-0001.png
10, 20, 30, 40, 50, Epoch [51/1200], loss_
Saving generated-images-0051.png
60, 70, 80, 90, 100, Epoch [101/1200], los
Saving generated-images-0101.png
110, 120, 130, 140, 150, Epoch [151/1200],
Saving generated-images-0151.png
160, 170, 180, 190, 200, Epoch [201/1200],
Saving generated-images-0201.png
210, 220, 230, 240, 250, Epoch [251/1200],
Saving generated-images-0251.png
260, 270, 280, 290, 300, Epoch [301/1200],
Saving generated-images-0301.png
310, 320, 330, 340,
```

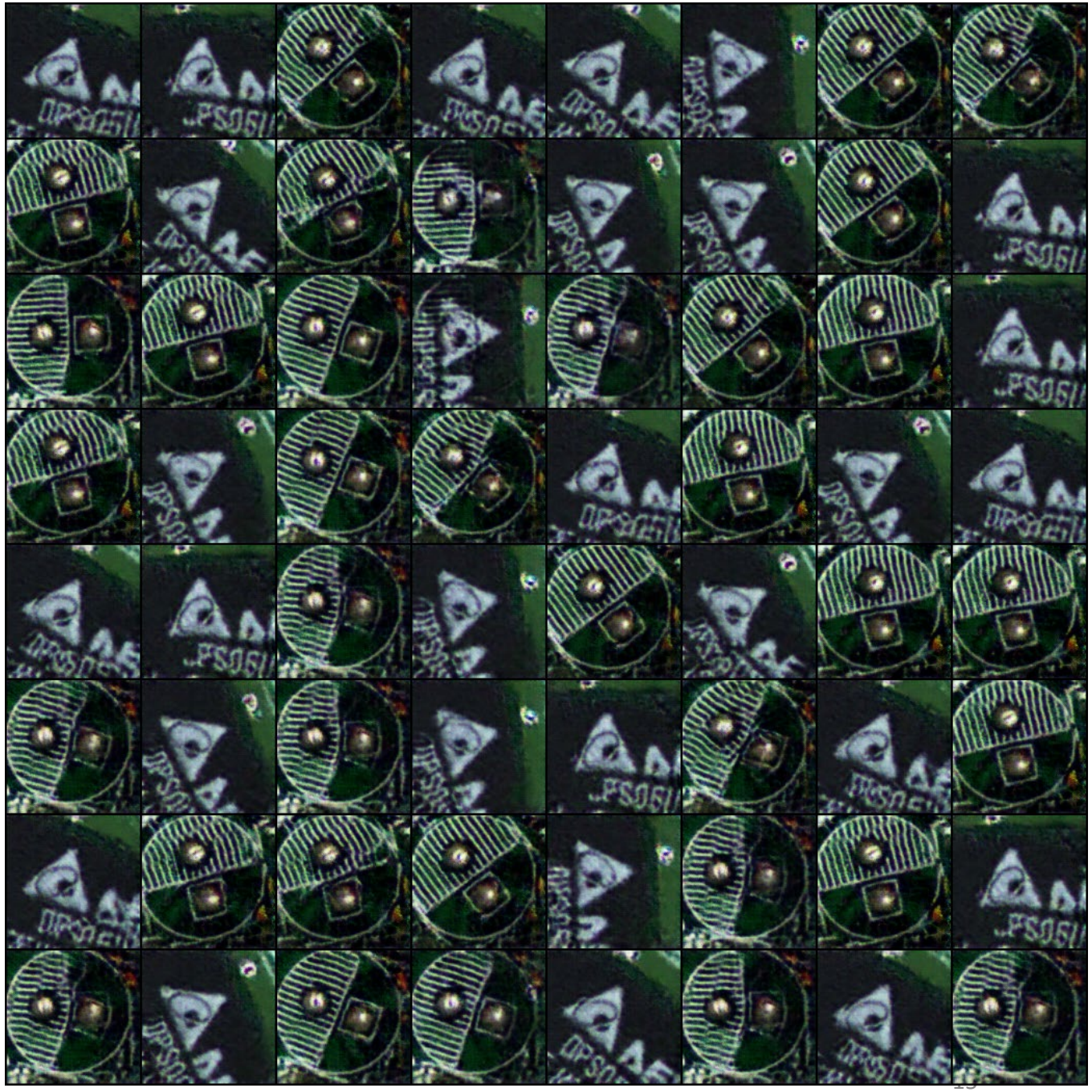
generated-images-0301.png



Images generated from *G* after training for 5651 epochs

Image size = 180x180x3
Class 1 = 100, Class 2 = 100
Latent vector size = 128
batch=32

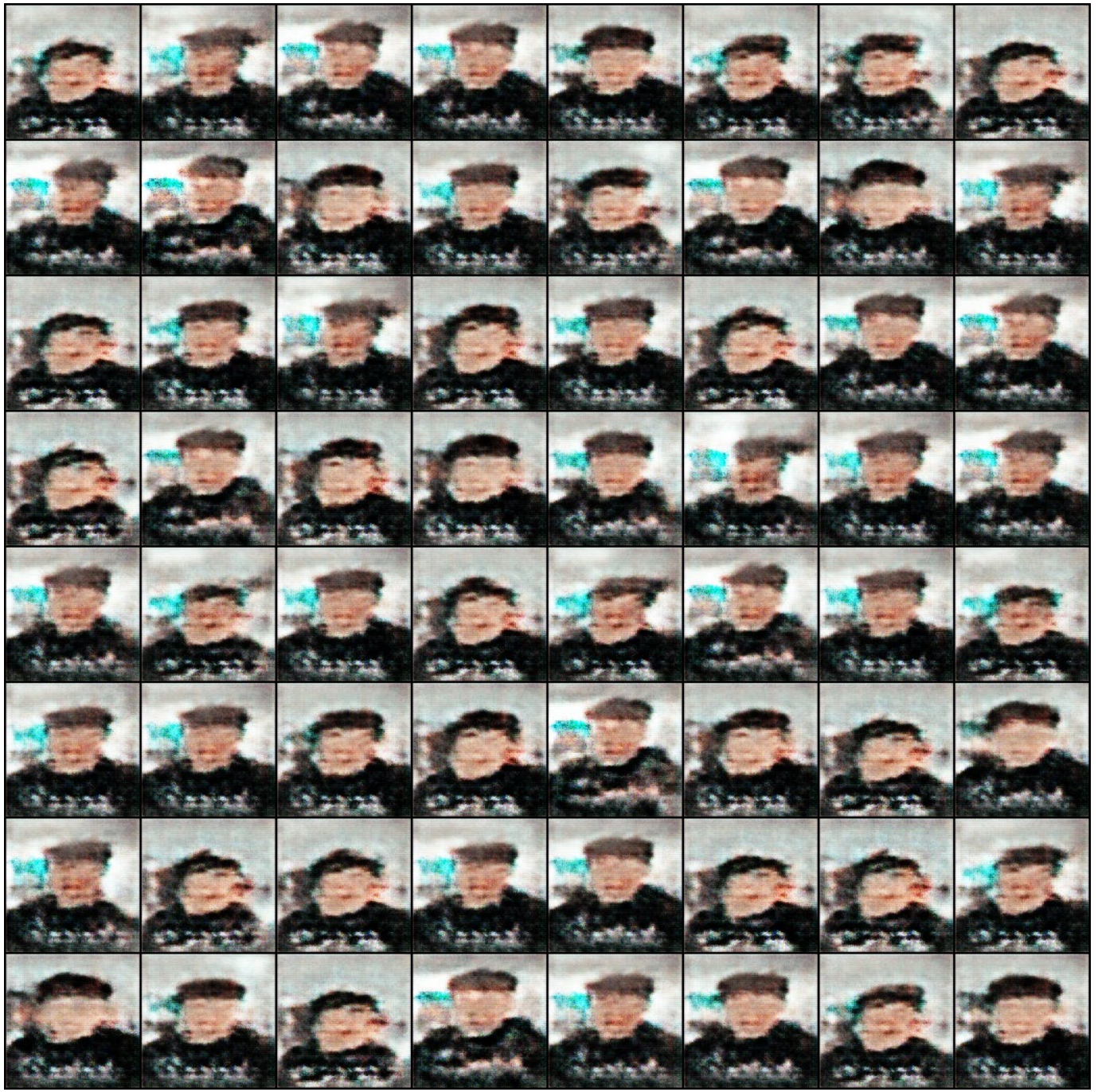
Run on 2080Ti, takes about 15 min.



Images generated from *G* after training for 3051 epochs

Image size = 128x128x3
Class 1 = 10, Class 2 = 10
Latent vector size = 128
batch=128

Run on Colab Telsa T4, takes about 60 min.

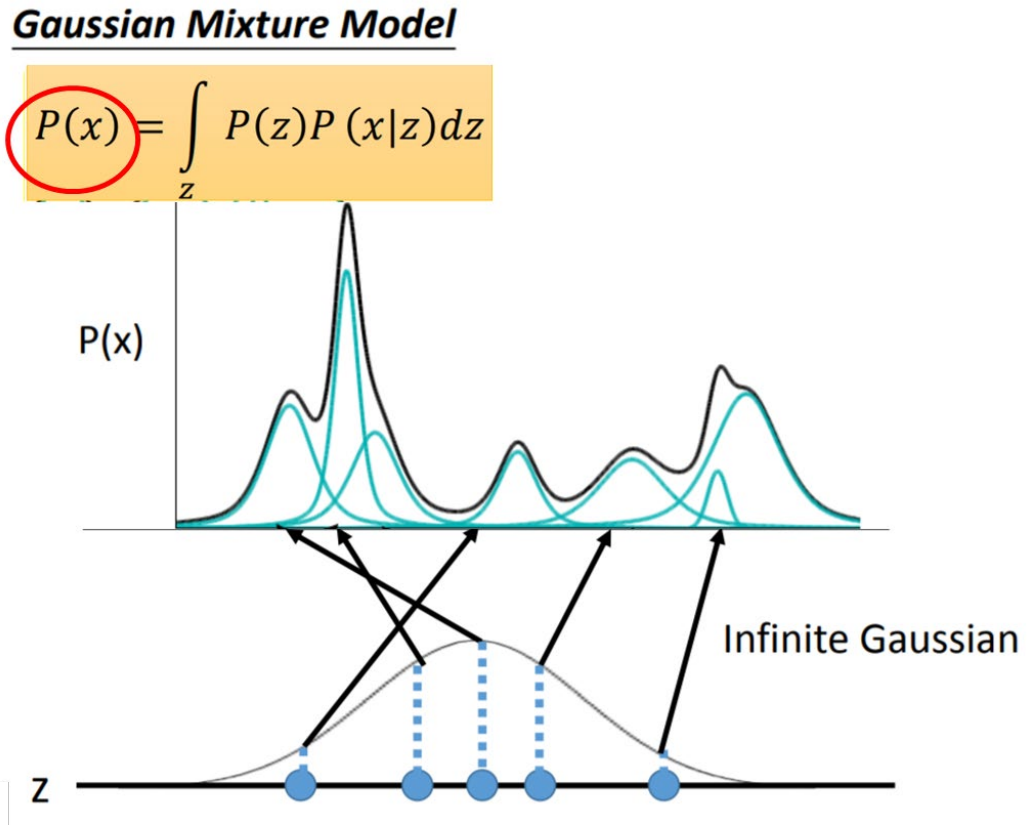


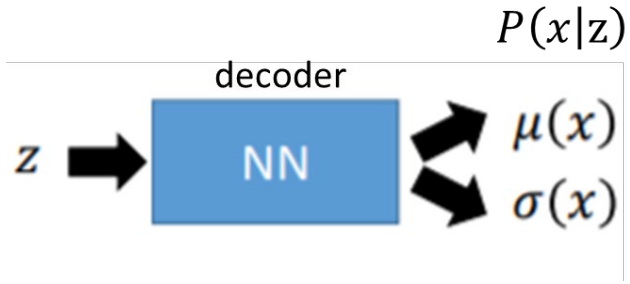
1061221 林大洋

Practice

- Run “8.1. GAN.ipynb" in Colab. Try to generate your own images

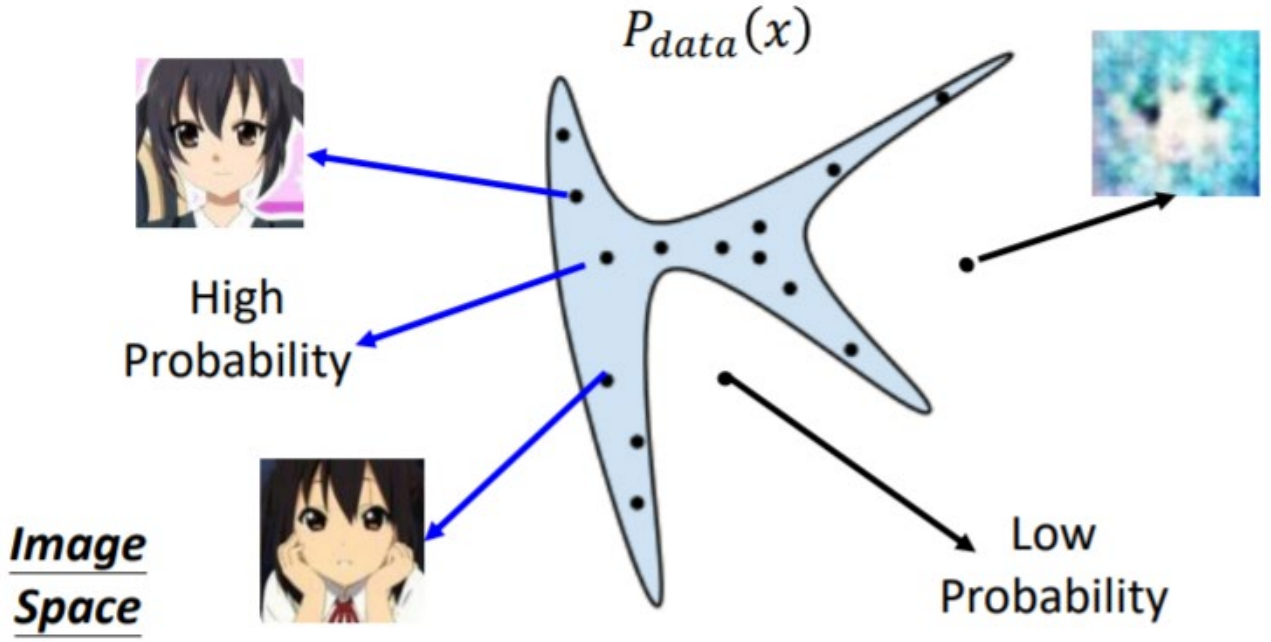
The generator can be modeled as a probability distribution model P_G





X: an image (a high-dimensional vector)

- We want to find data distribution $P_{data}(x)$



Reference: 李弘毅 GAN Lecture 4 (2018) https://youtu.be/DMA4MrNieWo

Based on the distribution model P_G, we want to maximize the likelihood of observing the training images x_1, x_2, …, x_m

- Given a data distribution $P_{data}(x)$ (We can sample from it.)
- We have a distribution $P_G(x;\theta)$ parameterized by θ
  - We want to find θ such that $P_G(x;\theta)$ close to $P_{data}(x)$
  - E.g. $P_G(x;\theta)$ is a Gaussian Mixture Model, θ are means and variances of the Gaussians

Sample $\{x^1, x^2, \ldots, x^m\}$ from $P_{data}(x)$

We can compute $P_G(x^i;\theta)$

Likelihood of generating the samples

$$L = \prod_{i=1}^{m} P_G(x^i;\theta)$$

Find θ^* maximizing the likelihood

Reference: 李弘毅 GAN Lecture 4 (2018) https://youtu.be/DMA4MrNieWo

Review: Based on the distribution model P_G, we want to maximize the likelihood of observing the training images x_1, x_2, x_3, …, x_m

HW6(2) – VAE

Maximizing Likelihood

$$P(x) = \int_z P(z)P(x|z)dz$$

P(z) is normal distribution

$x|z \sim N(\mu(z), \sigma(z))$

$\mu(z), \sigma(z)$ is going to be estimated

$$L = \sum_x logP(x)$$

Maximizing the likelihood of the observed x

$$L = p(x^1) \times p(x^2) \times p(x^3) \times \cdots p(x^m) = \prod_{i=1,\ldots,m} P(x^i)$$

HW4, 5 – MLP, CNN classifier

Training Data	x^1	x^2	x^3	… …	x^N
	C_1	C_1	C_2		C_1

$$L(w,b) = f_{w,b}(x^1)f_{w,b}(x^2)\left(1 - f_{w,b}(x^3)\right)\cdots f_{w,b}(x^N)$$

$$-lnL(w,b) = -lnf_{w,b}(x^1) - lnf_{w,b}(x^2) - ln\left(1 - f_{w,b}(x^3)\right)\cdots$$

$\hat{y}^n$: 1 for class 1, 0 for class 2

$$= \sum_n -\left[\hat{y}^n lnf_{w,b}(x^n) + (1 - \hat{y}^n)ln\left(1 - f_{w,b}(x^n)\right)\right]$$

Cross entropy between two Bernoulli distribution

Compare with RL PPO: Based on the distribution model $P_\theta(\tau)$, We want to maximize the likelihood of obtaining best rewards

$$\tau = (s_1, a_1, r_1, s_2, a_2, r_{2,} \cdots s_T, a_T)$$

See RL training video in my Github/Intelligent-Robot

$$p_\theta(\tau) = p(s_1)p_\theta(a_1|s_1)p(s_2|s_1, a_1)p_\theta(a_2|s_2)p(s_3|s_2, a_2)\cdots$$

$$R(\tau) = \sum_{t=1}^{T} r_t$$

The reward of doing this trajectory under current policy

$$\bar{R}_\theta = \sum R(\tau)\, p_\theta(\tau) = E_{\tau\sim p_\theta(\tau)}[R(\tau)]$$

$$\max_\theta E[\bar{R}_\theta]$$

Maximum likelihood estimation = minimum KL divergence

$$\theta^* = arg\max_\theta \prod_{i=1}^{m} P_G(x^i;\theta) = arg\min_\theta KL(P_{data}||P_G)$$

$$\theta^* = arg\max_\theta \prod_{i=1}^{m} P_G(x^i;\theta) = arg\max_\theta log\prod_{i=1}^{m} P_G(x^i;\theta)$$

$$= arg\max_\theta \sum_{i=1}^{m} logP_G(x^i;\theta)$$ $\{x^1, x^2, \ldots, x^m\}$ from $P_{data}(x)$

$$\approx arg\max_\theta E_{x\sim P_{data}}[logP_G(x;\theta)]$$

$$= arg\max_\theta \int_x P_{data}(x)logP_G(x;\theta)dx - \int_x P_{data}(x)logP_{data}(x)dx$$

$$= arg\min_\theta KL(P_{data}||P_G)$$ How to define a general P_G?

$$\int_x P_{data}(x)logP_{data}(x)dx = logP_{data}(x)$$

$$D_{KL}(q||p) = \sum_{i=1}^{N} q(x_i)\log(\frac{q(x_i)}{p(x_i)})$$

Reference: 李弘毅 GAN Lecture 4 (2018) https://youtu.be/DMA4MrNieWo

Compare with VAE and PPO: : Maximum likelihood estimation = minimum KL divergence

$$\theta^* = arg\max_{\theta} \prod_{i=1}^{m} P_G(x^i;\theta) = arg\min_{\theta} KL(P_{data}||P_G)$$

Variational AE

Minimizing $KL(q(z|x)||P(z))$

Minimize

$$\sum_{i=1}^{3}(exp(\sigma_i) - (1+\sigma_i) + (m_i)^2)$$

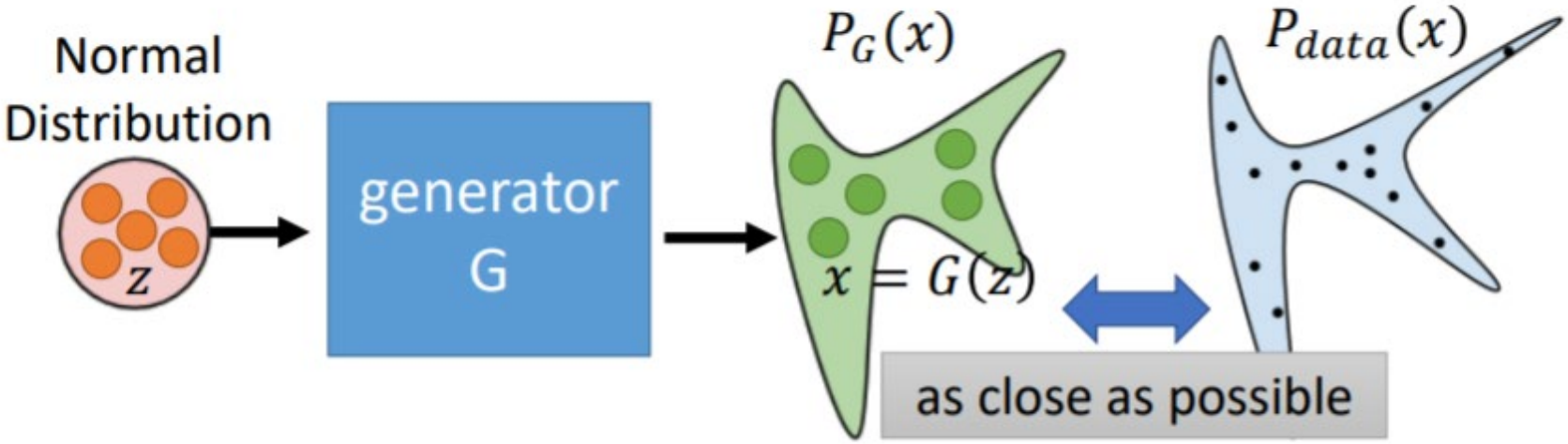
(Refer to the Appendix B of the original VAE paper)

Proximal policy optimization (PPO)

$$J_{PPO}^{\theta'}(\theta) = J^{\theta'}(\theta) - \beta KL(\theta,\theta')$$

How to define a general P_G? – use a generator *NN*

- A generator G is a network. The network defines a probability distribution P_G



$$G^* = arg \min_G Div(P_G, P_{data})$$

Divergence between distributions P_G and P_{data}

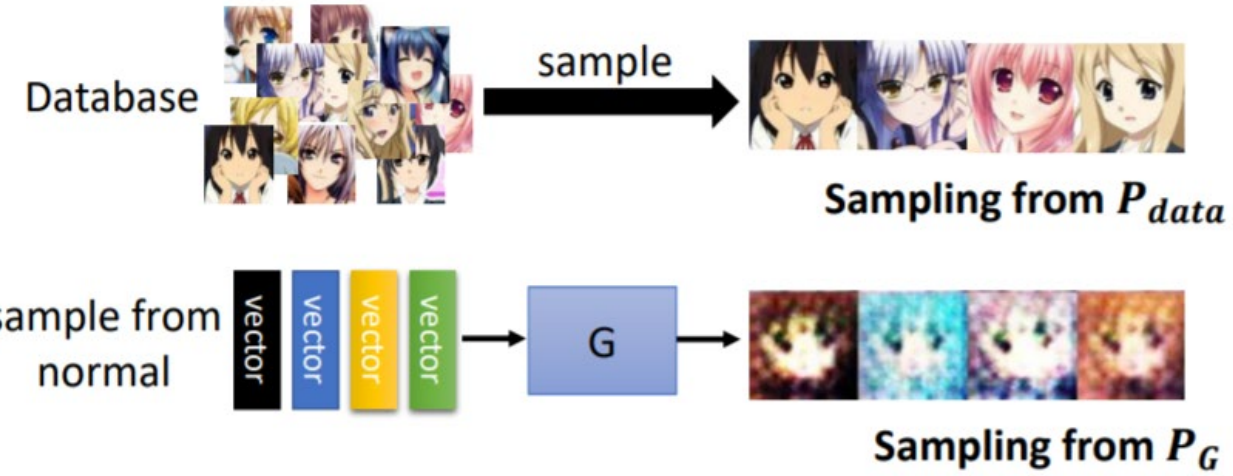
How to compute the divergence?

Reference: 李弘毅 GAN Lecture 4 (2018) https://youtu.be/DMA4MrNieWo

How to compute the divergence? – train a discriminator *NN* to compute the divergence

$$G^* = arg \min_G Div(P_G, P_{data})$$

Although we do not know the distributions of P_G and P_{data}, we can sample from them.




```
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        if(epoch % 10 ==0):
          print(epoch, end=",")
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          # Train discriminator
          loss_d, real_score, fake_score = train_discriminator(real_images.
          # Train generator
          loss_g = train_generator(opt_g)
```

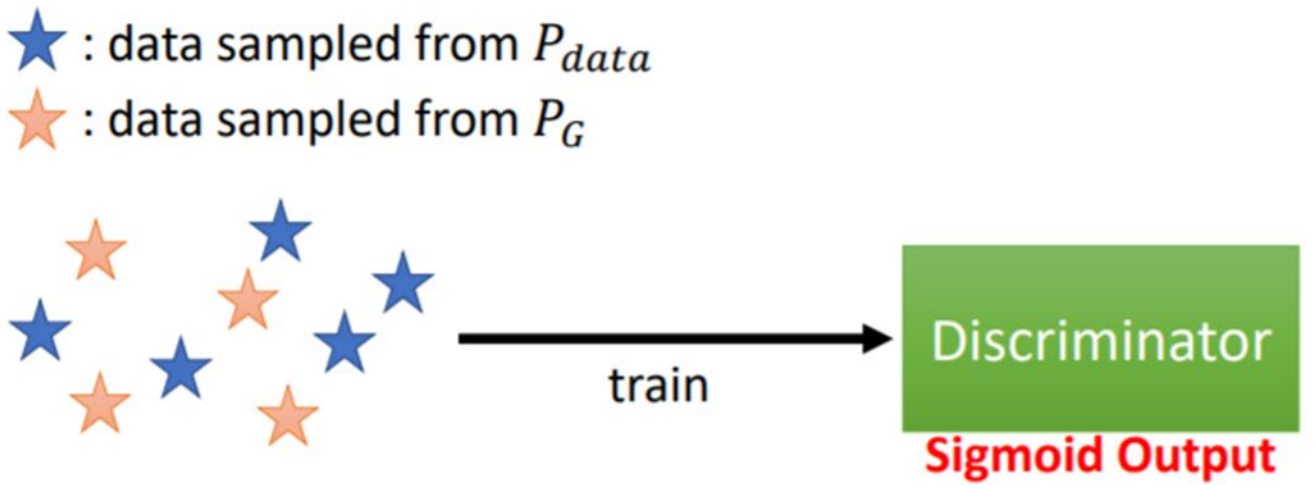
```
[19]: def train_discriminator(real_images, opt_d):
        # Clear discriminator gradients
        opt_d.zero_grad()

        # Pass real images through discriminator
        real_preds = discriminator(real_images)
        real_targets = torch.ones(real_images.size(0)
        real_loss = F.binary_cross_entropy(real_preds
        real_score = torch.mean(real_preds).item()

        # Generate fake images
        latent = torch.randn(batch_size, latent_size,
        fake_images = generator(latent.to(device))
```

Reference: 李弘毅 GAN Lecture 4 (2018) https://youtu.be/DMA4MrNieWo

Train a discriminator *NN* to compute the divergence



Example Objective Function for D

$$V(G,D) = E_{x\sim P_{data}}[logD(x)] + E_{x\sim P_G}[log(1-D(x))]$$

(G is fixed)

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

[Goodfellow, et al., NIPS, 2014]

```
[19]: def train_discriminator(real_images,
        # Clear discriminator gradients
        opt_d.zero_grad()

        # Pass real images through discrim
        real_preds = discriminator(real_im
        real_targets = torch.ones(real_ima
        real_loss = F.binary_cross_entropy
        real_score = torch.mean(real_preds

        # Generate fake images
        latent = torch.randn(batch_size, l
        fake_images = generator(latent.to(

        # Pass fake images through discrim
        fake_targets = torch.zeros(fake_im
        fake_preds = discriminator(fake_im
        fake_loss = F.binary_cross_entropy
        fake_score = torch.mean(fake_preds

        # Update discriminator weights
        loss = real_loss + fake_loss
        loss.backward()
        opt_d.step()
```

Reference: 李弘毅 GAN Lecture 4 (2018) https://youtu.be/DMA4MrNieWo

Review: Loss function for binary classifier

Using the example objective function is exactly the same as training a binary classifier.

The discriminator is a binary classifier (logistic regression) to classify real vs fake

Cross entropy:

$$C(f(x^n), \hat{y}^n) = -\left[\hat{y}^n ln f(x^n) + (1-\hat{y}^n) ln\left(1 - f(x^n)\right)\right]$$

$$V(D,G) = E_{x\sim P_{data}}[logD(x)] + E_{x\sim P_G}[\log(1-D(x))]$$

Adversarial neural networks G and D

So it's difficult to train!!

(1) Train generator – max. likelihood = min. KL divergence between P_G and P_{data}

$$\theta^* = arg\max_{\theta} \prod_{i=1}^{m} P_G(x^i;\theta) = arg\min_{\theta} KL(P_{data}||P_G)$$

(2) Train discriminator – max. divergence between P_G and P_{data}

★ : data sampled from P_{data}

★ : data sampled from P_G

small divergence

large divergence

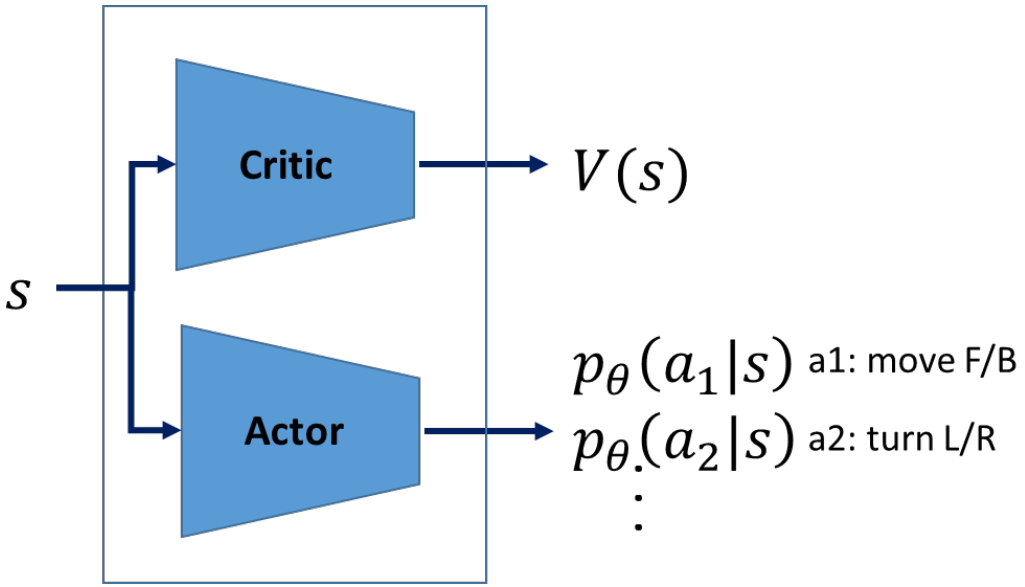
$$V(D,G) = E_{x\sim P_{data}}[logD(x)] + E_{x\sim P_G}[\log(1-D(x))]$$

Training:

$$D^* = arg\max_{D} V(D,G)$$

Compare with RL PPO: Train two neural networks actor and critic together

$$L = c_v L_v + L_\pi - \beta L_{reg}$$



(1) Actor – Learns the best actions (that can have maximum long-term rewards)

$$L_\pi = \sum_{(s_t,a_t)} min\left(\frac{p_\theta(a_t|s_t)}{p_{\theta'}(a_t|s_t)} A^{\theta'}(s_t,a_t), clip\left(\frac{p_\theta(a_t|s_t)}{p_{\theta'}(a_t|s_t)}, 1-\varepsilon, 1+\varepsilon\right) A^{\theta'}(s_t,a_t)\right)$$

(2) Critic – Learns the expected value of the long-term reward.

$$L_v = MSE\ of\ (return - v)$$

The objective function of D is related to JS divergence

$$V(D,G) = E_{x\sim P_{data}}[logD(x)] + E_{x\sim P_G}[\log(1-D(x))]$$

- Given G, what is the optimal D* maximizing

$$V = E_{x\sim P_{data}}[logD(x)] + E_{x\sim P_G}[log(1-D(x))]$$

$$= \int_x P_{data}(x)logD(x)\,dx + \int_x P_G(x)log(1-D(x))\,dx$$

$$= \int_x [P_{data}(x)logD(x) + P_G(x)log(1-D(x))]\,dx$$

Assume that D(x) can be any function

- Given x, the optimal D* maximizing

$$P_{data}(x)logD(x) + P_G(x)log(1-D(x))$$

Reference: 李弘毅 GAN Lecture 4 (2018) https://youtu.be/DMA4MrNieWo

The objective function of D is related to JS divergence

$$V(D,G) = E_{x\sim P_{data}}[logD(x)] + E_{x\sim P_G}[\log(1-D(x))]$$

$$\max_D V(G,D) = V(G,D^*) \qquad D^*(x) = \frac{P_{data}(x)}{P_{data}(x)+P_G(x)}$$

$$= -2log2 + \int_x P_{data}(x) log \frac{P_{data}(x)}{\left(P_{data}(x)+P_G(x)\right)/2} dx$$

$$+ \int_x P_G(x) log \frac{P_G(x)}{\left(P_{data}(x)+P_G(x)\right)/2} dx$$

$$= -2\log2 + \mathrm{KL}\left(\mathrm{P_{data}} || \frac{\mathrm{P_{data}}+\mathrm{P_G}}{2}\right) + \mathrm{KL}\left(\mathrm{P_G} || \frac{\mathrm{P_{data}}+\mathrm{P_G}}{2}\right)$$

$$= -2log2 + 2JSD(P_{data}||P_G)$$ Jensen-Shannon divergence

Reference: 李弘毅 GAN Lecture 4 (2018) https://youtu.be/DMA4MrNieWo

So the objective function of the generator G is a min max function

$$G^* = arg \min_G Div(P_G, P_{data})$$

$$D^* = arg \max_D V(D, G) \qquad V(D, G) = E_{x \sim P_{data}}[logD(x)] + E_{x \sim P_G}[\log(1 - D(x))]$$

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

- Initialize generator and discriminator
- In each training iteration:

  Step 1: Fix generator G, and update discriminator D

  Step 2: Fix discriminator D, and update generator G

Reference: 李弘毅 GAN Lecture 4 (2018) https://youtu.be/DMA4MrNieWo

Why the algorithm can solve the min-max optimization problem?

Reference: 李弘毅 GAN Lecture 4 (2018) https://youtu.be/DMA4MrNieWo

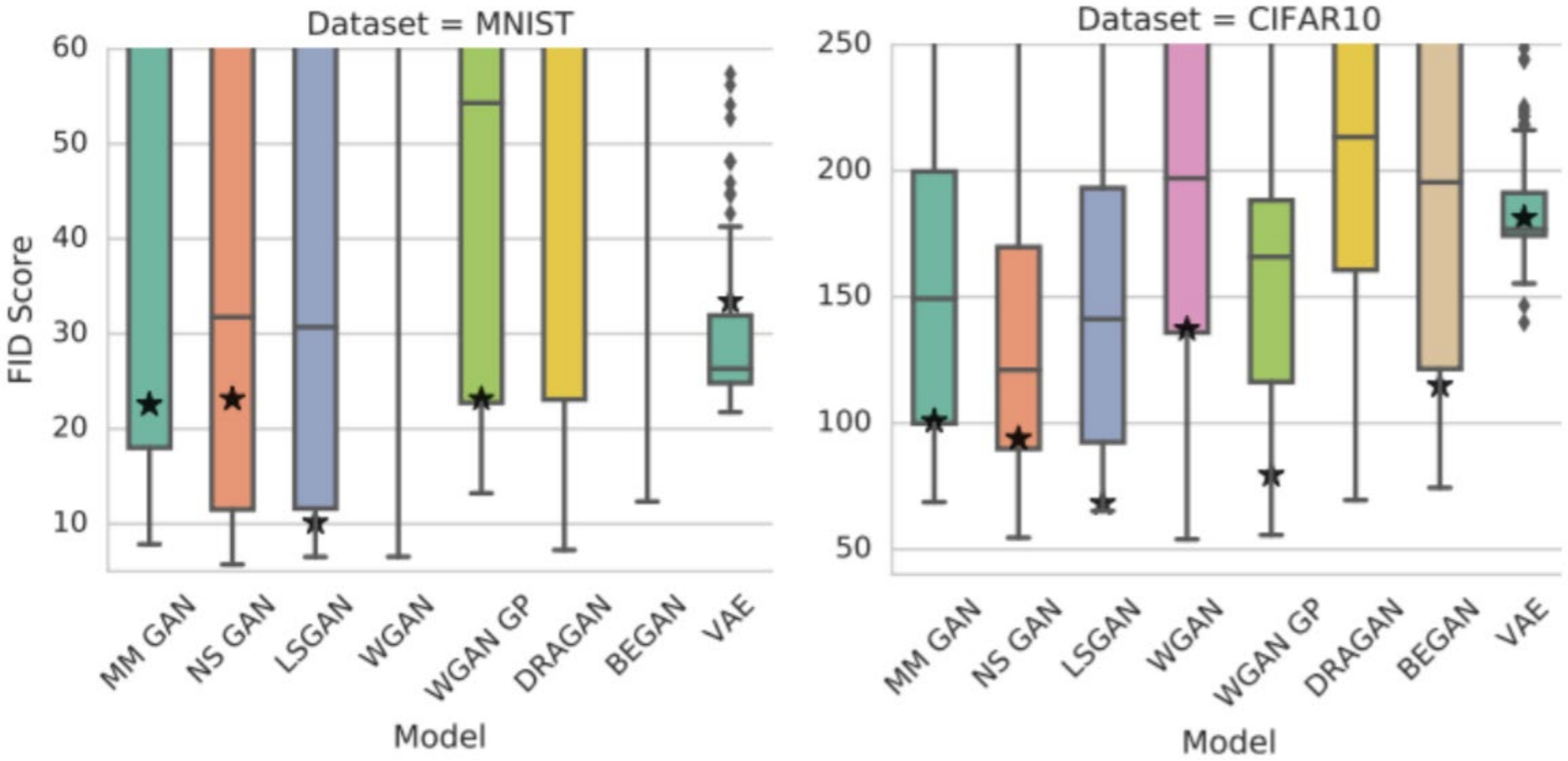
Solve the min-max optimization problem

Reference: 李弘毅 GAN Lecture 4 (2018) https://youtu.be/DMA4MrNieWo

Solve the min-max optimization problem

Reference: 李弘毅 GAN Lecture 4 (2018) https://youtu.be/DMA4MrNieWo

GAN is sensitive to hyper-parameter tuning and its performance range is large. Different GANs' performances are similar



Reference: 李弘毅 GAN Lecture 1 (2018): https://youtu.be/DQNNMiAP5lw