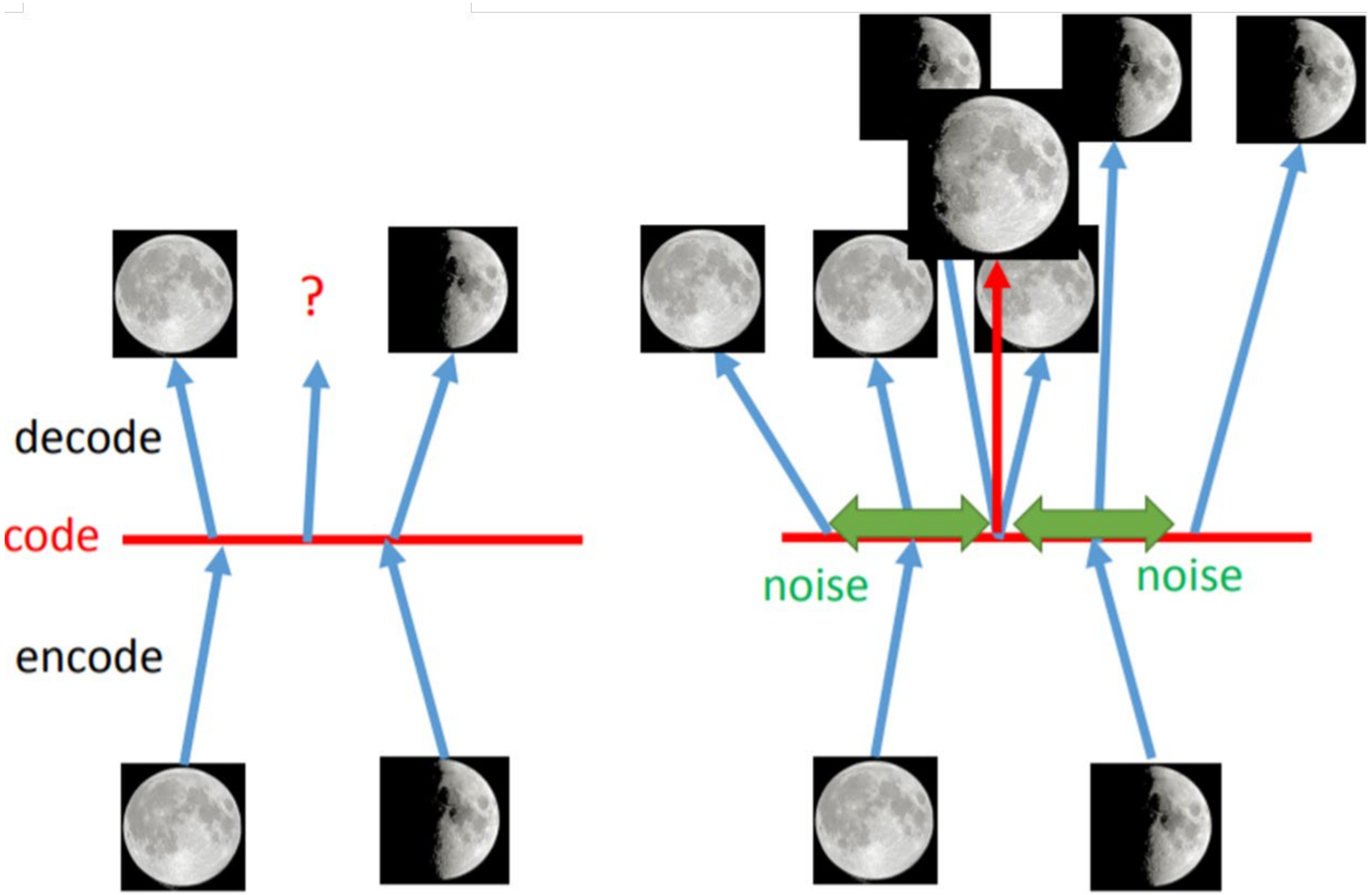
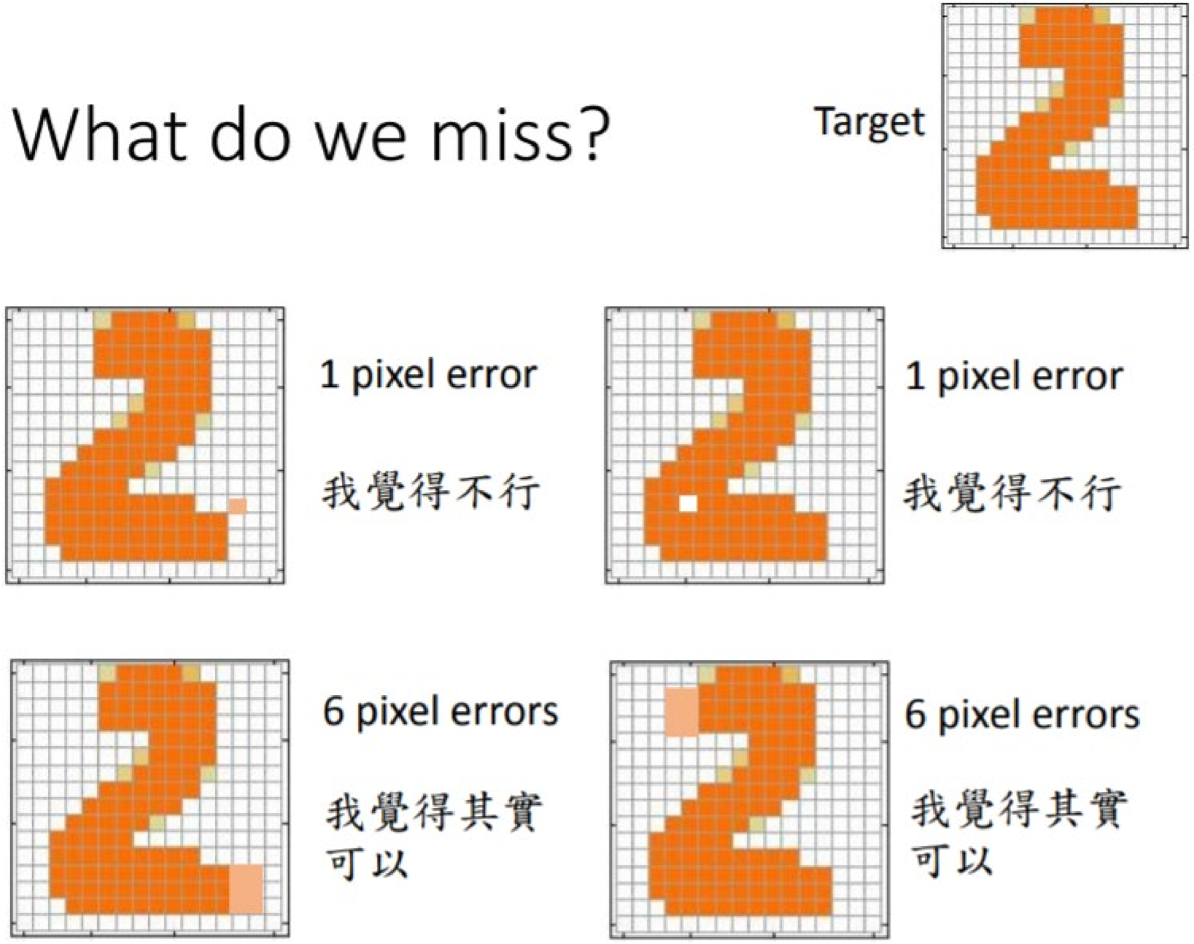
Generative Adversarial Network (GAN)

Images generated by AE/VAE are blur

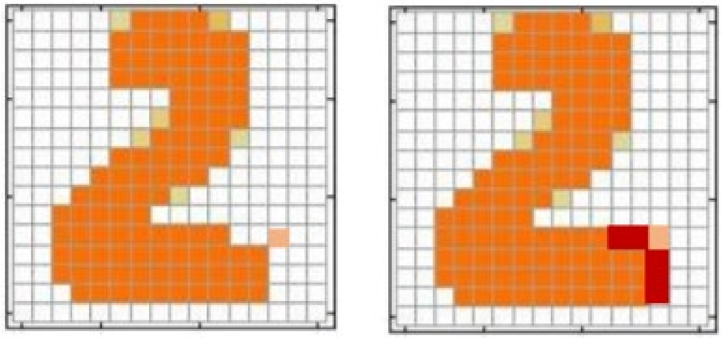


Decoder in AE or VAE generates images that minimize MSE + KL. It does not consider the context information

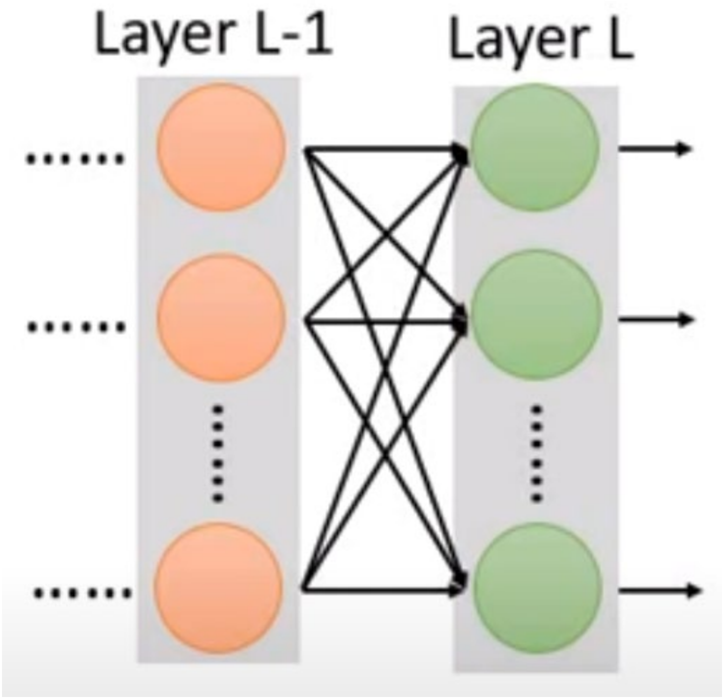


Reference: 李弘毅 GAN Lecture 1 (2018): https://youtu.be/DQNNMiAP5lw

The decoder does not consider the structured relationships between pixels



我覺得不行　我覺得其實可以



The relation between the components are critical.

Although highly correlated, they cannot influence each other.

Need deep structure to catch the relation between components.

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

Advantages of GAN

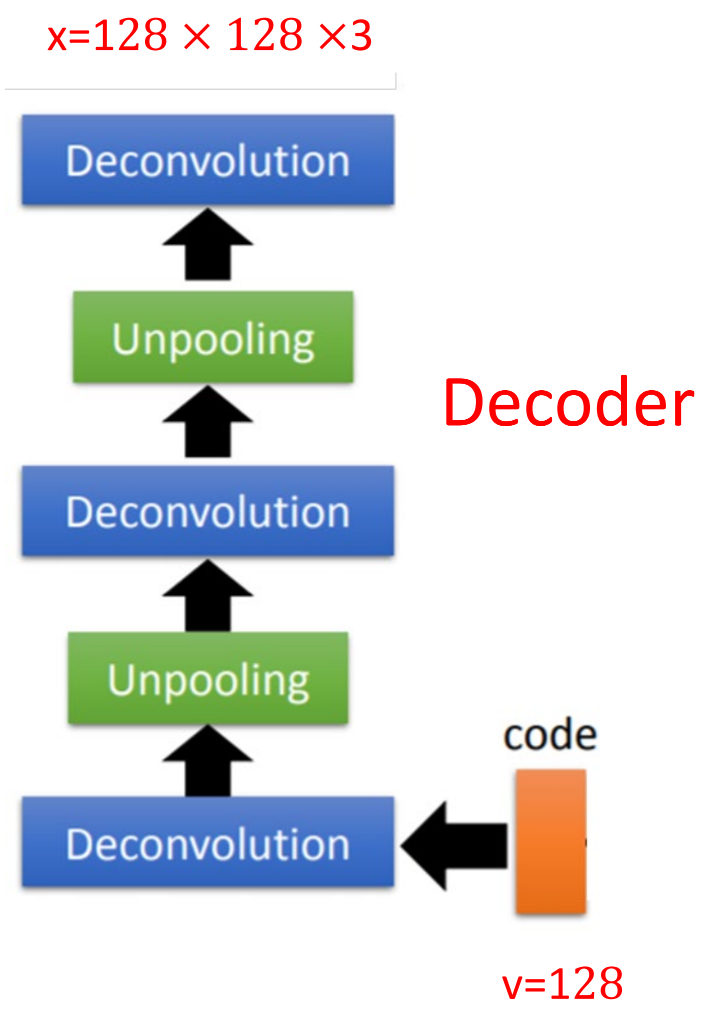
- Still generate the object component-by-component
- But it is learned from the discriminator with global view.

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

Practice

- Open “8.1. GAN.ipynb"

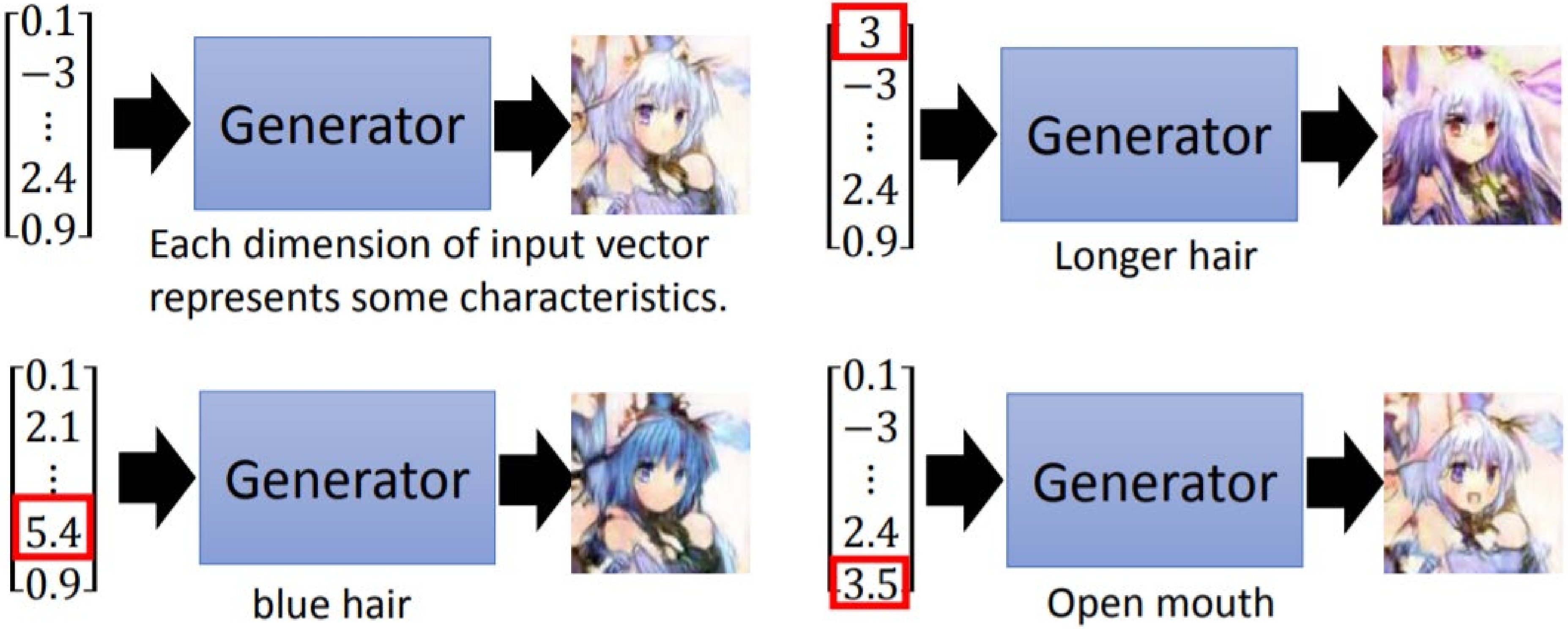
Generator




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

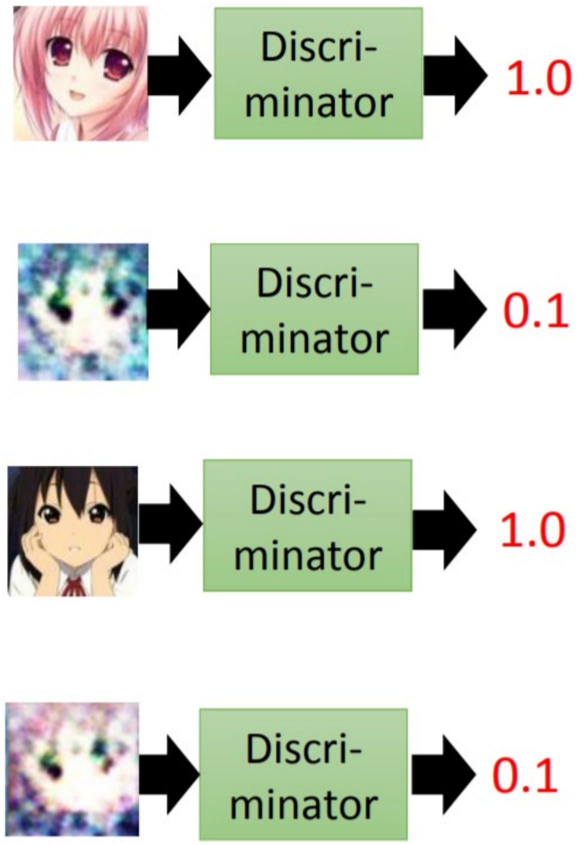
```
[11]: generator = nn.Sequential(
          # in: latent_size x 1 x 1

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

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

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

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

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

          nn.ConvTranspose2d(32, 3, kernel_size=4, stride=2, padding=1,
          nn.Tanh()
          # out: 3 x 128 x 128
      )
```

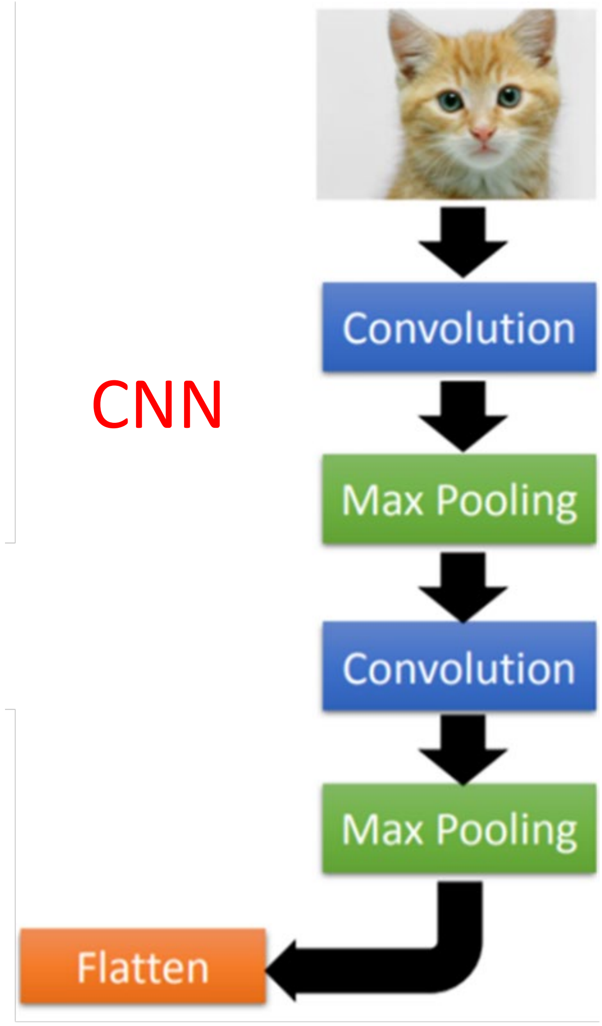
Each dimension in the feature vector represent a property of the output image



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

Discriminator






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

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

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

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

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

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

          nn.Conv2d(1024, 1, kernel_size=4, stride=1,
          # out: 1 x 1 x 1

          nn.Flatten(),
          nn.Sigmoid())
```

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

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

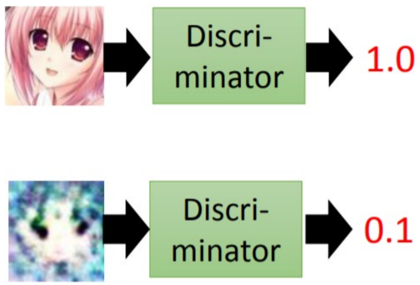
```
[16]: discriminator.to(device)
```

```
[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 D

- 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 $\{\tilde{x}^1, \tilde{x}^2, \dots, \tilde{x}^m\}$, $\tilde{x}^i = G(z^i)$



$$D(x^i) \rightarrow 1,\ \log D(x^i) \rightarrow 0$$

$$D(\tilde{x}^i) \rightarrow 0,\ \log(1 - D(\tilde{x}^i)) \rightarrow 0$$

log(0.xxx) <0

Update discriminator parameters θ_d to maximize

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

[19]:

```python
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
```

Review – Cross entropy

Measures the differences between the true probability p_i and the predicted probability q_i

$$H(p,q) = -\sum_i p_i ln(q_i)$$

A	B	C	D	E	F	G	H	I	J	K
z1	z2	y-hat	p1	p2	EXP(z1)	EXP(z2)	F+G	q1	q2	-(P1*LN(Q1)+P2*LN(Q2))
-0.018	0.0855	0	1	0	0.982	1.089	2.071	0.474	0.526	0.74624
-0.0244	0.0741	0	1	0	0.976	1.077	2.053	0.475	0.525	0.74361
-0.0187	0.085	0	1	0	0.981	1.089	2.070	0.474	0.526	0.74634
-0.0258	0.0687	1	0	1	0.975	1.071	2.046	0.476	0.524	0.64701
-0.0267	0.0617	1	0	1	0.974	1.064	2.037	0.478	0.522	0.64992
										0.70662

Step2 – Fix D and train G

Step 2: Fix discriminator D, and update generator G

Generator learns to “fool” the discriminator

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

[35]:

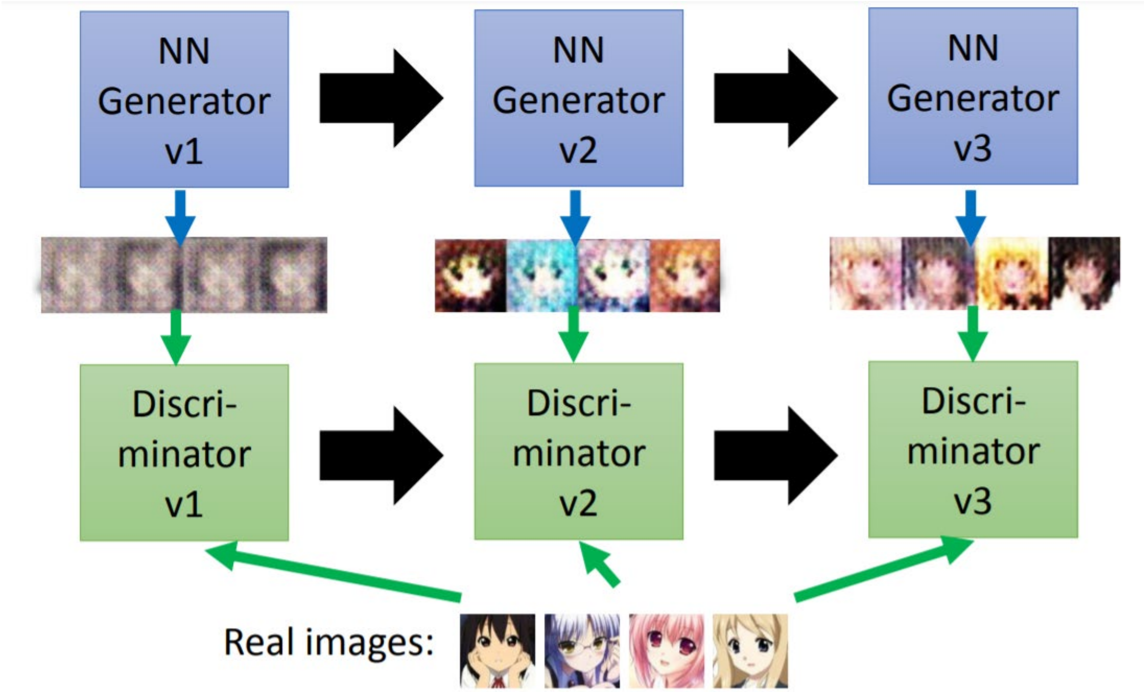
```
for epoch in range(epochs):
  if(epoch % 10 ==0):
    print(epoch, end=",")
  for real_images, _ in train_dl:
    # Train discriminator
    loss_d, real_score, fake_score =
    # Train generator
    loss_g = train_generator(opt_g)
```

[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

```
[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

Visualize fake images generated by *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
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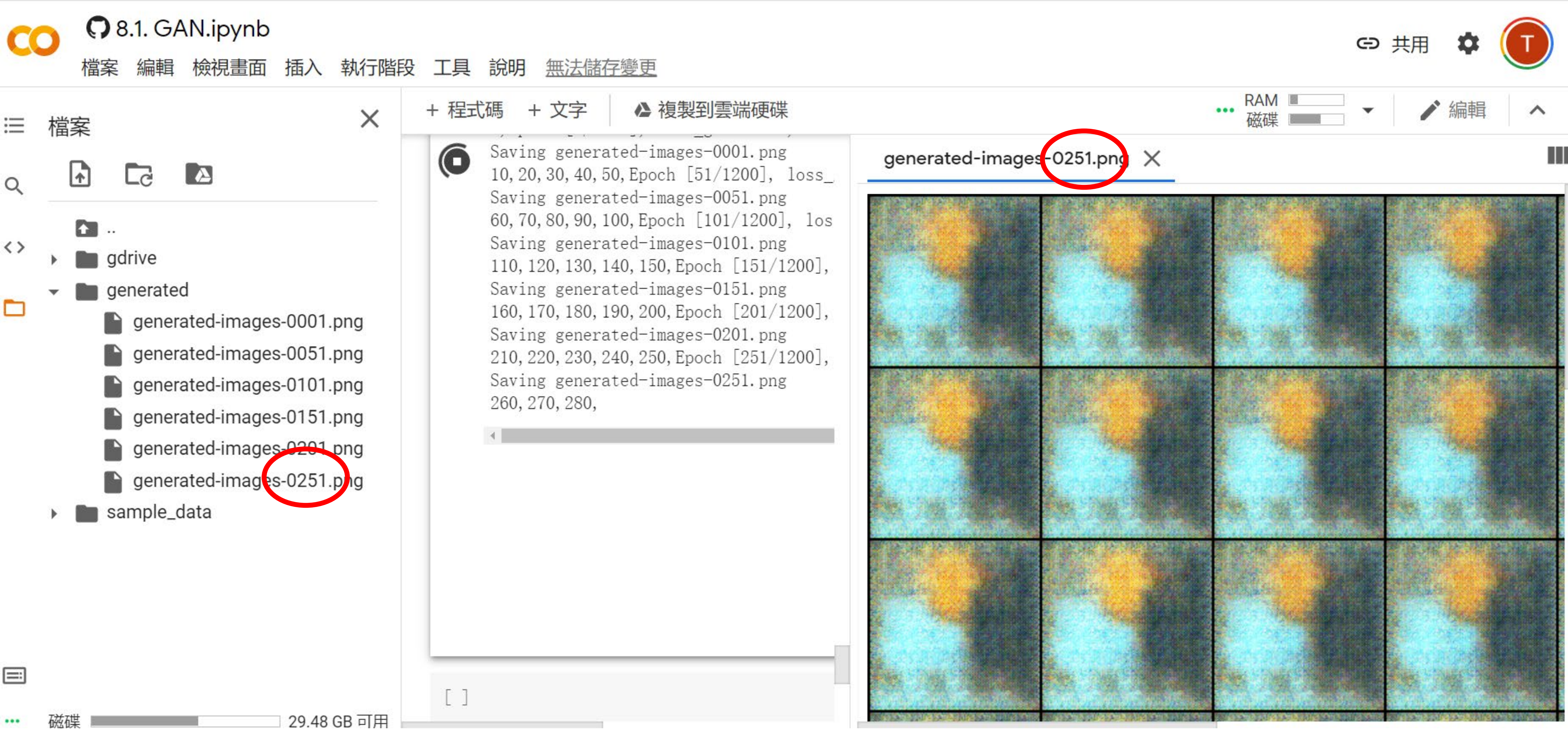
generated-images-0051.png
generated-images-0101.png
generated-images-0151.png
generated-images-0201.png
sample_data
Log losses & scores (l
print("Epoch [{}/{}], loss_
epoch+1, epochs, lo
# Save generated images
latent = torch.randn(batch_
save_samples(epoch+start_idx,
#save_samples(epoch+start_idx
0, 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


8.1. GAN.ipynb
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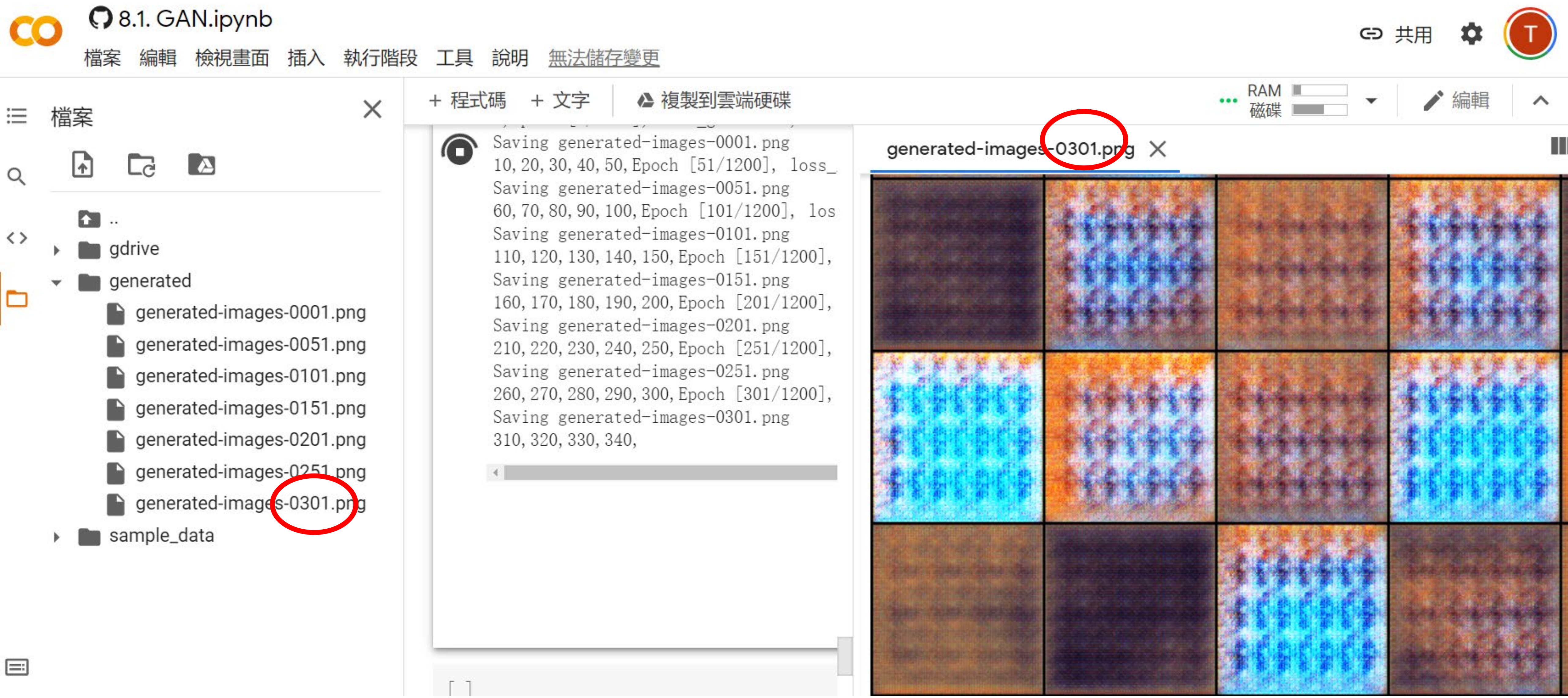
generated-images-0151.png
generated-images-0201.png
generated-images-0251.png
sample_data
Saving generated-images-0001.png
10, 20, 30, 40, 50, Epoch [51/1200], loss_
Saving generated-images-0051.png
60, 70, 80, 90, 100, Epoch [101/1200], los
Saving generated-images-0101.png
110, 120, 130, 140, 150, Epoch [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
磁碟
29.48 GB 可用


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
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

Epoch =41201

34151

28651

25901

23201

16401

15551

14301

Save the generated images as a video

```
[37]: img_array = []
for filename in files:
  img = cv2.imread(filename)
  height, width, layers = img.shape
  size = (width,height)
  img_array.append(img)

out = cv2.VideoWriter('GANTrainingVideo.avi',cv2.VideoWriter_fourcc(*'DIVX'), 15, size)

for i in range(len(img_array)):
    out.write(img_array[i])
out.release()
```

Tom & Jerry video https://youtu.be/uDEGITFmhiQ

HW7 (1)

- Use your own images, e.g., facial expression to train a GAN.
- Show the generated images.
- Try latent vectors like (all 1), (all 0.5), (all 0.3), (0, 0, 1, 0, ….), (one dimension goes from 0 to 1 and other dimensions fixed), … to see the generated images.

Study images generated with different latent vectors

[78]:
```
latent0 = torch.zeros(1, latent_size, 1, 1)
latent1 = torch.ones(1, latent_size, 1, 1)
latentNeg1 = -torch.ones(1, latent_size, 1, 1)

#let feature_idx dimension = a value and all other dimensions = 0 (or 1, -1)
NewLatent0 = torch.zeros(1, latent_size, 1, 1)
#NewLatent0[:, 3, :, :]= 50
NewLatent0[:, 123, :, :]= -50
```

[84]:
```
fake_img = denorm(fake_img)
plt.imshow(fake_img)
```

t[84]: `<matplotlib.image.AxesImage at 0x7fd9d8d14b50>`

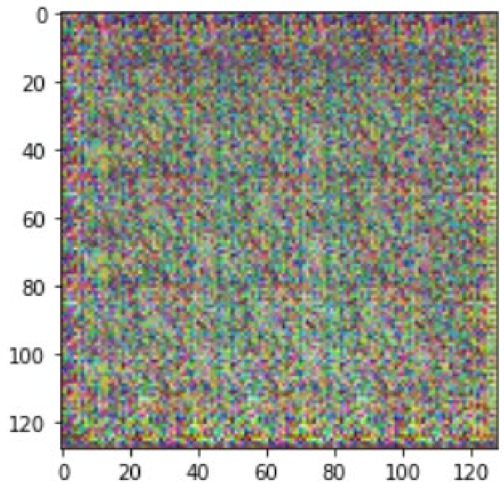
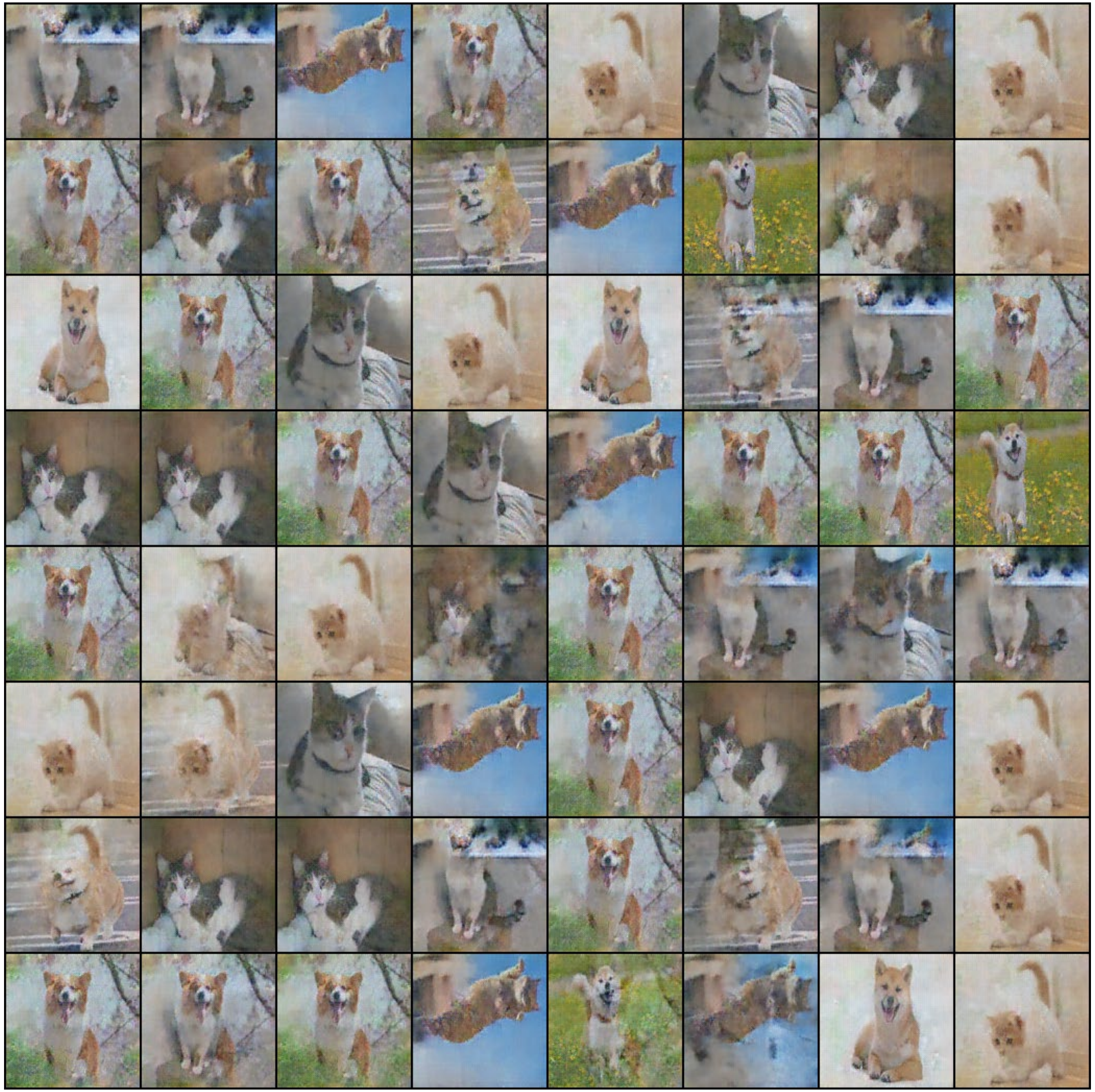


Image size = 128*128*3
Class 1 = 10, class2 = 10
Latent vector size = 128
Batch = 128
Colab run 30K epochs, 2-3hr



1071333 鄭皓文

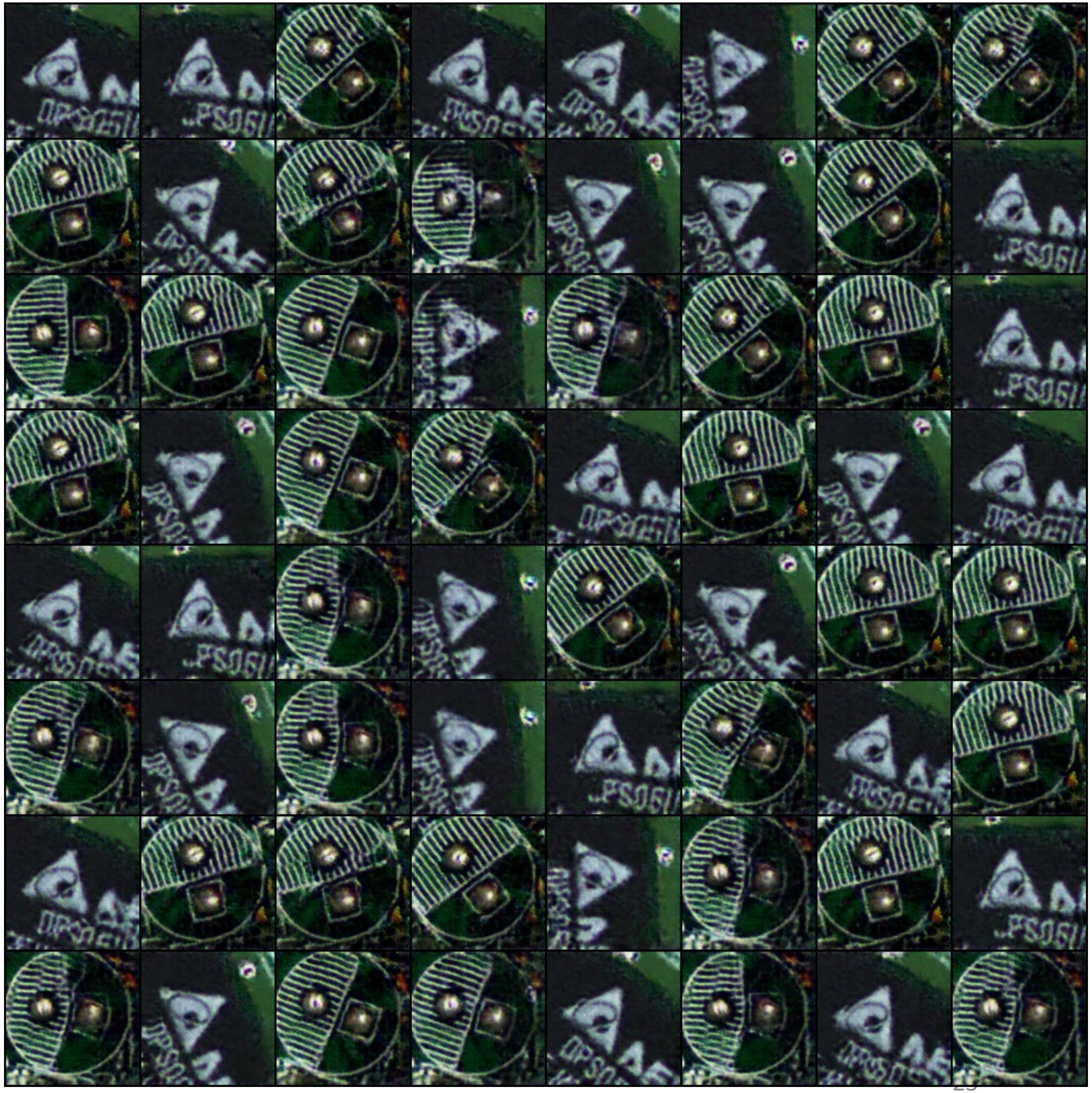
Image size = 128*128*3
Class 1 = 10, class2 = 10
Latent vector size = 128
Batch = 128
Anaconda run 23.4K epochs

1071333 鄭皓文

Images generated from *G* after 5651 epochs

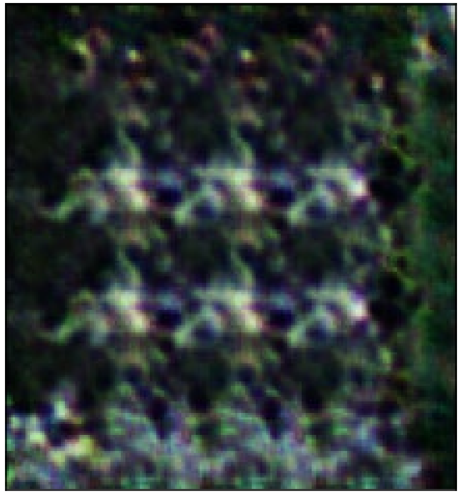
Image size = 180x180x3
Class 1 = 100, Class 2 = 100
Latent vector size = 128
batch=32

Run on 2080Ti, takes about 15 min.



Images generated from different latent vectors

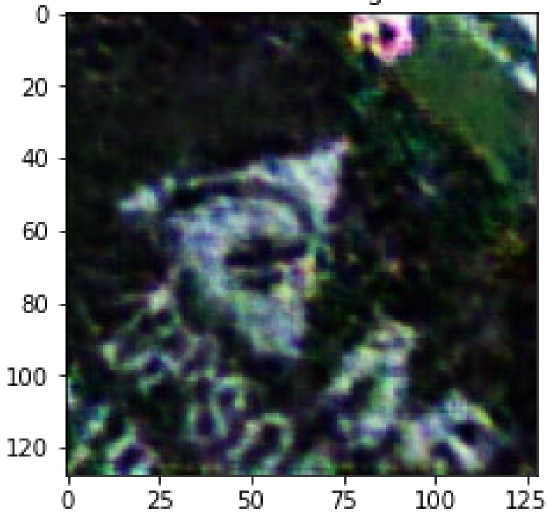
[0, 0, 0...0]



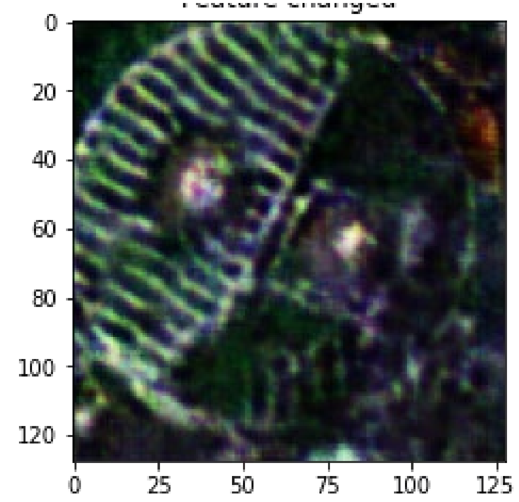
[1, 1, 1...1]

[-1, -1, -1...-1]

[1, 1, 1...1], feature 3=50

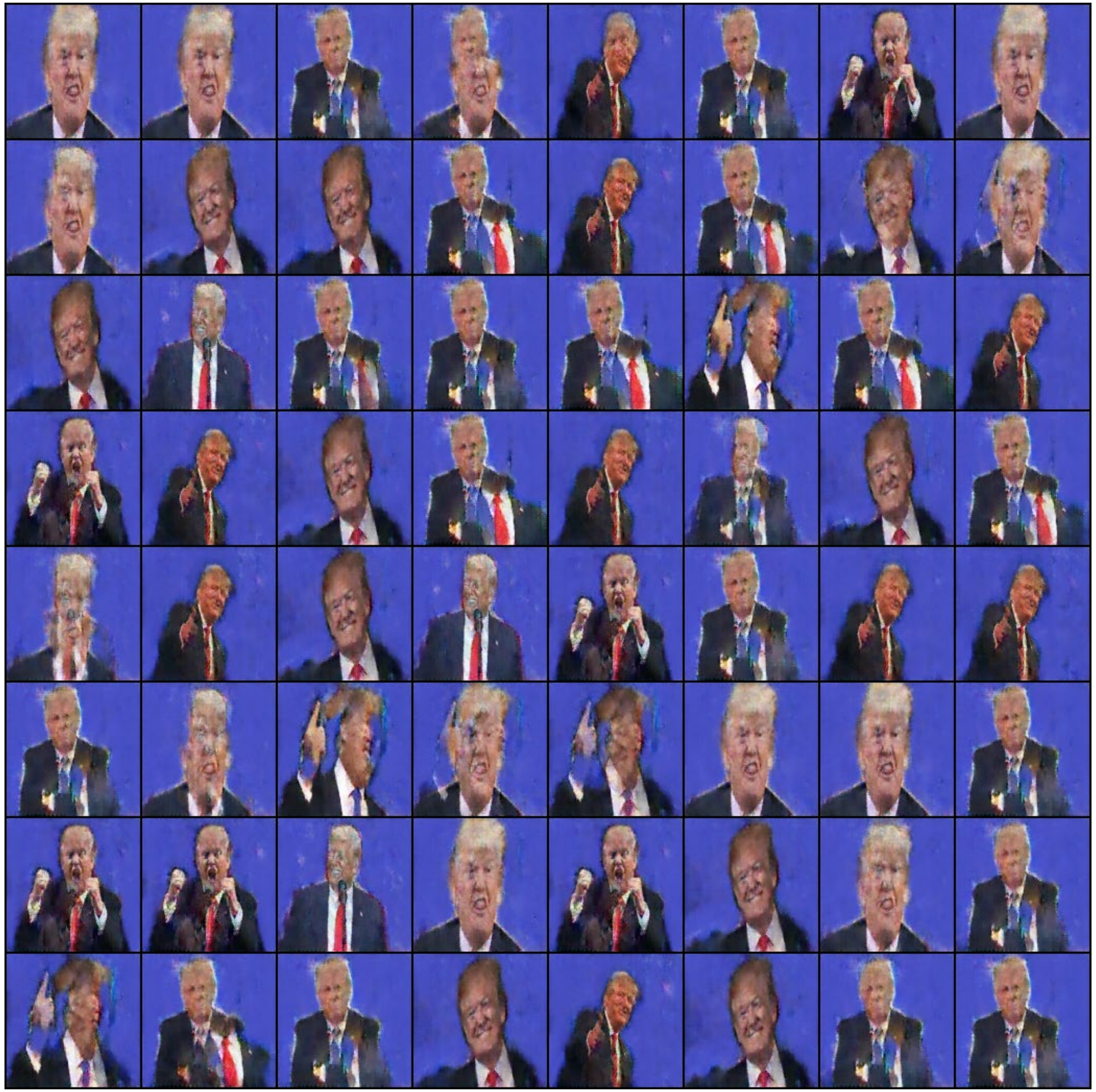


[1, 1, 1...1], feature 123=50

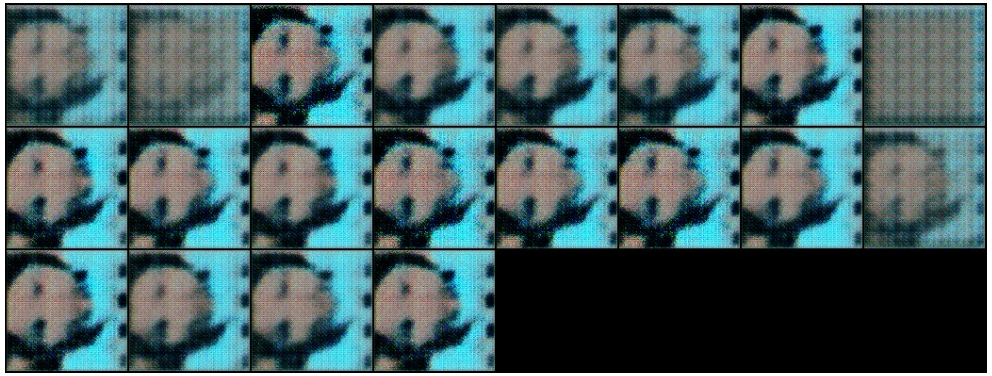


Epoch =8K

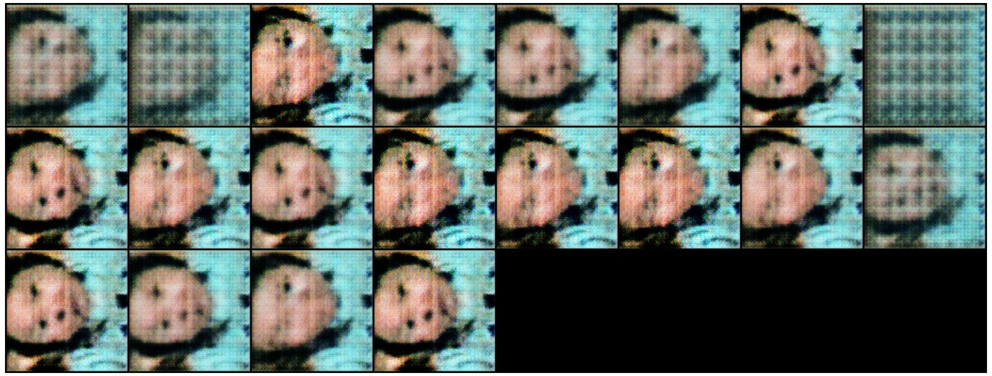
Epoch =20K



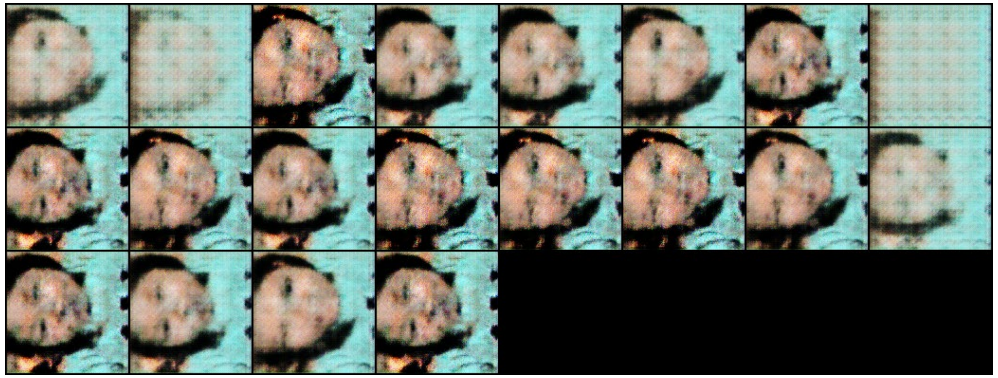
image_size = 128
batch_size = 64
latent_size= 1
epochs = 400



Epoch = 151



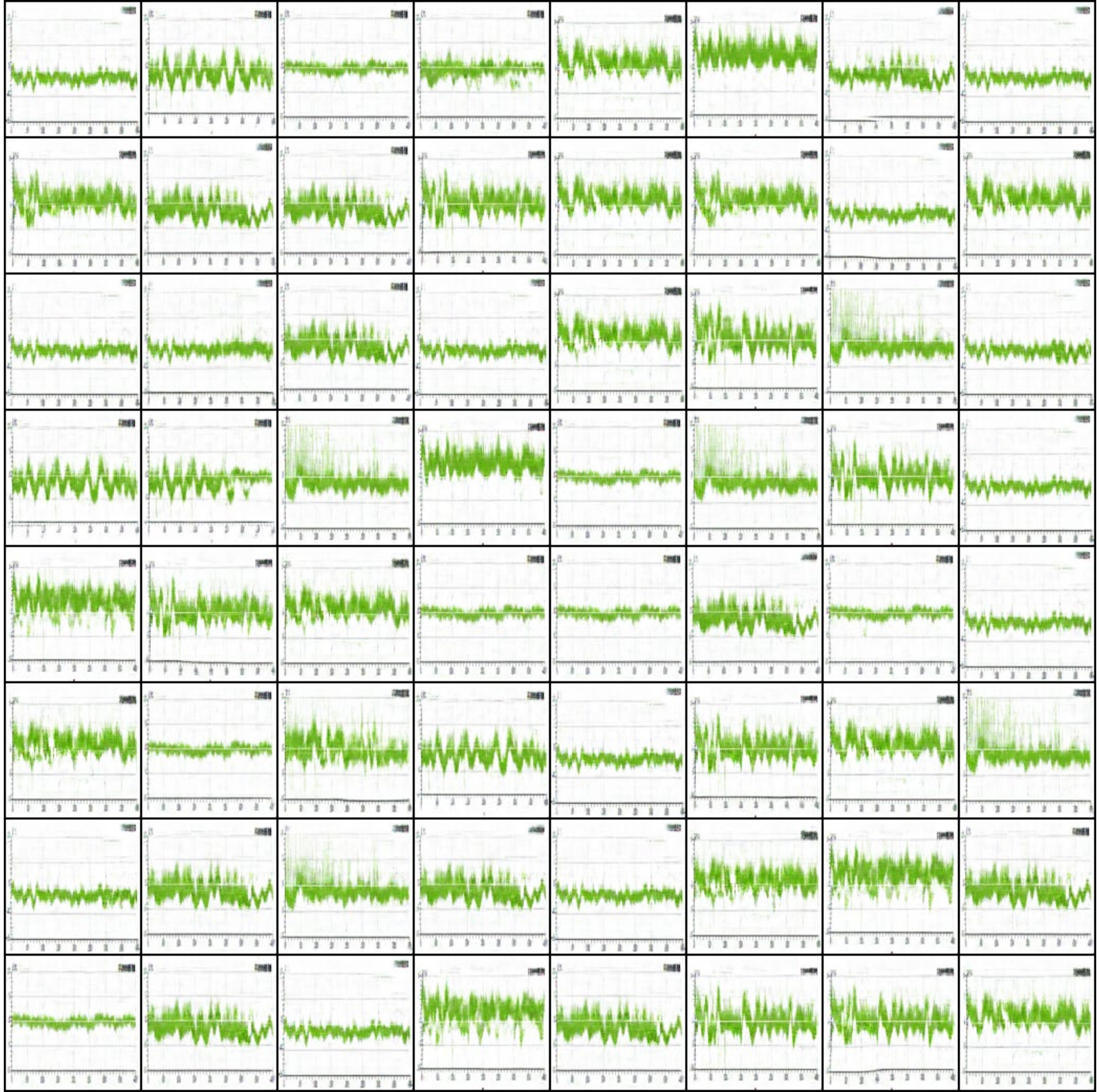
251



301

351

Images-19951



1071228 陳仁慶

Images generated from *G* after 2100 epochs

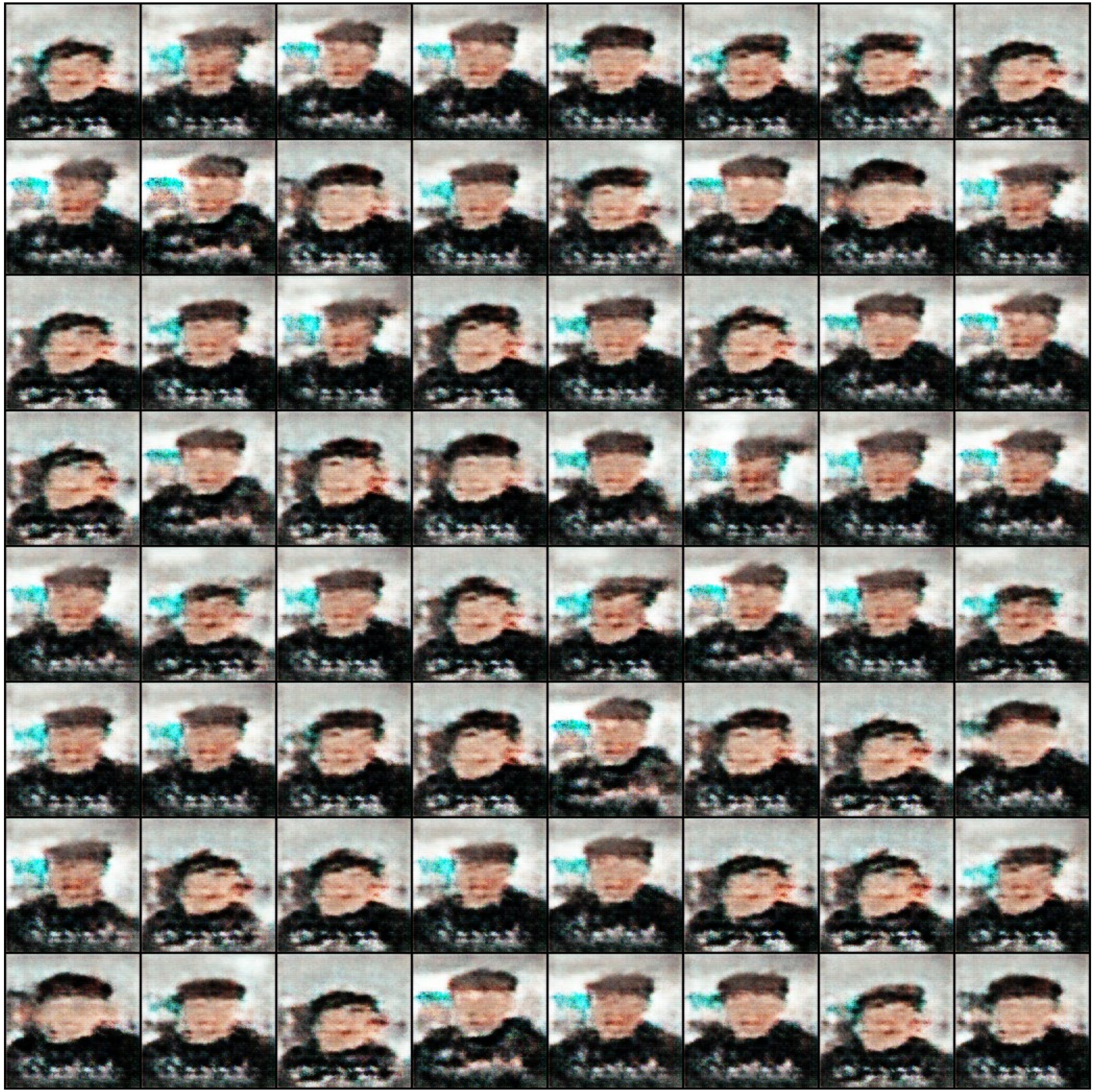
Image size = 128x128x3
Class 1 = 10, Class 2 = 10
Latent vector size = 128
batch=128

Run on Colab Tesla K80, takes about 120 min.

Images generated from *G* after 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.

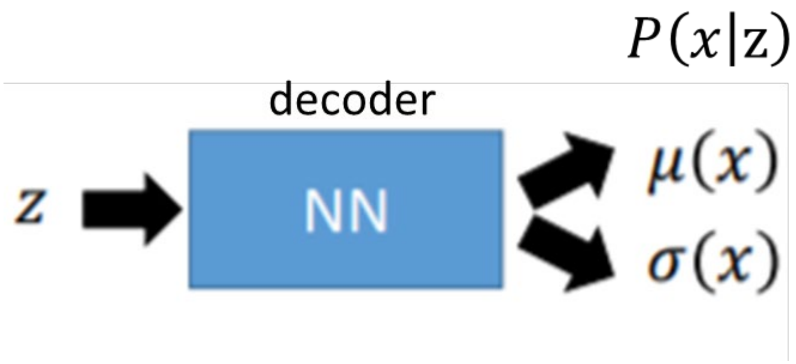


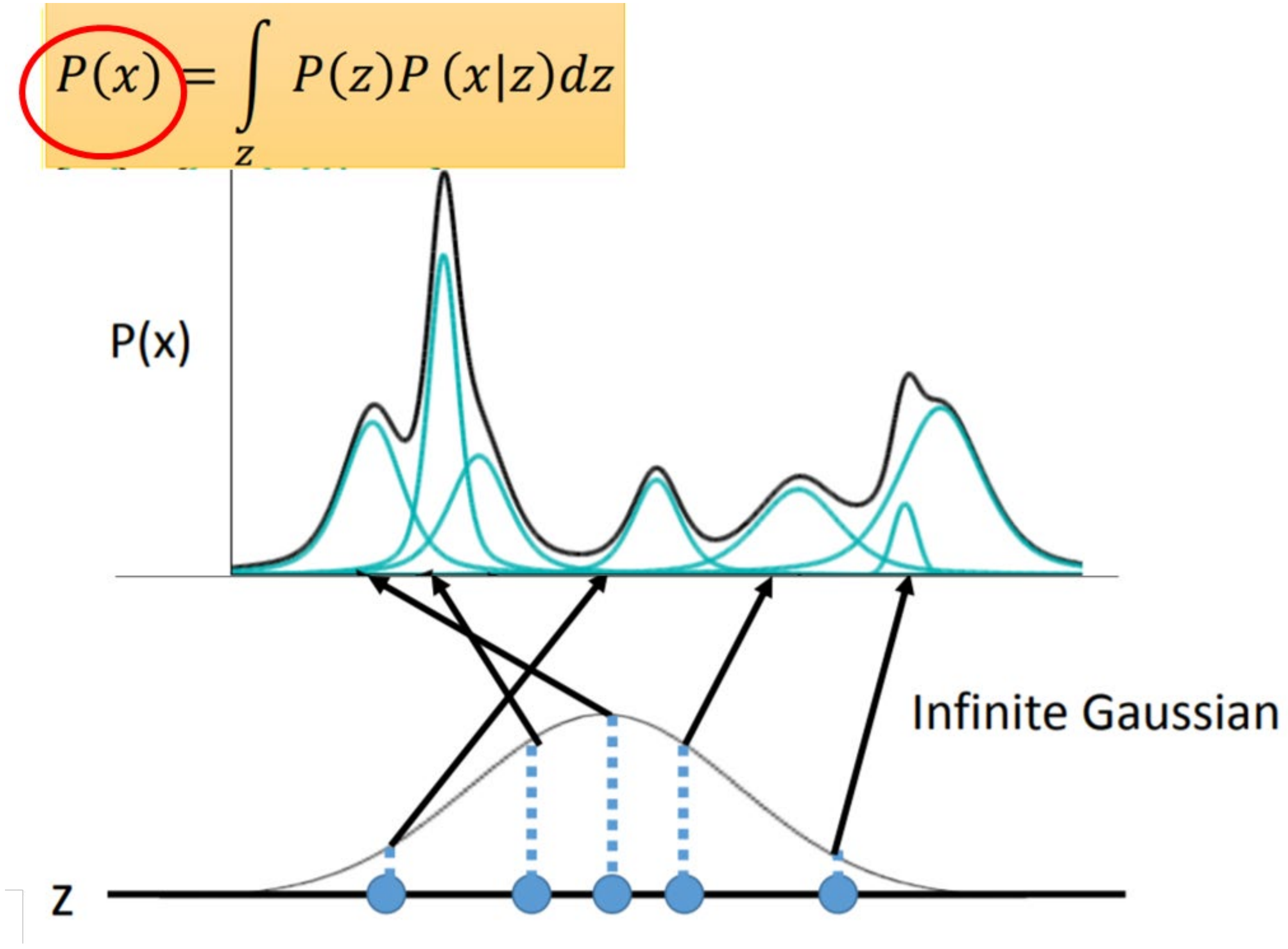
Theory behind GAN, VAE, PPO

The concept of deep generative model

1. Use probability distribution model to model the image generation process or the state-action generation process.
2. With this probability model, we want to maximize the likelihood to observe the training data or observe the trajectories with higher long-term rewards.
3. Maximize the likelihood can be achieved by minimizing the KL divergence.
3. Use DNN to represent a more general probability model.
4. Use DNN to represent a more general divergence measure.

(VAE) 1. Modelling the image generation process as a mixed Gaussian distribution model





Reference: 李弘毅 ML Lecture 18 https://youtu.be/8zomhgKrsmQ

(VAE) 2. Given the image generation model, we want to maximize the likelihood to observe the training images

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

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

Reference: 李弘毅 ML Lecture 18 https://youtu.be/8zomhgKrsmQ

(VAE) 3. Maximize the likelihood can be achieved by minimizing KL divergence

Max. L_b can be done by min. $KL(q(z|x)||P(z))$ and max. $\int_z q(z|x)logP(x|z)dz$. That is why loss = KLD + MSE (x, $\hat{x}$)

Minimize

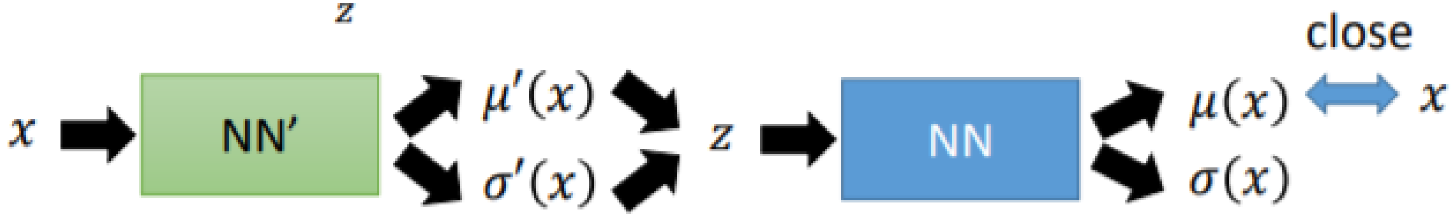
$$\sum_{i=1}^{3}(exp(\sigma_i) - (1 + \sigma_i) + (m_i)^2)$$

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

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

Maximizing

$$\int_z q(z|x)logP(x|z)dz \;= E_{q(z|x)}[logP(x|z)]$$



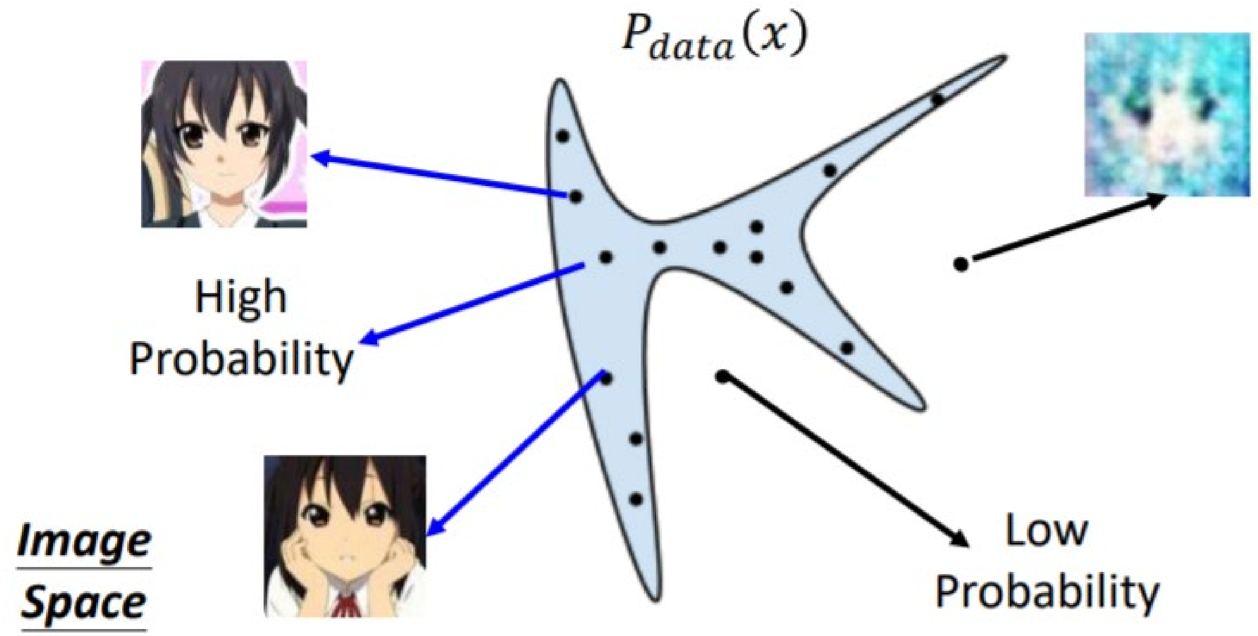
by min. $MSE(x, \hat{x})$

Reference: 李弘毅 ML Lecture 18 https://youtu.be/8zomhgKrsmQ

(GAN) 1. Modelling the generator 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

(GAN) 2. Given the image generation model, we want to maximize the likelihood to observe the training images

- 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

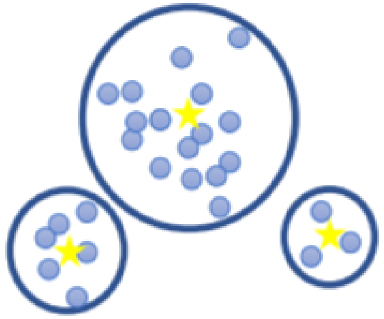
Sample $\{x^1, x^2, \dots, x^m\}$ from $P_{data}(x)$

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

(GAN) 3. Maximize the likelihood can be achieved by minimizing the KL divergence

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?

$$\int_x \mathrm{P}_{data}(x)logP_{data}(x)dx = logP_{data}(x)$$

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

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

(Classification) 1. Assuming the training data is generated from $y_1 = P_{w,b}(C_1|\, x) = \sigma(w \cdot x + b)$ 2. Maximize the likelihood to observe the training data

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

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

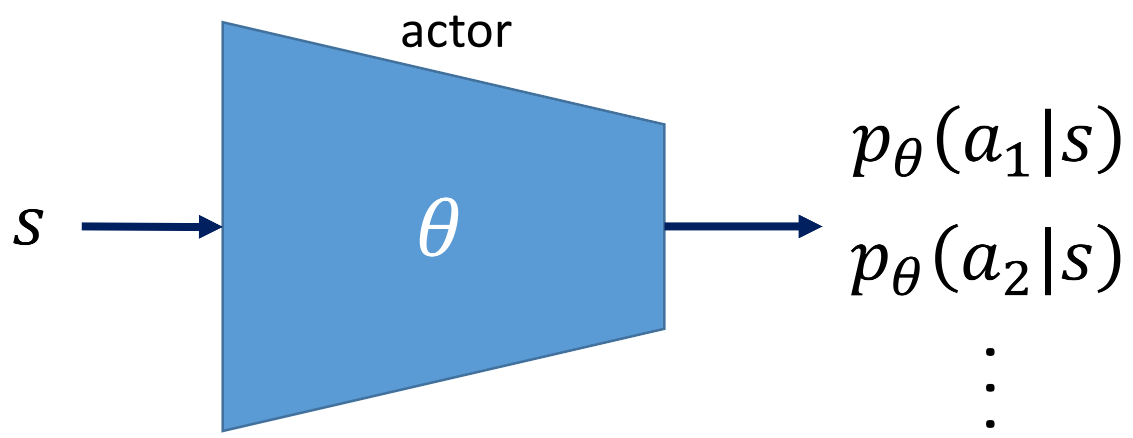
$$-lnL(w,b) = lnf_{w,b}(x^1) + lnf_{w,b}(x^2) + ln\left(1 - f_{w,b}(x^3)\right) \cdots$$

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

$$= \sum_n \underbrace{-\left[\hat{y}^n lnf_{w,b}(x^n) + (1-\hat{y}^n) ln\left(1 - f_{w,b}(x^n)\right)\right]}_{\text{Cross entropy between two Bernoulli distribution}}$$

Reference: 李弘毅 ML Lecture 5 https://youtu.be/hSXFuypLukA

(PPO) 1. Modelling the state-action mapping network as $p_\theta(a|s)$



(PPO) 2. Given the probability model, we want to maximize the likelihood to observe trajectories with higher long-term rewards

$$\tau = \left(s_1, a_1, r_1, s_2, a_2, r_{2,} \cdots s_\mathrm{T}, a_\mathrm{T}\right)$$

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

$$\bar{R}_\theta = \sum R(\tau)\,p_\theta(\tau) = E_{\tau\sim p_\theta(\tau)}[R(\tau)] \qquad \mathrm{R}(\tau) = \sum_{\mathrm{t}=1}^{\mathrm{T}} \mathrm{r}_\mathrm{t}$$

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

$$\nabla\bar{R}_\theta = \sum R(\tau)\,\nabla p_\theta(\tau) = E_{\tau\sim p_\theta(\tau)}[R(\tau)\nabla \mathrm{log} p_\theta(\tau)] \approx \frac{1}{N}\sum_{n=1}^{N} R(\tau^n)\nabla \mathrm{log} p_\theta(\tau^n)$$

$$= \frac{1}{N}\sum_{n=1}^{N}\sum_{t=1}^{T_n} R(\tau^n)\nabla \mathrm{log} p_\theta(a_t^n|s_t^n)$$

(PPO) 3. To facilitate off-policy sampling, we minimize the KL divergence

Off-policy

$$\nabla \bar{R}_\theta = E_{(s_t,a_t)\sim\pi_{\theta'}}\left[\frac{p_\theta(a_t|s_t)}{p_{\theta'}(a_t|s_t)}A^{\theta'}(s_t,a_t)\nabla \log p_\theta(a_t^n|s_t^n)\right]$$

Loss function

$$\mathrm{J}^{\theta'}(\theta) = E_{(s_t,a_t)\sim\pi_{\theta'}}\left[\frac{p_\theta(a_t|s_t)}{p_{\theta'}(a_t|s_t)}A^{\theta'}(s_t,a_t)\right]$$

Proximal policy optimization (PPO)

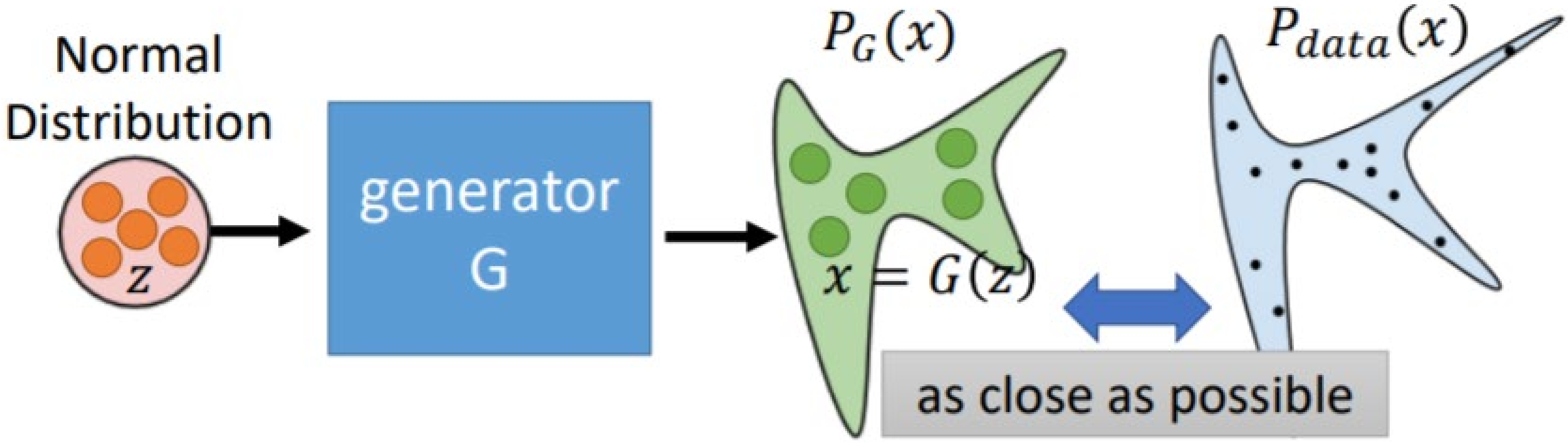
$$J_{PPO}^{\theta'}(\theta) = J^{\theta'}(\theta) - \beta KL(\theta,\theta')$$

$$J_{PPO2}^{\theta'}(\theta) = \sum_{(s_t,a_t)} min\left(\frac{p_\theta(a_t|s_t)}{p_{\theta'}(a_t|s_t)}A^{\theta'}(s_t,a_t), clip\left(\frac{p_\theta(a_t|s_t)}{p_{\theta'}(a_t|s_t)}, 1-\varepsilon, 1+\varepsilon\right)A^{\theta'}(s_t,a_t)\right)$$

Schulman, J., Wolski, F., Dhariwal, P., Radford, A., & Klimov, O. (2017). Proximal policy optimization algorithms. arXiv preprint arXiv:1707.06347.

4. Use DNN to represent a more general probability model

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



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

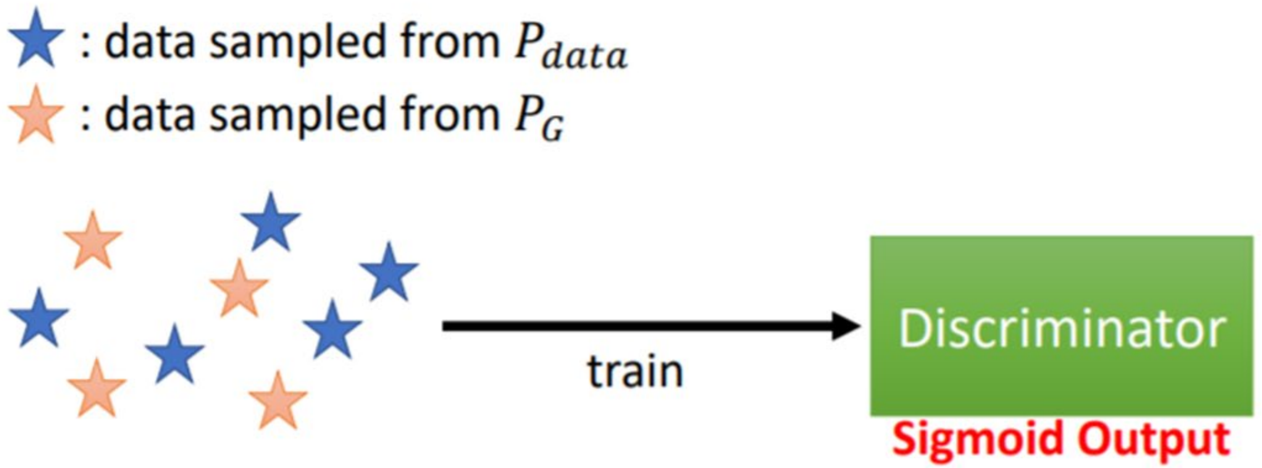
Divergence between distributions P_G and P_{data}

How to compute the divergence?

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

5. Use DNN to represent a more general divergence measure

How to compute the divergence when a NN is used to represent a more general probability model? – 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: $D^* = arg \boxed{\max_D V(D,G)}$

[Goodfellow, et al., NIPS, 2014]

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

The objective function for *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

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

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

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

Assume that D(x) can be any function

- Given x, the optimal D* maximizing

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

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

The objective function for *D* is related to JS divergence

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

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

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

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

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

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

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

The objective function for *D* is implemented as binary cross entropy

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

Binary Classifier

D is a binary classifier with sigmoid output (can be deep)

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

$\{\tilde{x}^1, \tilde{x}^2, \ldots, \tilde{x}^m\}$ from $P_G(x)$ ➡ Negative examples

Minimize Cross-entropy

Cross entropy:

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

(GAN) Two adversarial neural networks *G* and *D*

(1) Train generator

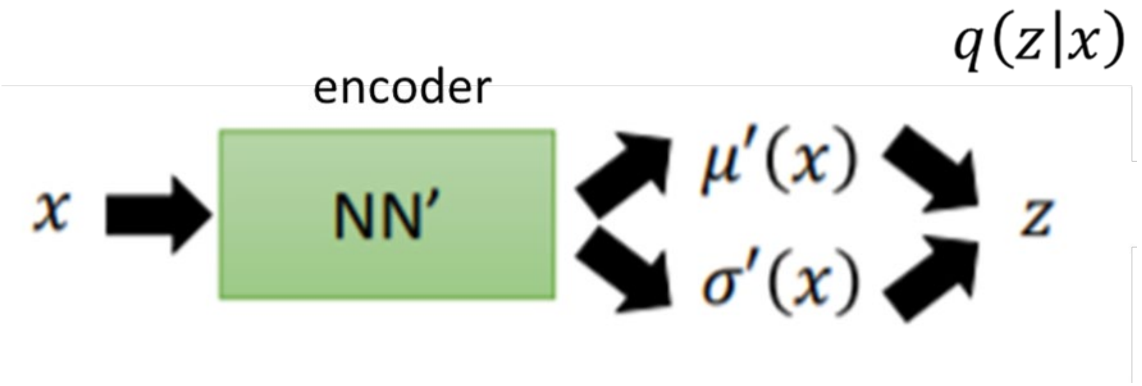
$$G^* = arg\min_G Div(P_G, P_{data})$$

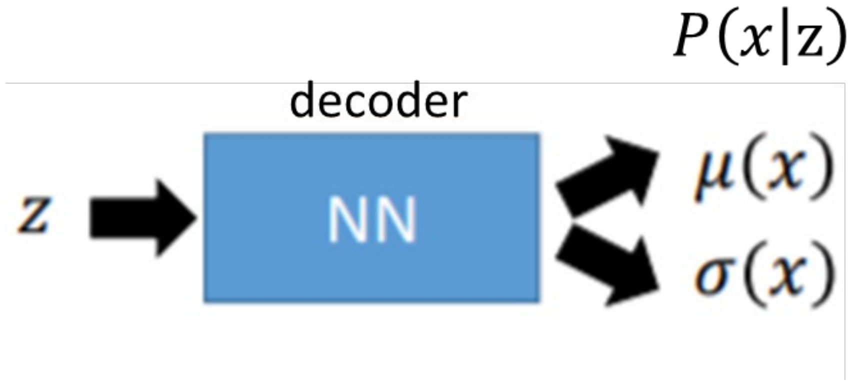
(2) Train discriminator

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

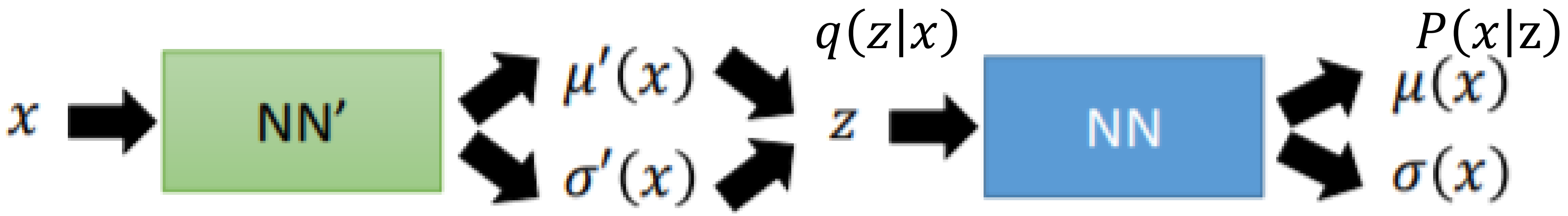
$$V(D,G) = E_{x \sim P_{data}}[logD(x)] + E_{x \sim P_G}[\log(1 - D(x))]$$

(VAE) Two sequential neural networks, one encode and one decode



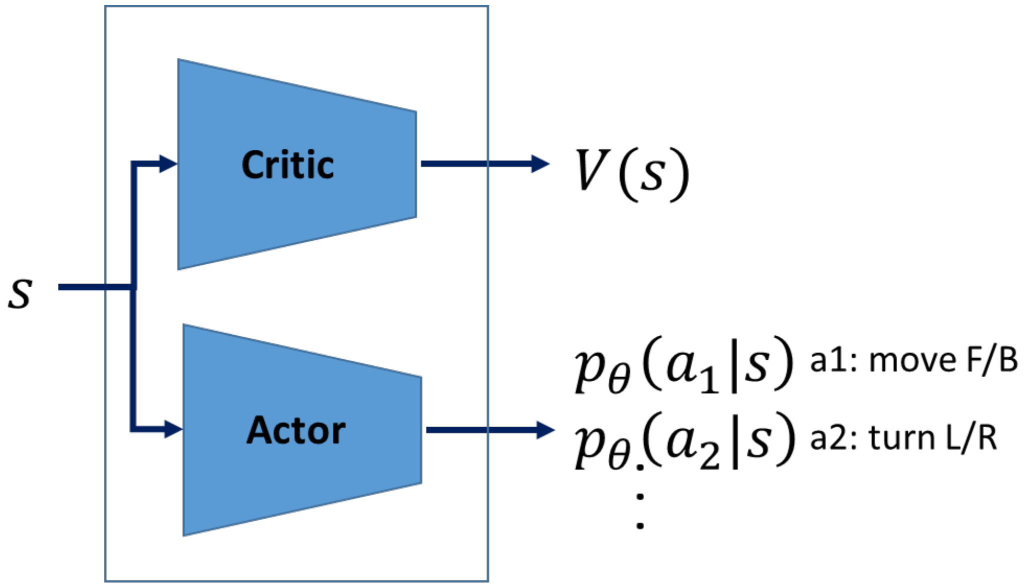


$$L = MSE(x, \hat{x}) + KL(q(z|x)||P(z))$$



(PPO-AC) Two parallel neural networks, one actor and one critic

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



(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.

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

Algorithm

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

- Given G_0
- Find D_0^* maximizing $V(G_0, D)$

$V(G_0, D_0^*)$ is the JS divergence between $P_{data}(x)$ and $P_{G_0}(x)$

- $\theta_G \leftarrow \theta_G - \eta \, \partial V(G, D_0^*)/\partial \theta_G$ ⟹ Obtain G_1 — Decrease JS divergence(?)
- Find D_1^* maximizing $V(G_1, D)$

$V(G_1, D_1^*)$ is the JS divergence between $P_{data}(x)$ and $P_{G_1}(x)$

- $\theta_G \leftarrow \theta_G - \eta \, \partial V(G, D_1^*)/\partial \theta_G$ ⟹ Obtain G_2 — Decrease JS divergence(?)
- ……

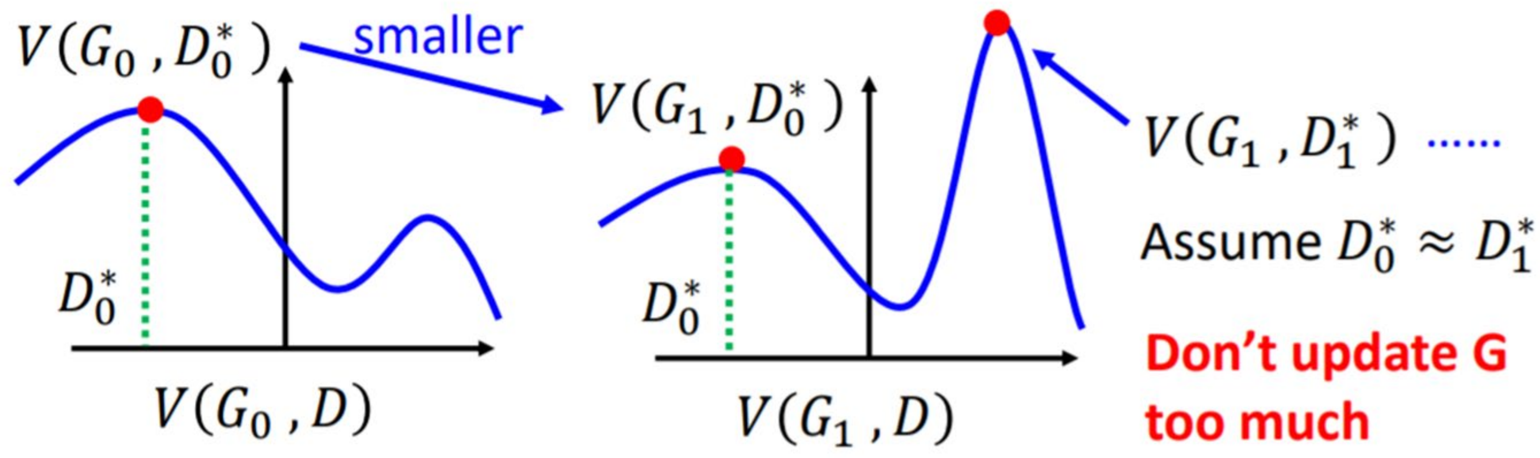
$$D^* = arg \max_D V(D, G)$$

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

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

Do not update G too much...

When we update G from G_0 to G_1, the divergence measurement function $V(G_0, D^*)$ will no longer fully represent the JS divergence between P_G and P_{data}



(PPO): We do not update $p_\theta(a_t|s_t)$ too much so that we can calculate $p_{\theta'}(a_t|s_t)$ off-policy

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

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

But we should update D as much as possible

- In each training iteration:

Learning D

$\boxed{\text{Repeat k times}}$

- Sample m examples $\{x^1, x^2, \dots, x^m\}$ from data distribution $P_{data}(x)$
- Sample m noise samples $\{z^1, z^2, \dots, z^m\}$ from the prior $P_{prior}(z)$
- 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
  - $\tilde{V} = \frac{1}{m}\sum_{i=1}^{m} logD(x^i) + \frac{1}{m}\sum_{i=1}^{m} log\left(1 - D(\tilde{x}^i)\right)$
  - $\theta_d \leftarrow \theta_d + \eta \nabla \tilde{V}(\theta_d)$

Learning G

$\boxed{\text{Only Once}}$

- Sample another m noise samples $\{z^1, z^2, \dots, z^m\}$ from the prior $P_{prior}(z)$
- Update generator parameters θ_g to minimize
  - $\tilde{V} = \cancel{\frac{1}{m}\sum_{i=1}^{m} logD(x^i)} + \frac{1}{m}\sum_{i=1}^{m} log\left(1 - D\left(G(z^i)\right)\right)$
  - $\theta_g \leftarrow \theta_g - \eta \nabla \tilde{V}(\theta_g)$

In [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), 1, dev
    real_loss = F.binary_cross_entropy(real_preds, real_t
    real_score = torch.mean(real_preds).item()

    # Generate fake images
    latent = torch.randn(batch_size, latent_size, 1, 1, c
    fake_images = generator(latent.to(device))

    # Pass fake images through discriminator
    fake_targets = torch.zeros(fake_images.size(0), 1, de
    fake_preds = discriminator(fake_images)
    fake_loss = F.binary_cross_entropy(fake_preds, fake_t
    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
```

For loop for *k* times?

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